Long-Term System Planning for Large-Scale Renewable Energy Integration: Methodology Development

Ph.D. Thesis

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by

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DECLARATION

I **PARTHA DAS**, declare that this thesis titled, "**Long-Term System Planning for Large-Scale Renewable Energy Integration: Methodology Development**", and the work presented in it, are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this university.
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- Where I have consulted the published work of others, this is always clearly attributed
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main source of help.
- Where the thesis is based on work done by myself, jointly with others, I have made clear exactly what was done by other and what I have contributed myself.

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CERTIFICATE

This is to certify that the thesis entitled **"Long-Term System Planning for Large-Scale Renewable Energy Integration: Methodology Development"** being submitted by **Partha Das, ID: 2013RCV9566** is a bonafide research work carried out under our supervision and guidance in fulfillment of the requirement for the award of the degree of **Doctor of Philosophy** in the Centre for Energy and Environment, Malaviya National Institute of Technology Jaipur, India. The matter embodied in this thesis is original and has not been submitted to any other University or Institute for the award of any other degree.

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Abstract

Renewable energy (RE) generation is based on natural resources (*e.g.* solar, wind), which by their inherent characteristics have spatial and temporal intermittency. Generation and capacity potential of these RE sources are subjected to geographical variation within a region or country. Temporal variation ranges from seconds to seasons, and has different relevance on the power system depending on the nature of the resource. Large-scale integration of these resources introduces additional uncertainty to an existing system. This change in generation paradigm underscores the need for additional flexibility to maintain reliable power system operation.

Long-term system planning activities need to capture RE resource variability by appropriate spatial and temporal considerations to design future energy systems for large-scale RE penetration. Mathematical models used in these planning exercises adopt simplified spatial and temporal resolution, which is often necessary to limit computational complexity. Spatial resolution of these models are defined according to the economic or political boundary of the study area (*e.g.* large-scale region/ state/ country), rather than RE resource zones. Thus, they do not capture intra-regional variability of RE potential at suitable spatial and temporal scale. Further, the number of time slices in these models are not adequate to address temporal variability of RE generation potential at a suitable resolution. Additionally, due to the lack of various technical constraints of system components, these planning models take an aggregated approach to address the impacts of RE variability on system operation. These issues lead to inaccurate quantification of future RE capacity and overall system portfolio.

Therefore, there is a need to develop new methods to address RE variability and its operational impact at the planning stage, for improved planning of future energy system portfolio. Present research work contributes in this regard by developing methodological approaches to consider the intra-regional RE variability and analyze its operational impact at the planning stage. First, it presents the development of a multi-region long-term energy system model with higher spatial and temporal resolution using a technologically rich bottom-up optimizing framework (TIMES: The Integrated MARKAL EFOM System). The planning model considers regional specifications at state levels and intra-day time slices at hourly level to address intermittency of RE resources. Second, GIS (Geographic Information System)

and statistical tools are utilized to calculate intra-regional capacity and generation potential of solar and wind energy resources at geographical grid-cell level. Capacity potential of RE resources are calculated for various resource classes, and for each class, time slice wise capacity factors are quantified. This information is further incorporated in the planning model using additional constraints. The third approach focuses on analyzing the impact of operational scale RE variability at the planning stage. For this purpose, a power system operational model is developed, which works on intra-regional nodes and optimizes daily generator scheduling at hourly resolution throughout the year in a rolling horizon fashion. In contrast to the planning model, the operational model has various technical constraints which ensures realistic dispatch of the generating units. It, therefore, provides additional system operational insights for a capacity portfolio calculated by the planning model.

The developed methodological approaches are demonstrated through the case of North Indian power sector. The model application is performed in two part. First, long-term system evolution is analyzed under 243 model cases constructed from three scenarios of five key parameters (*i.e.*, cost of solar PV, wind and energy storage, and price of CO_2 and coal), for a planning horizon up to 2050, using the planning model having intra-regional RE potential information. Second, a specific RE penetration case targeting 2030 is analyzed by linking the operational model with the planning model.

For the first model application, discussed results include a detailed analysis of RE penetration and curtailment levels, technology capacity, role of storage and inter-regional energy exchange, coal supply, and CO_2 emission. Time-slice wise power dispatch of generators and activity profile of storage and transmission lines are also detailed for overall study area and individual regions. Various model cases indicate system transition towards large-scale RE penetrated generation portfolio. Solar energy curtailment is prominent in high RE penetration scenario. Regional RE share and curtailment are higher than overall penetration level in RE rich states. Coal-based power plants are important generation options, unless high CO_2 price is imposed. Storage systems work as energy arbitrage device for integrating solar energy and reducing curtailment. Storage capacity in various model cases is in direct relation to solar capacity development.

For the second model application, comparison of generator activity levels and power dispatches respectively from the planning and operational model are compared. Results from the operational model highlight insights of RE penetration levels, RE curtailment, and dispatch profiles of thermal generators. Result comparison suggests that, non-consideration of the operational constraints at the planning stage, leads to over estimation of RE capacity and under estimation of RE curtailment for a system portfolio designed by the planning model to meet certain RE penetration targets. A simplified bi-directional model linking method is outlined in this regard to incorporate these operational insights in the planning model itself for better calculation of technology capacities.

Adoption of higher modeling definitions within the planning model, and its interlinking with GIS, and operational models suggests major revision of current system planning approaches for long-term energy policy studies in India. Consideration of RE variability and its operational impact should be addressed by improved methods to quantify realistic future system portfolio corresponding to various policy scenarios.

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Chapter 1

Introduction

1.1 Background

Concern for climate change and energy security has brought global consensus over the need to adopt new strategies for power generation, transmission, and utilization. Power production using fossil fuels, such as coal, has been one of the largest contributors to global net greenhouse gas emissions. Electricity demand would continue to increase, with new areas of direct application (*e.g.* electric vehicles); necessitating switch to cleaner generation options. Therefore, decarbonization of power sector is one of the key agendas of current century [1]. Renewable energy (RE) sources have evolved as the most attractive options in this regard as they are clean, secure and sustainable, compared to other options such as nuclear energy. Penetration of RE sources in generation mix is gradually increasing worldwide. Some countries have already added a fair share of variable RE (*e.g.* solar, wind) in their generation mix (*e.g.* Germany, Ireland, Denmark), while others are rapidly moving towards it (*e.g.* India, China). It is expected that, new policy mechanisms and market structures will ensure large-scale RE penetration in global as well as various national energy systems [2–5].

Among various RE resources, global policy interests are mostly focused on solar and wind for power generation. Despite several benefits, these RE sources are associated with new set of challenges which are redefining traditional power system operational and planning practices. The main challenges associated with these resources are their variability and uncertainty in spatial and temporal scale. These properties have profound impact on day-to-day power system operation, which is constrained to ensure system reliability by maintaining supply and demand balance at every point of time. As grid operators have little control over the output from these intermittent RE generators, they cannot schedule and dispatch them similar to thermal or hydro plants [6]. This uncontrollability of RE generation causes frequency and voltage fluctuation, leading to system imbalance and instability [7, 8]. Additional mitigating measures are required to increase system flexibility, so that sudden fluctuations due to combined effects of RE and demand can be quickly suppressed. Scarcity of balancing resources may force the operators to curtail certain portion of available RE generation which may have several economic and planning related consequences [6, 9–11].

Operational challenges associated with large-scale RE penetration directly translate to system planning. The ability of a system to cope with RE intermittency and uncertainty depends not only on adequate capacity but also on the quality of existing resources. Real-time operational efficiency depends on existing system portfolio, for which the planning needs to start several years ahead. Unless the system is planned for flexibility adequacy, future renewable penetration targets are difficult to achieve [12]. Long-term system planning studies identify new generation and transmission capacity requirement, and also retirement/ replacement of existing stock to satisfy projected demand. These studies take an extended outlook covering years to decades to design future strategies. As flexibility services can be procured from a variety of resources, like storage, interconnection and demand response, proper planning is needed to channel timely investment into suitable techno-economic options.

Energy system planning strategies utilize various mathematical models and tools to design future energy system portfolio, formulate new policies, and chalk out optimum pathways to achieve those policy targets. Over the years, various models and associated tools have evolved with varying philosophies suiting different applications [13, 14]. These models provide least cost solutions to meet future energy demand in different techno-economic scenarios. Though these model cover multiple energy sectors, present work focuses on power sector only, as RE intermittency primarily impacts power system operation.

Irrespective of different kinds of models used in the planning study, their definition and granularity do not allow tracking the effect of short-term RE resource variability (*e.g.* at hourly/ sub-hourly level) on system operation. Due to computational complexity in large-scale system models, aggregation of spatial and temporal definition is often necessary, which leads to unrealistic representation of intra-regional RE variability. Apart from these limitations, system models often do not consider the technical constraints of thermal generating units or physics of power flow through transmission line. As a consequence, they overestimate the role of renewable sources and underestimate the requirement of flexible capacity like energy storage. They often focus on capacity adequacy rather than quality of resource, and therefore, undervalue system flexibility need. Therefore, these aggregated modeling practices make RE integration planning a challenging task, and restrict designing a optimal power system from an operational point of view [15–19]. Overhaul of traditional system planning approaches is therefore necessary to address short-term RE variability at proper scale.

1.2 Research Questions

There has been some recent attempts made to address these issues concerning RE integration. While endogenous approaches try to improve inherent model definition and equation, hybrid methods utilize various additional models/ tools [19]. Endogenous approaches adopt higher spatial and temporal resolution or use a stylized representation of operational constraints in their long-term modeling paradigm [20–25]. Hybrid approaches utilize uni/ bi-directional link with external power system models to capture operational scale information [26, 27].

Despite various attempts, these planning approaches do not consider intra-regional variability of RE resources in the system models at proper scale. Even when separate models are used to simulate realistic power system operation, current approaches do not often consider intra-regional nodes. Selection of spatial resolution often does not focus to capture RE resources' variability. For multi-regional models also, intra-regional RE variability is not often considered.

These research gaps also apply for India where current energy system planning studies still do not employ a proper methodology to address RE variability. Spatial and temporal definitions in earlier studies are not suitable to address the intra-regional geographical variability of capacity, as well as generation potential of RE sources. As variable renewable energy sources would play a major role in future generation portfolio of India, a revision of current planning methodologies is therefore required.

1.3 Objectives

The present work tries to answer some of the research questions mentioned above. Based on the literature review, following are the research objectives for this thesis. This is followed by a short discussion on the methodological approaches in the following section.

- Developing methodologies to incorporate short-term resource intermittency, demand dynamics and system operational constraints in a long-term energy system planning model

- Application of aforesaid methodologies in long-term planning of North Indian power sector for analyzing system transition to high renewable energy penetration scenarios.

1.4 Methods

The background and research questions outlined above are supported by a detailed literature review presented in the Chapter 2. To address the research objectives, various methodologies, scenario development, model applications are undertaken. The overall approach is illustrated in Figure 1.1. Following is a brief discussion of the same.

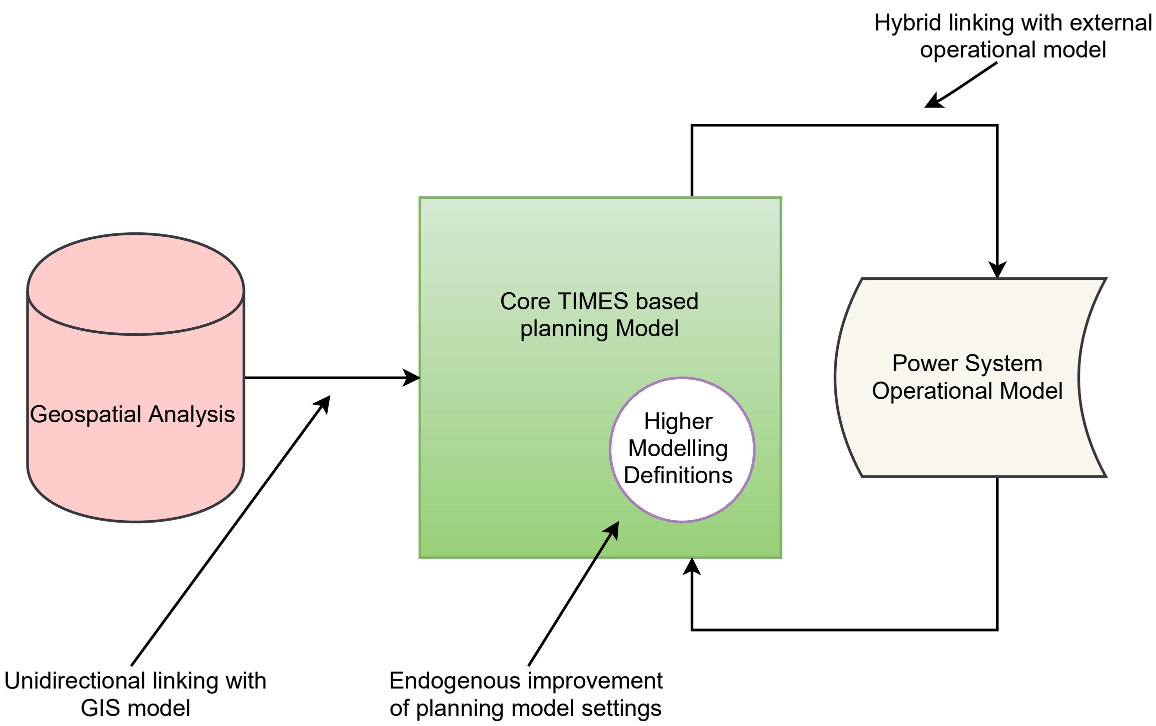


Figure 1.1 Various modeling approaches outlined in the present work

1.4.1 Endogenous Improvement of Energy System Model

To accomplish the first objective, three different methods are outlined in this thesis. The methods have a cumulative impact on modeling improvement (*e.g.* the second approach builds on the first). The first method adopts higher temporal and spatial definitions within a long-term planning model. Multi-region structure and higher number of annual time slices allow to define RE capacity factors and load curve in much higher granularity. In this method, other modeling improvements like multiple base year and unequal model periods are also implemented for improved data calibration and model performance. Consideration of higher number of annual time steps allows model to check the demand and supply balance for each time slice, leading to calculate better activity profile of technologies. Higher number of model regions on the other hand help to define spatial variation of RE potential at state level. Chapter 3 discusses these aspects in detail.

1.4.2 Energy System Model Linking with GIS Model

Though the first approach allows the planning model to consider RE variability and demand dynamics at a certain scale, it does not facilitate addressing the intra-regional geographical variability of RE potential. Hence, in the second approach, geospatial models are developed to quantify intra-regional RE related data sets at suitable spatial resolution. As GIS platforms are widely utilized for spatial calculations, GIS and other associated tools and open domain spatial data sets are utilized for this purpose. Further, the intra-regional variability of RE resources are incorporated in the planning model with a set of additional processes and user constraints. Chapter 4 discusses these aspects in detail.

1.4.3 Energy System Model Linking with Power System Operational Model

Though the previous approach allows planning model to consider RE variability at intra-regional scale, it does not consider the impact of this variability on system operation. Therefore, in the third approach a method is outlined where a separate unit commitment model is developed and used to optimize daily system operation of generator scheduling considering various operational constraints for a single year. Comparison of the technology activity levels from the planning and operational model is undertaken. Methodology is described by which information of the operation model can further be fed back to the planning model to recalculate technology capacity. Chapter 6 elaborates these issues in detail.

1.4.4 Study Area

The second objective talks about the application of modeling approaches for the Indian power sector targeting large-scale RE integration scenarios. The outlined methods are applied for long-term planning of North-Indian (NI) power sector. Geographical area coverage (31%), share of total population (30%), large-scale RE integration plans, diverse generation options, and energy access issues, make this area a well representative region to study future energy system evolution of India. Various futuristic scenarios involving techno-economic parameters are constructed, which translate into various RE penetration cases. The numerical results corresponding to the model application cases discuss regional RE penetration levels, curtailments, generator dispatch profiles, role of energy storage and inter-connection, coal supply, CO_2 emission, *etc* for various futuristic scenarios. Chapter 5 discusses these aspects in detail.

1.5 Thesis Outline

Present thesis is divided into seven chapters. This first chapter describes the background, scope and purpose of the thesis. Chapter 2 presents detailed discussion on large scale RE integration impact on system operation and planning. It also highlights the methodological limitations of existing planning strategies to address RE variability, and recent approaches adopted in literature to address them. Development of long-term energy system planning model (NIMRT) is described in Chapter 3 along with model settings, data, and assumptions. Chapter 4 outlines the method of quantifying the intra-regional RE capacity and generation potentials by GIS, and the process to incorporate them in NIMRT model. Description of various scenarios and corresponding numerical results with NIMRT model are discussed in the Chapter 5. Chapter 6 describes the development of a power system operational model, along with various methods and assumption for data preparation. It also discusses the numerical results of uni-directional soft-linking between operational and planning model, along with proposed methodology for bi-directional linking. Overall summary, conclusion, and future work related to the research are presented in Chapter 7.

1.6 Publications from the Research Work

Journal Articles

- **Partha Das**, Jyotirmay Mathur, Rohit Bhakar, and Amit Kanudia. Implications of short-term renewable energy resource intermittency in long-term power system planning. Energy Strategy Reviews, 22, 1-15, 2018.

- Ankita Singh Gaur, **Partha Das**, Anjali Jain, Rohit Bhakar, and Jyotirmay Mathur. Long-term energy system planning considering short-term operational constraints. Energy Strategy Reviews, 26, 100383, 2019.

- **Partha Das**, Parul Mathuria, Rohit Bhakar, Jyotirmay Mathur, Amit Kanudia, and Anoop Singh. Flexibility options for large-scale renewable energy integration in Indian power system: Technology, policy and modeling options. Energy Strategy Reviews. (Under Review)

- **Partha Das**, Amit Kanudia, Jyotirmay Mathur, Rohit Bhakar. Long-Term Energy System Planning Considering Intra-Regional Renewable Energy Resource Variability: Scenario Analysis of North-Indian Power Sector. Renewable and Sustainable Energy Reviews. (Under Review)

Conference Papers

- **Partha Das**, Jyotirmay Mathur, Rohit Bhakar, and Amit Kanudia, Long-term renewable energy integration planning in India: Challenges and opportunities. 1st International Conference on Large-Scale Grid Integration of Renewable Energy in India. 6-8 September 2017

- **Partha Das**, Jyotirmay Mathur, Rohit Bhakar, and Amit Kanudia. Geographical information system based renewable energy integration planning: Quantifying solar energy potential in North India. 1st International Conference on Large-Scale Grid Integration of Renewable Energy in India. 6-8 September 2017.

Chapter 2

Literature Review

Energy system planning studies generally model multiple interlinked energy sectors. As large-scale variable RE integration primarily challenges traditional power system operation and planning, present study focuses exclusively on power system. This chapter begins with a brief discussion of additional challenges associated with large-scale RE integration on traditional power system operation and planning. Need of extra flexibility in the system and its possible sources are identified thereafter. A discussion is presented to compare the ability of various kinds of planning models to consider short-term RE variability, while optimizing system's operational flexibility requirement in long-term. Limitations of large-scale energy system optimization models and recent approaches to mitigate them are highlighted in this regard. A comparison of those strategies are drawn henceforth. As the present study is focused on Indian power system (specifically North-India), India specific issues related to existing planning strategies are highlighted. Finally, summary of the literature review and key takeaway points are highlighted.

2.1 Power System Planning and Operation

A power system comprises of various interconnected entities, like generators, transmission & distribution network, and load. Traditionally these entities within a particular geographical area were owned by highly regulated vertically unbundled public utilities. The planning, operation, and control of this kind of system were done by the same utility that owned it. Due to economic and operational inefficiencies of this monopolistic structure, deregulation and restructuring are being adopted to promote competitiveness and efficiency. In a restructured environment, the ownership of power system components is distributed among various private or government players, regulated by a separate independent body. An electricity market is often designed for these players and customers to trade power, utilizing open access over the transmission network [28, 29].

Power system planning activities can be classified as short-term, medium-term, and long-term. Short-term planning is associated with day-to-day system operation. Medium-term planning involves maintenance of existing system assets, while long-term planning relates to new capacity additions (Figure 2.1).

2.1.1 Short-Term Power System Planning

Short-term power system planning involves scheduling generating units from day-ahead to week-ahead. Due to policy obligation, RE generators are often operated in must-run condition. Therefore, conventional generators serve the residual or netload, which fluctuates widely due to the combined variability from RE and demand. Conventional thermal generators (*e.g.* coal-fired plants) have several operational constraints which need to be considered at scheduling stage to maintain stable operation. They cannot be shut down, started, or frequently ramped up/ down due to concerns of efficiency degradation, carbon emission increment, equipment deterioration, and lifetime reduction. They also cannot accommodate excess RE generation by lowering their output beyond a certain limit. Due to reliability purpose, operators also need to maintain a certain quantum of additional generating capacity in the form of spinning and non-spinning reserve. Spinning reserve is spare capacity of already connected units after serving load and losses. Non-spinning reserves is the capacity of units not synchronized to the grid but can be brought online within a small-time frame. Spinning and non-spinning reserves together constitute total operating reserve of the system. The operators also takes into account certain agreement between power producers and consumers and also regulatory norms (*e.g.* power purchase agreement (PPA), must run status on RE generators in India) [30, 31].

These constraints constitute a mixed integer optimization (MIP) problem. System operators solve it to decide optimal generator commitment schedule at minimum cost of operation. The choice of MIP problem formulation (*e.g.* MIQP, MIQCP, MILP, MINLP) [1] and solving approach for generator scheduling differs for various system operators according to the nature of system, grid codes, available solvers, computational infrastructures etc. The problem can further be deterministic with perfect foresight, deterministic with forecast error, stochastic with scenario tree etc. Various commercial solvers like CPLEX, FICO-Xpress, Gurobi, Baron etc. are used for solving MIP problems. Heuristic methods like genetic algorithm etc.

[1] MIQP: MIP models with a quadratic objective but without quadratic constraints, MIQCP: MIP models with quadratic constraint, MILP: MIP models without any quadratic features, MINLP: MIP models with nonlinear functions in the objective function and/or the constraints

are also of interest for solving unit commitment problems because of their faster solution searching capability [32, 33].

Calculated generator operation schedules should lead to secure system operation, *i.e.* the system should withstand contingency event such as failure of a generating unit without major loss of load. Consideration of security is crucial in a large interconnected system, as failure of a single component may drive cascading events leading to other equipment outage and ultimately system collapse. For analyzing system security, operators perform simulations considering contingent scenarios of dispatch, load, transmission capacity, *etc.* An optimal power flow problem is run in conjunction with contingency analysis to examine whether the strategies would satisfy thermal limits of transmission lines or not. The plans are revised if they appear to be insecure. Reliability standards dictate contingency criteria [2] that operators need to maintain.

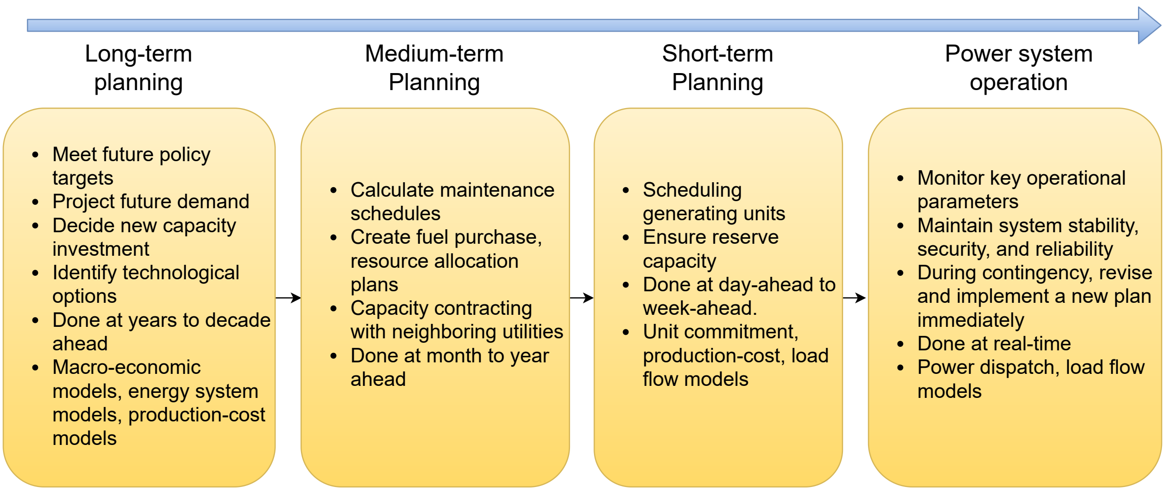


Figure 2.1 Planning and operational activities of Power System

2.1.2 Power System Operation

Grid operators monitor various operational parameters in real-time to maintain system stability, security, and reliability. Generation levels of power plants, transmission line thermal limit, system frequency, node voltage and angle, *etc.* are critical parameters which operators maintain within a particular threshold to ensure reliable operation. Under normal conditions, planned schedules should hold good with some revision based on updated load forecasts.

[2]The contingency criteria are often denoted as N-k; where N is the total number of the system component, and k is the number of equipment which have failed. For example, N-1 contingency criterion implies that system should continue to operate even if a single component, may it be generating, transmitting or any other (the largest possible), fails.

During a contingency, operators implement a new plan immediately to rescue the system. The severity of contingency event depends on its location and system status. Unplanned outage of a small generating unit or intra-hour demand deviations are often handled by governor response and automatic generation control mechanisms of spinning reserves units. Additional non-spinning reserves are brought online or load shedding schemes are enforced depending on the severity of generation outage. Daily load variation is quite predictable, and sudden loss of demand on a significant scale is uncommon, unless there is a transmission line loss. Line outage is often handled through additional transmission reserve margins or via alternate paths maintained for reliability purpose. During severe line outages, interconnected control areas coordinate by either reducing or increasing generation to relieve the contingency [31].

2.1.3 Medium-Term Power System Planning

In timescale, medium-term planning resides between short and long-term planning, and covers the tasks of creating maintenance schedules of generation and transmission equipment, fuel purchase, resource allocation, and capacity contracting with other neighboring utilities. These activities are usually undertaken with months/ seasons/ yearly outlook. Medium-term planning decisions are distinct from long-term planning in a sense that it only deals with existing resources compared to new capacity addition. Also, the medium-term decisions are set long before short-term dispatch planning. Medium-term planning is relevant as, if supply assets are not maintained properly, they may fail under severe loading conditions. Also, knowledge of the yearly/ seasonal availability of supply assets is vital for short-term operational planning.

2.1.4 Long-Term Power System Planning

Long-term planning studies are undertaken in extended time horizon (years to decades) considering future demand growth and technology, or policy targets. They deal with upgradation of existing infrastructure or installation of new capacity, which may be in the form of generators, transmission or distribution lines, based on some policy inputs. They simultaneously identify quantity, type, year, and location of new capacity and the corresponding cost of new investment. Planning studies of power utilities focus exclusively on the electricity sector, ignoring or aggregating the effects of other energy sectors. These studies are also often static, *i.e.* they analyze targeted future year in a single stage. On the other hand, national or regional level energy system planners take a dynamic approach by evaluating the solution for targeted year(s) in multiple stages. They take an integrated overview of various energy systems at a time. The power sector is often studied as a part of the whole energy systems, though there are attempts to study it exclusively. Static planning is simpler and computationally easier compared to dynamic ones, but they often give unrealistic results as they do not consider chronological evolution of whole energy system. Due to significantly different approaches in various studies, mathematical models also differ correspondingly. Merits and demerits of each approach have been discussed in detail in Section 2.3.

2.2 Effect of RE Intermittency on Power System Operation and Planning

In India long-term power purchase agreement (PPA) between power generating utility and DISCOMs also limits dynamic operators of thermal power plants.

In time dimension, uncertainty or variability in power system can be either short or long-term. Long-term uncertainties can be in economic parameters, future technology development and policy, which are analyzed in the longer time frame via scenario analysis. Short-term operational uncertainties mainly arise from uncontrollable demand fluctuation or generation changes. Power system operators have been handling real-time demand variations since the setup of the first interconnected grid system. There are well-established load forecasting methods, network operation protocols, codes, and strategies, which operators follow to maintain stable and reliable grid operations.

2.2.1 Time-line of RE Variability Impact on Power System

Though the power output from dispatchable generators is controllable and rarely subjected to large-scale random variation, output from RE generators is intermittent. It imposes additional challenges on the grid operators to maintain system balance at operational stage. There are three main challenges associated with large-scale solar and wind energy integration; temporal variability, output uncertainty, and location specificity [34]. Temporal intermittecy of RE generation makes the supply uncorrelated with demand pattern, thus creating system management related challenges for operators. Uncertainty of output from RE plants creates scheduling related challenges, as generation forecasts deviate significantly at real time of operation. Finally, sudden generation inrush from RE generators at high resource potential regions create localized network congestion. Present work specifically focuses on short-term RE variability (spatial and temporal) and their impact on long-term planning. Modeling of uncertainty (*i.e.* stochasticity) associated with RE generators is not undertaken in this study.

Large-scale integration of solar and wind energy impacts both power system operation and planning strategies (Figure 2.2). Short-term operation and planning of a system with

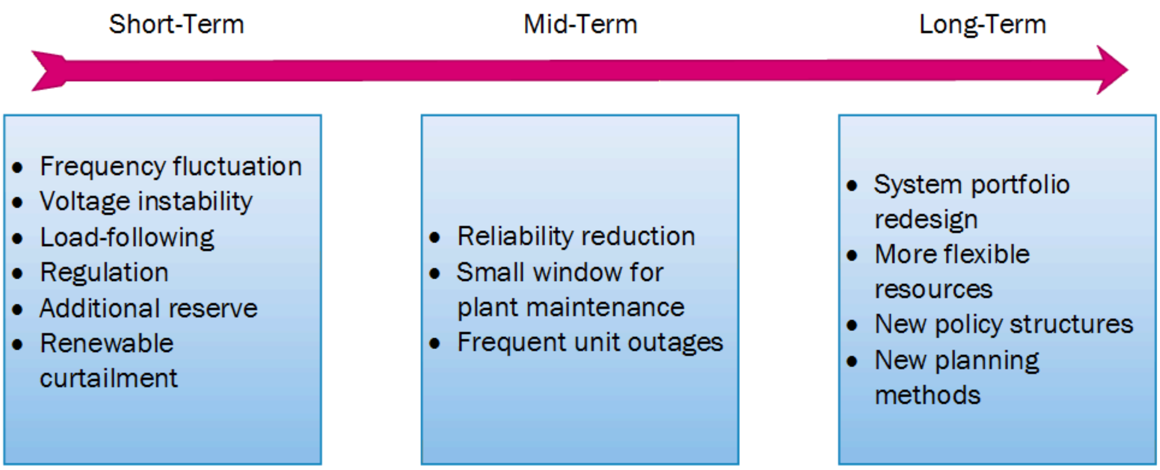


Figure 2.2 Time-line of RE variability impact on Power System

large-scale RE share involves managing the RE variability with existing assets, while long-term planning aims to design optimal system portfolio to meet future penetration targets. Inability to manage system variation at operational scale may lead to RE curtailment. On the other hand, inefficient planning methods (*i.e.* ignoring the short-term RE variability) may lead to sub-optimal investment in flexible capacity. These issues are elaborated in the current and following sections.

2.2.2 Short-Term planning against RE Intermittency

Grid operators schedule generators according to forecasted demand, and dispatch power following real-time load requirement. Due to policy obligations and low operating cost, RE generators are often considered in priority. As they are non-dispatchable, operators need to have a forecast of their power output in advance to schedule other conventional asset serving residual load [3]. Accurate and adequate forecast of intermittent renewable generation is therefore highly valuable for system operators to perform short-term planning and real-time operation. With an accurate prediction of RE generation and thereby residual load, available RE could be better utilized, reducing total operation cost and increasing system reliability.

Various RE forecasting methodologies have evolved over the past years [35]. The choice of prediction method depends on available data and planning horizon. Time series prediction models with statistical learning methods are traditionally used for intra-hour time horizon. Satellite and sky imagery are used for solar radiation prediction purpose in the absence of ground monitoring systems. These methods rely on height detection and cloud movement, and are used in a longer look-ahead time frame. Sequential satellite or sky images help

[3] RE generation subtracted from total demand

in the short-horizon forecast, but it is expensive compared to other methods. Numerical weather prediction models are popular for long-term forecasting of both wind speed and solar radiation, with time horizon ranging from a few hours to a couple of days. They are also used for shorter time scales using rapid-update systems [36–38]. Various attempts utilize hybrid methods to benefit from the strengths of two or more techniques [39–42].

There are different methods for short-term planning against RE fluctuations. Deterministic scheduling and reserve calculation approach perfectly relies on forecasts, without considering associated uncertainty. Despite the development of various advanced forecasting techniques, power output from RE plants in real time differs significantly and randomly from predicted values. Therefore, this approach to consider only the RE variability offers limited scope to handle uncertainty. Stochastic optimization methods, on the other hand, consider probabilities of a selected number of scenarios of future uncertainties associated with forecast to decide commitment decisions [43–46]. As compared to deterministic models, these advanced methods could give more confidence to operators. However, that does not necessarily imply that the solution would satisfy every stochastic scenario during dispatch. Ultimately it depends on the existing resources whether their characteristics could support short-term RE variation or not. There are also approaches like robust optimization, which aim to determine a feasible solution for any realization of uncertain parameters [30].

2.2.3 RE Intermittency and Power System Operation

In real time, operators can mitigate RE generation fluctuation using scheduled reserves if it is within a certain limit. But, drastic deviation from forecasted power output of RE is a challenge to maintain system balance. Therefore, extra balancing resources are needed to support this fluctuation. Operators do face similar difficulties in case of extreme load variation, but years of experience and intuition have worked well for them to manage demand variability, except for extreme contingencies.

Conventionally, the system demand at a particular time is served by three type of generators: base, intermediate, and peak. Base load power plants only serve firm load and are characterized by high load factor, high start-up and shut-down time, and low ramp rate. Large coal-fired or nuclear based thermal power plant are typical examples. Intermediate load power plants have good load following ability and their start-up, shut-down time, and ramp rates are between base and peak load plants. Small coal-fired, combined cycled, and hydroelectric plants are often used for intermediate-load operation. Peak load generators usually operate at low annual load factors. These units have high ramp rates, small start-up and shut-down time. Combustion or simple cycle turbines fueled by natural gas are preferred as peak load plants. Internal combustion engines fueled by natural gas, and hydro generators with pumped storage also operate during peak time.

In the current power system structure of countries like China, India, and the USA, base load plants constitute a significant percentage of installed generation capacity. Integration of variable RE mainly causes two challenges in such scenario. First, it decreases residual load and second, residual load fluctuates excessively [47]. During times of high penetration, RE generation tends to take up the firm demand being served by base-load power plants. Due to minimum production limit, base load power plants are unable to lower their output to accommodate RE generation. Also, limited ramp rate and high start-up time do not allow fast operation of base-load plants to support short-scale residual load fluctuation. There should be a fair share of load-following units with high ramping ability, and sufficiently low minimum production capacity in the overall generation portfolio to mitigate these issues [48]. Hydropower plants with reservoir, gas fired units have high ramp rate and can help to mitigate system variability. But, environmental and irrigation constraints and high fuel price often restrict their balancing capabilities. Network congestion due to insufficient capacity or security regulations also restraint excess RE power to be evacuated.

2.2.4 RE Intermittency and System Flexibility

Traditional power systems handle uncertainty from generation, network, and demand using operating reserve, contingency and security analysis. RE increases existing variability and uncertainty in wide spatial and temporal scale, which necessitates faster response and increased operational frequency of system balancing resources. The property of a system to cope up with any externally imposed variabilities/ imbalances is termed as its flexibility.

Flexibility of a system resource can be understood in three dimensions: range of power output (MW), speed of power output change (MW/ min), and duration of providing energy (MWh). A single resource cannot always respond in these three different dimensions, and the operators need to maintain a diverse portfolio of flexible components for day-to-day balancing. Resources having wide range between maximum and minimum output, can respond to a large range of variation, while others having fast response time can damp any quick imbalance within a short duration, saving the system from any negative consequences. Entities with the ability to deliver energy at longer time span can provide flexibility to address disturbances for stretched duration [49, 50].

An interconnected power system could harness flexibility from different sources, may it be from supply, demand, or transmission side. Though there is consensus on the importance of flexibility with respect to increased RE penetration, identification of appropriate technological option for a national energy system is still challenging. Techno-economic uncertainty of new flexible resources like storage and their higher cost *vis-a-vis* existing options (*e.g.* gas fired plants), and inefficient planning methods are main reason behind this.

Sources of Power System Flexibility

Generation Flexibility: Flexibility on the generation side can be obtained from fast acting gas, oil-fueled, modern coal-fired, and hydropower plants. Modern nuclear power stations can also provide limited level of flexibility [51–53]. Load following and frequency regulation are the key flexible services that could be obtained from generation side.

Flexibility using Demand Side Management: Demand side management (DSM) actions are measures to obtain a load curve favorable to both customers and utility. Thus, DSM can potentially act as a flexible resource. Peak shaving, valley filling, load shifting, strategic load reduction and growth, *etc.* are some DSM mechanisms [54, 55]. DSM can either be incentive based or price based. Price based DSM refers to changes in electricity usage pattern by customers, in response to the price change. Some price based DSM mechanisms are time-of-use tariff, real-time pricing, and critical-peak-pricing, *etc.* Incentive based DSM programs give customers benefit additional to their retail electricity rate. Direct load control, demand bidding/ buyback programs, capacity and ancillary services market mechanisms are some incentive based DSM measures [56–58].

Flexibility using Energy Storage: Energy storage technologies, either in generation or demand side, provide a range of services which system operators could utilize to meet their flexibility need [59, 60]. Storage system could be used either in energy management, power back up, or power quality applications. Bulk storage systems such as pumped hydro, compressed air, and battery storage technologies like sodium sulfur, vanadium redox, lithium ion, and zinc bromide are suitable for energy management services (energy arbitrage, load leveling, transmission and distribution capacity deferral, *etc.*) due to their long discharge time [61]. Power quality, system stability, and frequency regulation applications require discharge time from seconds to minutes. Small-scale storage such as flywheels and capacitors are useful for this application. Power backup service requires storage system to follow the load with high ramping capability, with a discharge rate between minutes to hours. Lead acid, Nickel metal hydride, and nickel-cadmium batteries could provide these services. Small-scale storage, *e.g.* batteries and electric vehicles on demand side, could also provide DSM services [62–64]. Thus, storage systems could be useful in integrating large-scale fluctuating RE [65–67].

Flexibility using Inter-Connection: System operational flexibility can also be obtained from other regions connected via transmission lines when flexibility in one area is not sufficient or expensive [68]. Availability of transmission capacity plays a crucial role in mitigating residual load fluctuations due to increased penetration of variable RE generators [69]. A robust and interconnected network is critical to ensure large-scale RE penetration [70–73].

Renewable Energy Curtailment

Stable power system operation requires load and generation balance at every point of time. At times of RE over-generation, inflexibility of thermal generators and network security criteria may restrict its full utilization [6, 74, 75]. This reduction of generation from variable RE generators is referred to as RE curtailment, which has operational as well as economic consequences [11]. RE over-generation occurs when residual demand is lower than firm-load served by must run base load plants. Also, output variation of base load plants (to support RE fluctuation) is limited by their ramp up/down rates. Therefore, if sufficient balancing resources, reserve capacity, and storage facility to support RE fluctuation in real time are not available, operators are forced to curtail some part of the available RE power to maintain system stability [6]. A sudden unplanned increase in RE generation creates network congestion, which often leads to RE generation curtailment [76]. Significant RE penetration can also cause fluctuation in voltage and frequency, thereby giving back-down signals to RE generators. Curtailment decreases capacity factor of renewable power plants, and thereby reduces project profitability, increases financing cost, weakens investor confidence in RE, and makes it challenging to meet carbon emission reduction targets [74, 77].

In several countries, RE curtailment has been a problem associated with large-scale RE integration. Its degree and impact largely depends on RE penetration level and system configuration. Levels of wind energy curtailment experienced in the United States differ substantially by region and utility. In Electric Reliability Council of Texas (ERCOT), 17% wind energy curtailment was observed in 2009 which reduced to 4% in 2012 and 1.6% in 2013. Transmission inadequacy, oversupply, and inefficient market design are the primary reasons in this case [78]. In California Independent System Operator (CASIO), curtailment predominantly occurs due to oversupply, generator ramping constraints, line congestion, and must run status of hydropower plants in spring. Here, in early 2014, 19.39 GWh of wind curtailment was witnessed [74]. Bonneville Power Administration (BPA) reports around 2% wind curtailment, mainly due to shortage of reserve capacity. Wind curtailment level of 1%–4% in Midcontinent Independent System Operator (MISO) and 1%–2% in Public Service Company of Colorado are usual [78]. In China, total curtailed wind power during

2010–2013 was around 60 TWh, with some provinces having around 30% curtailment in 2012. This was mainly due to limited transmission capacity and mismatch between generation and consumption profile [79–82]. Curtailment rates of several European countries are low, despite having significant RE penetration levels. Strongly interconnected network and well-functioning international power market are the two supporting factors here [82].

2.2.5 RE Intermittency and Long-Term Power System planning

The importance of system flexibility needs to be understood with extended outlook, due to the difference in lead-time of technologies. Real-time operational efficiency depends on existing system portfolio, for which the planning needs to start several years ahead. Unless the system is planned for flexibility adequacy, future renewable penetration targets may not be attainable [48, 12, 83]. Apart from quantifying optimum capacity of flexible resources, identifying suitable location of installation, identifying proper technology, and planning progressive introduction of flexible resources over a long time frame is essential for national power system development, as discussed hence.

Suitable Location Identification: Location specificity of RE resources is one of the major planning related challenge. Good resource sites (high solar intensity, wind power density), situated far away from load centers often create transmission related challenges. High capacity inter-regional transmission lines are therefore needed to evacuate RE based generation. But, it is also noteworthy, that developing massive transmission corridor exclusively for RE is often uneconomical, as it may be underutilized due to natural variability or generation curtailment. Planning for RE power plant siting is also important as geographical aggregation of RE generators over a large area using electricity network leads to significant statistical smoothing of fluctuations from individual generators, reducing associated integration challenges [84]. Significant planning related to siting of RE plants, erection of transmission lines and coordination between area balancing authorities are needed in this regard.

Suitable Technology Selection: As operational flexibility could be harnessed from various sources, like storage, interconnection, DSM, and flexible generation, analysis is needed to assess the utility of these options under different techno-economic scenarios [83]. These resources also need innovative policy thrust to compete with existing ones. Effects of these policies, along with technology learning, cost reduction potential, market and social acceptability, *etc.* need to be understood in a long time frame for optimal portfolio planning.

RE Curtailment Implication: RE curtailment occurs due to operational inflexibility, but it has planning related implications, because development of flexible capacity such as transmission corridors, storage, *etc.* has higher lead time than renewable power plants. Though, curtailment is undesirable from economic point of view, it provides system flexibility when other measures are either unavailable or costly [85]. Allowing curtailment would lead to overbuilding of RE capacity. On a national perspective, it could lead to a massive increase in effective cost of energy supply which would be detrimental to its growth prospects. But, restricting curtailment leads to extra wear and tear of conventional thermal generators, affecting their lifetime, emission and efficiency [86]. It can also lead to severe load shedding events when there is a ramping capacity shortage [10]. RE curtailment can also help in mitigating associated large-scale investment in grid infrastructure expansion which is often underutilized [11]. In an electricity market, allowing generation curtailment during negative energy price (RE over-generation), may encourage investors to invest in flexibility measures, which ultimately helps the transition towards a low-carbon power supply system [87]. Therefore, planning activities need to evaluate whether curtailment has long-term positive or negative effects and decide its optimum allowable level from a system design perspective [10].

2.3 Power System Flexibility and Planning Models

With additional dynamics and variability from RE, system resource capacity simultaneously needs to be adequate and flexible to manage supply and demand variability. Consideration of flexibility in long-term planning models requires high granularity in temporal and spatial resolution, and a detailed representation of system operational constraints [88, 89]. A high level of intra-annual time resolution is critical to track variability of demand and supply commodities. Higher spatial resolution is required to represent geographical diversity of RE resource potential, and power flow between supply and load centers. Operational constraints are crucial to describe technical characteristic of different entities (generating, transmitting and demand technologies) in the modeling paradigm. In this section, ability of different planning models to analyze system flexibility requirement to address short-term RE resource intermittency has been discussed.

System planning models used in power sector can be categorized into several groups like optimization, simulation, top-down, bottom-up, hybrid, and general equilibrium [13, 89, 90]. Here, these are broadly classified in two categories, namely energy system and power system models, depending on their focus and application area (Figure 2.3). While the first group

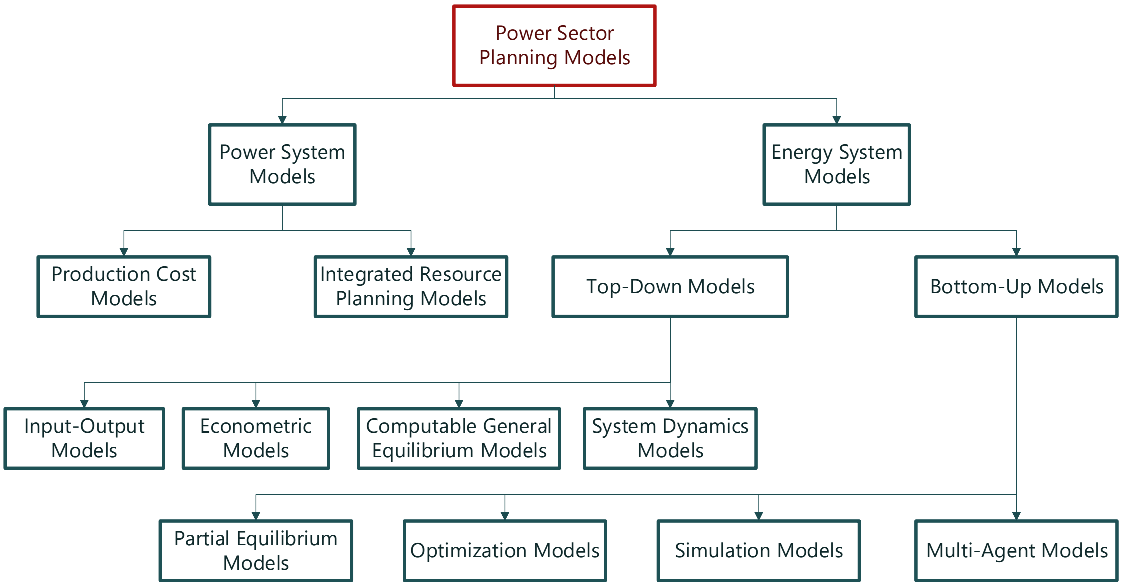


Figure 2.3 Classification of Power Sector Planing Models

of models answers broader questions related to national or global energy policy, the second group focuses exclusively on regional/national electricity sector.

2.3.1 Energy System Models

Energy system models provide a strategy for national or global level decision makers to formulate new energy policies and chalk out different pathways to achieve those policy targets. These models have widely been used to analyze the perspective, feasibility, and impacts of future energy demand and supply options. They can broadly be classified into two groups, top-down and bottom-up.

Top-down models take an economic approach and often do not incorporate explicit descriptions of technology details. They take an aggregate view of energy sectors and economy on national or regional level. These models apply macroeconomic theory and econometric techniques to model demand, and the supply from various energy sectors. They can be further categorized into four subsets, *i.e.* input-output models, econometric models, computable general equilibrium models, and system dynamics models.

Compared to top-down models, bottomn-up energy system models adopt an engineering approach and have a relatively higher degree of technological details. Though these models do not consider macroeconomic impacts of energy or climate policies, they can portray a detailed picture of existing and future demand and supply technologies. As these models take a disaggregated approach involving multiple energy sectors, they are generally more data intensive. Bottom-up model classes can further be divided into partial equilibrium models, optimization models, simulation models, and multi-agent models [91].

Among different top-down models, present study deals with optimization models which minimize total discounted cost or maximize total surplus over the planning horizon. These models, by considering inputs of future demand projection, technological options, current resource stock, and specific policy information, generate full energy system pathways for study horizon. They identify proper technological option for energy supply, transformation, and end-use. Application areas of these models are quite vast and diverse. It ranges from the feasibility study of specific policy targets, to role of a particular technology or policy in future energy system. Usually, these models are intended for whole energy system analysis, *i.e.* interrelated energy sectors of a country or world [92, 93]. But, they have also been used for the study of specific sectors like electricity, transportation, and agriculture of a particular country or region [94, 95].

2.3.2 Flexibility and Energy System Models

Long-term energy system models have several inherent modeling limitation to address short-term RE variability. Thereby, these models are weak in evaluating flexibility requirement for different system configurations.

Time Resolution in Energy System Models

Planning horizon of energy system models is often multi-year or decade. The entire time horizon is split into some periods, each consisting of an equal or a different number of years. A selected set of inter-annual time slices is used to represent a year to limit computational complexity and model size [89]. Thus, within a model period, a year is depicted by only a selected number of seasons, days of week, and time of day [20]. Though it is theoretically possible to represent days in hourly or sub-hourly resolution, chronology of demand or RE time series are not considered by these models. It is also noteworthy that, during model simulation, dynamics of assumptions associated with time slice are not taken into account and are represented only by their annual averages throughout the period.

Figure 2.4 further illustrates the inability of time slice definition to represent RE variability. It shows the effect of temporal aggregation for a system model which considers one representative day in hourly resolution for each month, *i.e.* 24 time slices per month. The sub-figure on the left indicates hourly capacity factor of a 4 kW PV power plant in New Delhi,

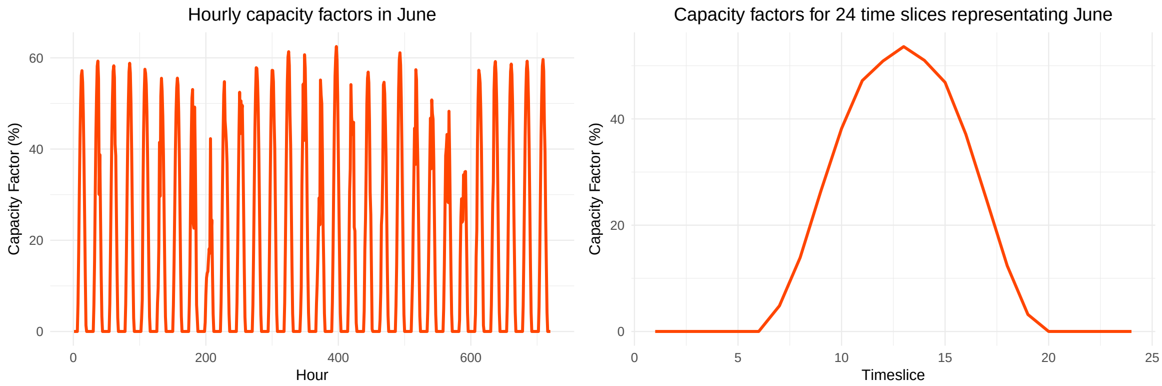


Figure 2.4 Effect of time slice wise aggregation of hourly solar generation potential for June in Delhi, India (28.63^{0}N, 76.94^{0}E)

India (28.63^{0}N, 76.94^{0}E)) throughout the month of June [96] [4]. From the hourly generation values, time slice wise capacity factors are calculated and displayed in the sub-figure on the right side. It is clearly observed that 24 time slices cannot reflect inter-day as well as inter-hour variability of PV generation potential of the whole month. Therefore, short-term RE intermittency from RE generators are not traceable by time slices alone.

Spatial Resolution in Energy System Models

In energy system models, the geographic region under study (country, world, *etc.*) is often considered as a single copper plate [5]. Therefore, the effect of spatial variation of RE resource (capacity factor, *etc.*), and inter or intra-regional commodity flow (fuel, electricity, water, *etc.*) are often not tracked. With multi-region models, region specific RE power plant capacity factors, resource potential and cost of commodity flow between regions can be incorporated into the modeling paradigm. In this approach also, model regions are considered as single nodes and intra-regional variability of RE resources are replaced by averages. Theoretically, spatial resolution can be increased by considering many sub-regions, but computational complexity and data unavailability restrict this. Apart from this, in planning models physical aspects of power flow through electricity grid are often considered as a basic transportation problem. Thus, these models cannot consider network congestion or spatial RE resource variation while calculating inter-regional transmission capacity.

Figure 2.5 illustrates high granular annual average solar global horizontal irradiance (GHI) (kWh/ m^2/ Day) data (10 km spatial resolution) corresponding to North Indian states [97]. GHI values are further aggregated to $1^0 * 1^0$ grid cells, and states respectively in

[4] PV generation data is taken from PVWatts online calculator. The hourly solar radiation is from the typical meteorological year (TMY) data.

[5] Single node model

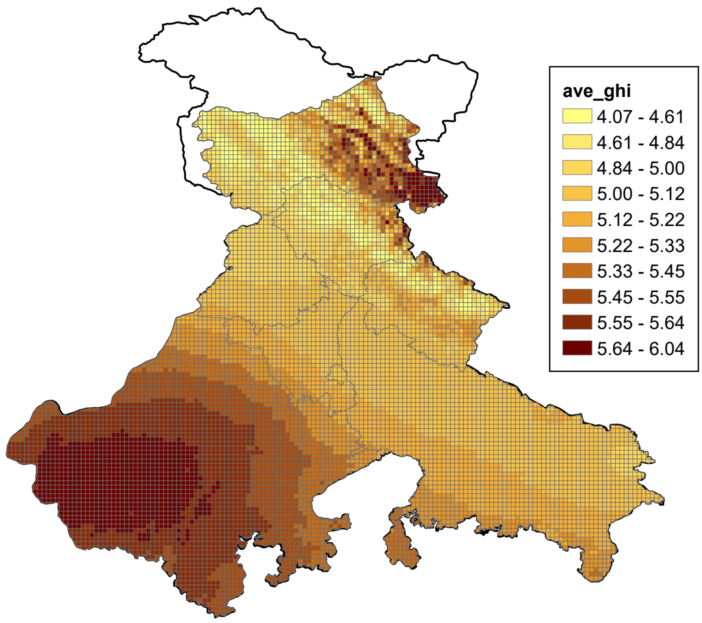
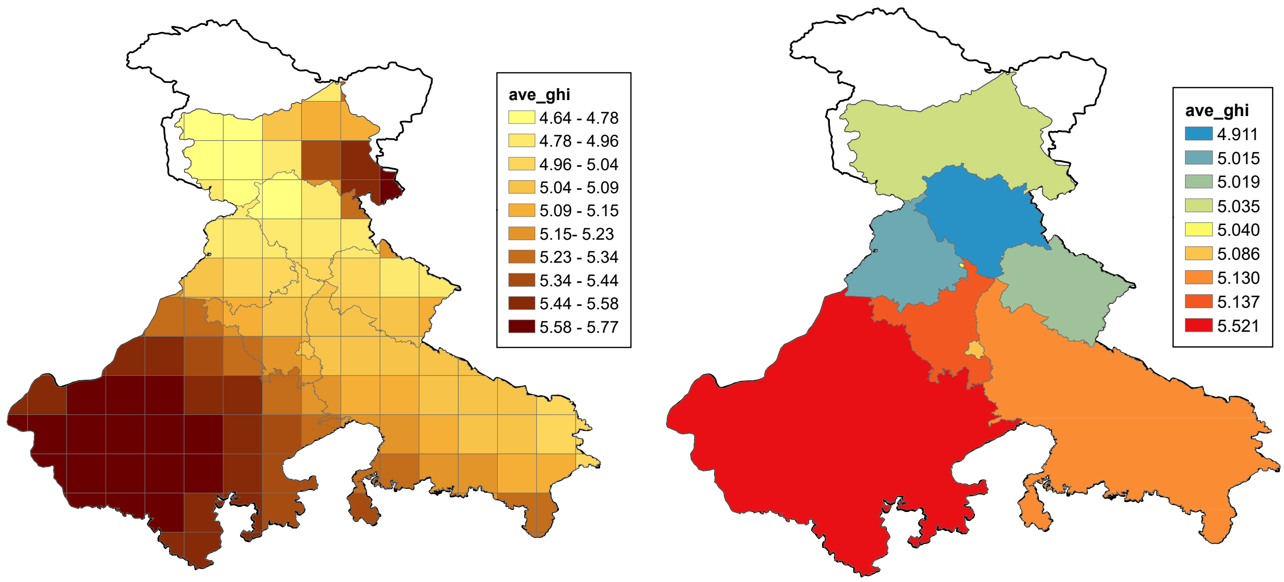


Figure 2.5 GHI (kWh/ m^2/ Day) in North India at 0.1 degree resolution [97]



(a) Aggregation to 1 degree resolution (Mean)

(b) Aggregated to States (Mean)

Figure 2.6 GHI values of Figure 2.5 aggregated to 1 degree resolution grid cells, and states of North India

Figure 2.6. Sub-figure 2.6b clearly illustrates that state level regional definition leads to loss of intra-regional spatial variability of solar generation potential. Unless intra-regional variability is considered at suitable spatial granular level (as illustrated in Figure 2.6a), coarse spatial definition will lead to inaccurate representation of regional RE generation and capacity potential.

Operational Constraints in Energy System Models

Energy system models often use linear programming technique with linearized objective function and constraints. The nonlinear functions are represented as a stepped sequence of linear functions. Though it leads to loss of granularity, it is often a rational choice to keep model within a computational limit. Core focus of energy system models is not to optimize daily generator scheduling or dispatch; rather their strength lies in chronological investment planning. Dispatch of generators in these models is only restricted by a user defined availability factor corresponding to each time slice. System operational constraints on generators, transmission line, *etc.* are often ignored, or their representation becomes unrealistic due to limited temporal and spatial resolution. Due to the lack of operational constraints, renewable and conventional power plants are treated equivalently (differences are cost, capacity factor, efficiency, and time slice definition, *etc.*). Therefore, variability from RE power plants is often not traceable. These models do not provide any facility to maintain flexibility or reliability metrics for reliable portfolio calculation [48, 98, 99].

Modeling in absence of operational constraints in low temporal and spatial resolution can lead to overestimation of system capability to assimilate renewable energy, underestimation of operational costs and undervaluation of the requirement for flexible resources [15, 16, 18, 100, 21]. Therefore, it is not guaranteed that the system's resources planned by these models could be operated in a flexible and reliable manner in real time.

2.3.3 Flexibility and Power System Models

Power system utilities regularly perform long-term capacity planning to serve their demand in a stable, credible and economical way. They determine size, timing, and type of generation and transmission capacity expansion required to meet future demand. Expansion planning activities focus on the selection of least-cost generation or transmission alternatives, by minimizing the sum of capital and operation cost while maintaining reliability constraints. Reliability criteria can be deterministic (*e.g.* percentage reserve capacity) or probabilistic (*e.g.* loss-of-load probability, expected unserved energy) [101, 102].

Capacity planning tools used by power utilities can be categorized into two main groups, production costing, and resource optimization. Production cost models simulate unit commitment and dispatch operations of a system through chronological optimization, often at hourly or sub-hourly resolution, to determine annual energy production cost. These models do not quantify new capacities directly and serve as a reliability evaluation tool for the planner, who applies intuition to select the best portfolio choice [103]. Resource optimization models endogenously identify the least-cost capacity expansion options from a set of technology types and sizes, to satisfy constraints such as reliability levels.

Traditionally, power utilities use these models for investment and capacity expansion planning. Development of liberalized electricity markets in various countries has added a new dimension to these models. Modern power sector tools incorporate the characteristics of market players, market operation and effect of different market mechanisms and policy.

Time resolution of power system models is quite high (up to seconds). The production-cost models offer a detailed representation of system operational constraints and can simulate day-to-day generator scheduling and dispatch. Spatial depiction of regions in these models is done by several nodes or buses, which could represent load centers, RE rich area, large thermal generators, substations, *etc.* Spatial variability from RE resource or demand pattern can be exogenously represented in these models. They also provide a facility to incorporate reliability criteria in their planning paradigm. In general, power sector specific planning models can analyze the operational aspect and RE resource variability with higher resolution.

2.3.4 Comparison of Energy and Power System Model to Quantify Flexibility

Both energy and power system models are used for capacity planning of electricity sector but are utilized to asses different goals. While power system models select least-cost capacity expansion options, energy system models quantify new capacity requirement to meet a particular policy goal with minimum cost.

Utilities use power system models focusing solely on the electricity sector, leaving aside interactions with other energy sectors. They do not provide a long-term vision of national or global system development and do not consider long-term dynamics of socioeconomic and environmental parameters. Thus, these models are not very useful for long-term national level energy policy analysis (*e.g.* national carbon emission reduction targets) [90]. Energy system models are used by national and global energy system planners. Focus of these models is to identify the least-cost pathway over a long-term, multiple period horizons, to satisfy a policy target. Power sector is represented within these model endogenously, and it is affected by the dynamics of other energy sectors. Therefore, these kinds of model can optimize the capacity expansion needed in power sector considering various policy input.

Both model types have their advantage and disadvantages. Power system models can analyze system operational aspect and RE resource variability with high resolution in a limited spatial and temporal horizon. Energy system models, on the other hand, cannot adequately cover short-term RE intermittency or uncertainty, due to an extended outlook. Therefore, there is an urgent need to utilize best features of these two type of models for planning flexible capacity, and designing policies related to RE penetration and emission reduction targets of national or global scale power system.

2.4 Addressing RE Intermittency in Energy system Models

Motivated by increasing penetration of intermittent RE resources, consideration of short-term RE intermittency and reflecting power system operational aspects in long-term planning is becoming increasingly relevant [104]. Power system models can quantify system flexibility need and address short-term RE uncertainty on a suitable scale. Improvement in their modeling paradigm is targeted towards chronological investment planning or interaction with other energy sectors. Energy system models are better suited for long-term national level capacity planning, as they dynamically consider interaction with other areas. Therefore, interest of this article is on approaches to increase the ability of energy system models to handle short-term RE intermittency.

Methodological improvement of energy system models can be done endogenously, *i.e.* within the model itself or exogenously, using separate models. Endogenous methods tend to adopt either higher temporal and spatial resolution, or incorporate various operational constraints within the planning model itself, or both. In exogenous approach, a separate power system model is either soft or hard linked to the energy system model (Figure 2.7). Soft-link approach usually adopts an iterative process and the data transfer between models is controlled by the user. On the other hand, in hard-linking method, the two models are fully integrated and solved in a simultaneous optimization framework [105]. In this section, various modeling studies employing these methods are discussed and compared for their usefulness.

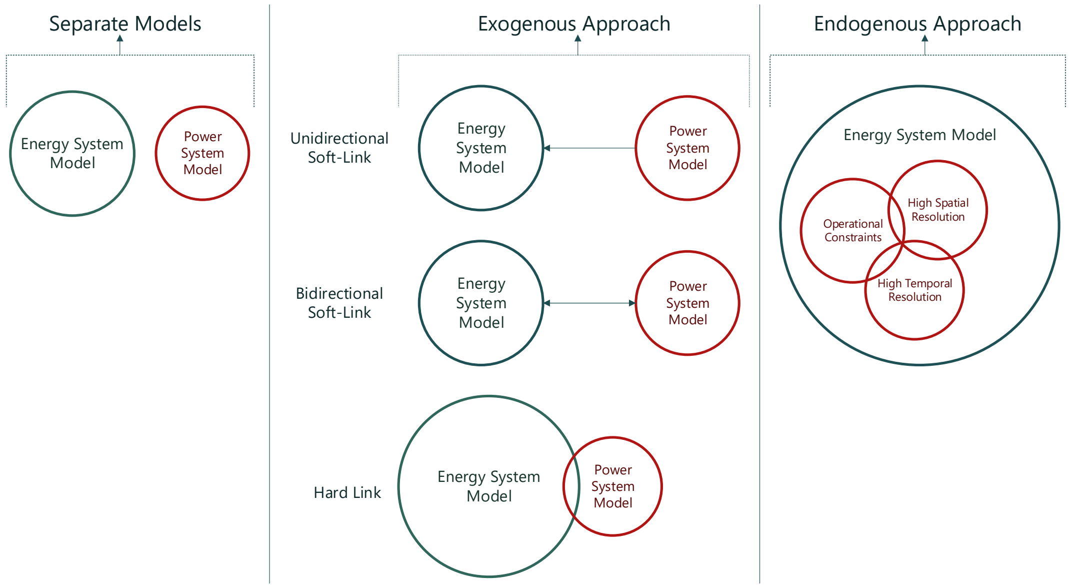


Figure 2.7 Different approaches to address short-term RE intermittency in energy system models

2.4.1 Endogenous Approaches for Methodological Improvement

Time Resolution Enhancement:

Selection of high temporal resolution plays a crucial role in representing the dynamics of diurnal and seasonal electricity load curves in energy system models. It also allows a user to depict high granular RE availability factor by time slice and operational constraints. For this, higher temporal disaggregation of load and RE has been performed by considering twenty annual time slices in the long-term UK-MARKAL model. High resolution helps to improve load balancing and electricity dispatch simulations and analyze the role of demand and supply side storage options [20]. There are instances of adopting a high number of annual time slices with hourly diurnal resolution to capture hourly, daily and seasonal supply and demand dynamics [21, 106, 107]. Coarse temporal resolution leads to sub-optimal investment in future RE technologies as well as flexible capacity. Higher time resolution is, therefore, crucial to assess the real impact of a particular energy policy, especially in high RE-penetrated systems. But, high temporal resolution doesn't necessarily mean that model can handle RE stochasticity; it is only the variability which is being captured. Deterministic representation of system uncertainty is sufficient in planning studies, as long as the time resolution of system operation and the model are similar [108].

Limited number of time slices can be compensated by improving other aspects like model formulation, and higher spatial resolution. Short-term system fluctuations have been captured by only 49 annual time slices (four seasons with three typical days, four diurnal and an additional super peak time slice) in LIMES-EU$^+$ model [109]. The model has a high spatial representation of the planning area (Some part of Europe and the Middle East/North Africa (MENA) regions), which has been divided into 20 geographical entities connected by 32 transmission corridors. Similarly, major modeling enhancement has been performed by considering reserve capacity, day-night and seasonal electricity storage, RE curtailment, industrial DSM, smart grids and endogenous transmission and distribution network with 78 yearly time slice in Belgium-TIMES model [110]. Twelve annual time slices have been utilized in EU-TIMES model with major mathematical improvement in TIMES model (The integrated MARKAL EFOM system) formulation by including a detailed representation of power flow in transmission lines [111, 112]. Also, different availability factors of RE technologies pertaining to each time slice is considered in this model.

In long-term energy system planning models, it is not feasible to consider consecutive time series of demand or RE generation. Selection of time resolution depends mainly on annual, seasonal and daily load curve, rather than RE time series fluctuations. Normally, there is no yardstick or guideline available to select optimum number of time slices for a given system, and it is often decided by examining available data, study focus, system in hand, and computational resources. Recently, some studies have utilized only a set of typical days within a year considering the historical RE and demand time series. This approach can decrease computational requirements of planning models by reducing temporal resolution but without compromising on the reliability of results. Different methods such as heuristics, random selection, optimization models, hierarchical clustering algorithm, and hybrid methods can be adopted for this purpose [113, 114]. Consideration of only six typical days, *i.e.* 48 selected annual time slices in LIMES-EU model is sufficient to capture temporal dynamics, which can only be obtained with much higher temporal resolution in standard approach [114].

Uncertainty in historical wind power and electricity price has been represented in a long-term model by two stage scenario tree constructed by joint probability distribution [115]. The focus in this approach is on simultaneous optimization of investment (first stage) as well as on operational decisions (second stage). Compared to a deterministic version of the model with peak reserve constraint, stochastic model reports less wind capacity and system cost for model years. Stochastic approach makes it possible to endogenously optimize reserve capacity for intermittent RE integration.

Spatial Resolution Enhancement:

Spatial resolution selection in energy system models is often driven by political or economic boundary, rather than RE resource variations. Various attempts have been made to improve spatial resolution by dividing the planning area into many regions. Fifty load areas and 124 existing and new transmission corridors have been considered in SWITCH model for capacity expansion study in western North America [22]. Five model regions are considered within German transmission system control area to track spatial variation of RE resources, as well as the effect of transmission capacity expansion to meet the future load growth and wind energy integration [116]. Thirty two model regions have been considered in a TIMES based planning model of USA power sector namely, FACETS [23]. Despite high granularity of spatial assumptions in these attempts, power flow between model regions is often represented as a transportation problem, *i.e.* the physical aspects of electrical load flow are ignored. Power flow constraints like bus voltage and angle limit, and transmission line capacity limit are often not considered. Linearized DC power flow equations with simplified N-1 security constraints have been incorporated in long-term model generator TIMES for better representation of transmission grid [117]. This feature has been utilized in some studies for long-term system planning [111, 26].

Enhancing the Representation of Technical Constraints:

To simulate the effect of RE intermittency, high temporal and spatial resolution should be complemented by a detailed description of operational constraints in the mathematical formulations of models [25, 118]. Various approaches have tried to endogenously incorporate additional operational constraints to capture the effect of RE variability.

Residual load duration curve (RLDC) [6] captures the relation between RE variability and demand, and reveals the associated integration challenges [119]. In long-term models, it allows defining constraints on the minimum production level of thermal units. It also helps to determine the storage capacity, flexible generation, and RE curtailment for expected variations in residual load and RE generation [120]. Thus, it provides simultaneous optimization of investment planning and system operation. Traditional RLDC representation can be improved by piece-wise linearization into three parts; base load, intermediate, and peak including reserve margin. In REMIND-D model, representation of demand and RE variation using this approach leads to 35%, and 27% reduction in generation from variable RE plants in the base, and ambitious green house gas mitigation scenario respectively in 2050 compared to a model version without any description of variability [24]

For any power system, critical operational constraint are related to generating units as described in Section 2.1 and 2.2. There are recent attempts to include these constraints in long-term modeling frameworks like OSeMOSYS, TIMES, and eMix [25, 118, 121, 122]. The

[6] RLDC is the load duration curve minus total RE generation.

motive of these approaches is to endogenously simulate short-term power system operation within long-term planning models.

2.4.2 Exogenous Approaches for Methodological Improvement

Enhancing Time Resolution and Representation of Operational Constraints

Production-cost models can simulate short-term system operation considering demand as well as RE variability. These models are often exogenously used in conjunction with energy system models to capture the effect of RE or load variation on system operation. This method is often called hybrid modeling framework, which can involve two or more models. In this approach, system model optimizes investment decisions while operational model optimizes hourly or sub-hourly grid balancing. Link between operational and energy system models can be unidirectional or iterative. In unidirectional approach, capacity calculated by system model about a target year is fed to the operation model to check its feasibility. On the other hand, the iterative approach involves bi-directional data flow between models.

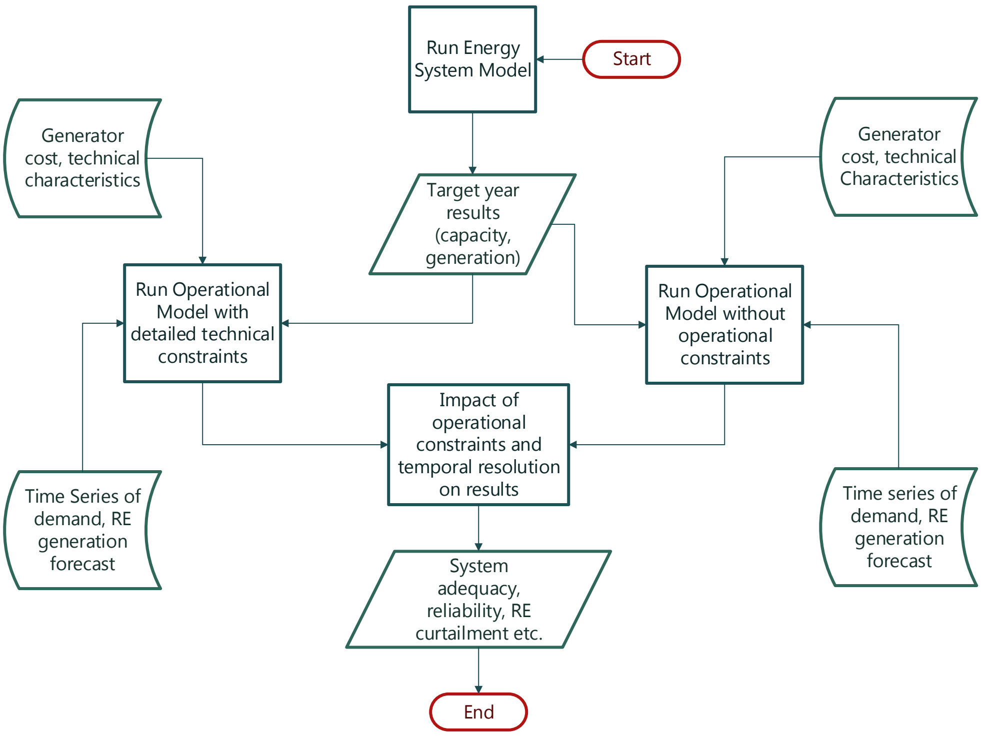


Figure 2.8 Unidirectional Soft-Linking Methodology [15]

Unidirectional linking methods: Unidirectional soft-linking methodology provides a useful method to cross-check technical feasibility of system portfolio calculated by an energy model. One way soft-linking of a system model namely Iris-TIMES and a production cost model PLEXOS is detailed in Figure 2.8 [15]. This particular analysis shows that, though optimized portfolio from the Irish-TIMES model is adequate, essential flexible elements, namely storage, gas based generators, and wind curtailment are undervalued while CO_2 emission has been overestimated. Belgium-TIMES electricity sector planning model has been linked with a unit commitment model LUSYM. In this study, it has been observed that low level of operational detail leads to overestimating RE generation and underestimating operational costs; but these effects are only prominent at a high share of RE (35%–50%) [16]. A dispatch model namely highRES has been utilized with long-term planning model UKTM (UK TIMES model) to evaluate technical feasibility of energy system pathways. Results show that the planning model favors base load capacity over flexible generation option, which leads to wind curtailment and load shedding in dispatch model [123, 124]. Transferring results from system model into an operational model is challenging due to the mismatch in spatial and temporal definitions. The task of constructing input data set for a production cost model, using the output from a system model, can be automated with the help of optimization tools [125].

Bidirectional linking methods: Among hybrid approaches, iterative methods are more popular than uni-directional ones. Here, after verification of system portfolio by operational model, information is fed back to the system model, and new solutions are attempted. Overall method of bi-directional soft-linking is elaborated in Figure 2.9. A multi-regional energy system model PERSEUS-RES-E and a dynamic dispatch simulation model AEOLIUS are connected via a hard link, *i.e.* each model generating its own output file [126–128]. Manual iteration is performed to analyze the differences in results after each data exchange and model run. Using the simulation results from the operational model, additional constraints representing reserve capacity, partial load operation, start-ups, and shut-downs, *etc.* are included in the system model for better presentation of RE intermittency.

A TIMES based energy system model and a probabilistic production simulation model ProPSim are connected via an iterative soft-link [26]. The methodology requires system model to run first and calculate RE penetration level. The probabilistic model then simulates system operation and calculates balancing capacity, and storage needed to support residual hourly load variation for that penetration level. These results with updated utilization factors are then fed back to TIMES model which then attempts a new solution. Convergence is achieved when there is no need for new investments for system balancing. MARKAL based long-term system model MARKAL-NL-UU has been soft-linked to unit commitment and economic dispatch (UCED) model REPOWERS [129, 27]. The long-term model calculates

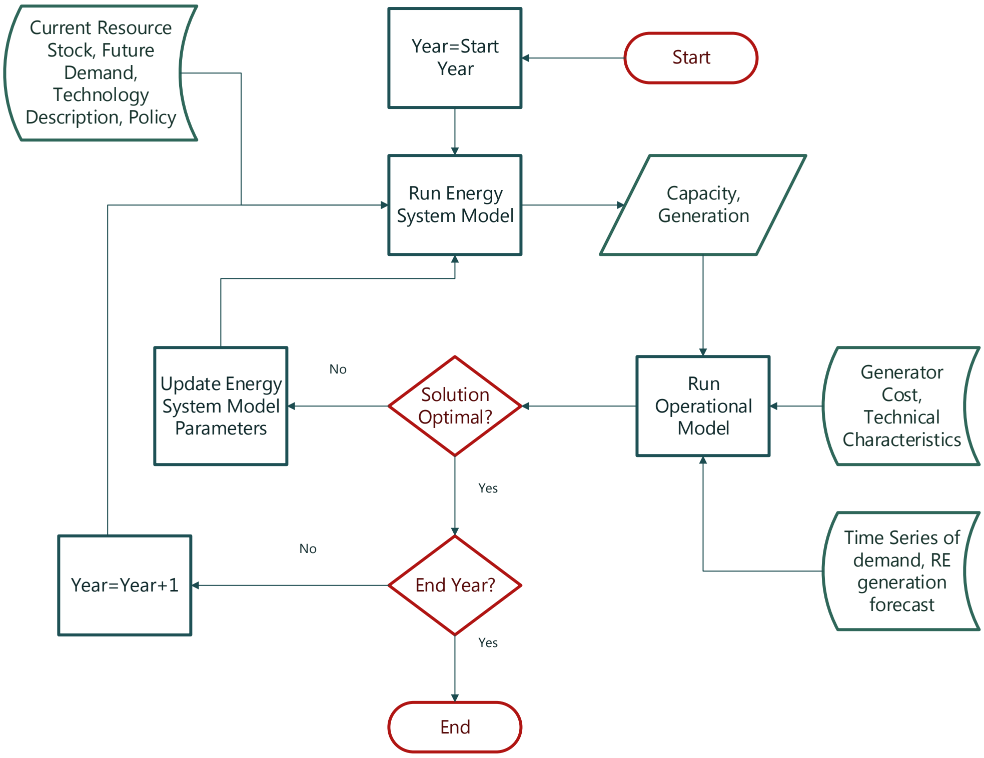


Figure 2.9 Bi-directional iterative Soft-Linking methodology

technology capacity and serves input data to UCED model, which then optimizes hourly scheduling and dispatch of generation units over a whole year. Analyzing result from UCED model, actual reserve capacity and efficiency of generators are calculated and fed back to long-term model to obtain a new solution. Similar integrated modeling frameworks involving long-term optimization model, and hour-by-hour simulation model have been reported [17, 130]. The simulation model is used to evaluate the reliability of capacity portfolio obtained from the optimization model. The capacity is adjusted if it does not satisfy the simulation model.

Spatial Resolution Enhancement

Consideration of higher spatial definition in planning models is often prohibitive due to unavailability of data at desired resolution. Also, higher spatial resolution adopted in endogenous approaches does not allow model to address intra-regional RE variability. System models can utilize separate tools to model geographical RE variability at suitable scale, develop data, and incorporate them in planning models. Geographic Information System (GIS) tools are useful in this regard to develop realistic RE capacity and generation related potential. ReEDS (Regional Energy Deployment System) model endogenously considers high spatial resolution [131]. The USA has been divided into five type of resource regions to account for geospatial differences in resource quality, transmission needs, and electrical political boundaries. Total transmission network of the USA has been represented by 134 nodes connected by 300 lines. Linearized DC-power flow has been considered to track power flow between regions. But, a major improvement in representing intra-regional spatial variation of RE sources is made exogenously using GIS tools. For each region and class of RE resource, new supply curves are developed to capture additional grid integration cost for connecting new RE plants to nearby transmission lines. Thus, geographical value of a particular site regarding resource quality is considered by this approach. This information is valuable as new RE capacity installation often takes place at remote areas associated with high integration cost which traditional models fail to consider.

2.5 Comparison of Methods to Consider RE Intermittency in Energy System Models

Considering high temporal and spatial resolution, or adopting technical constraints endogenously within long-term model improves result accuracy. But exclusive attempt to incorporate only individual improvement (*e.g.* time resolution only) does not provide significant advantage [16, 132]. For example, if a model has only high time resolution excluding operational constraints, it cannot reflect the effect of short-term RE generation fluctuation in system operation. On the other hand, adoption of operational characteristics within a low temporal resolution framework fails to simulate short-term dispatch operations. There is no hard and fast rule to decide whether time resolution or operational constraints affect the result most [16]. Adoption of high time resolution has been criticized for excessive computational burden and design complexity [107]. Again, direct representation of operational constraints in long-term models is often stylized and may not reflect physical processes of unit commitment and dispatch [16].

A model is built considering a particular focus and application area. Altering its core functionalities, philosophies and pushing it to new limits like adding several new constraints and adopting incredibly high time resolutions often reduces the reliability of results and increases computational complexity. A judicious compromise can be made to create significant improvement in results from endogenous approaches also, but soft-linking approach better captures generator dispatch profiles [25].

Model linking methodologies (soft or hard) have been applied widely in energy system analysis. Various existing applications integrate detailed macro-economic outputs of top-down models to technologically rich bottom-up models [133–136]. Model linking methods find wide application in analyzing long-term climate or energy policies [105, 137, 138]. In various model generating platforms, model linking facility is available as an add-on or module (*e.g.* TIMES-MACRO), to be activated as required [139]. Therefore, hybrid methods present a strong case to use dedicated operational models exogenously to consider RE variability in large-scale system models. This reduces the mathematical and computational complexity of endogenous approaches. So, exogenous approaches offer better results when system is planned for large-scale RE integration in long-term. But care has to be taken so that burden of developing and maintaining additional models and setting up proper data exchange methods do not overwhelm modeling benefits.

There is complementarity between long-term system models and power sector-specific production cost models. Strength of power sector models lies in representing accurate physical system operations, and detailed reliability analysis of future power system's portfolio. Thus, their output (*e.g.* RE integration costs, RE curtailment factor, electricity storage activity) might help to calibrate long-term energy modeling tools. On the other hand, strength of long-term models lies in analyzing the evolution of interlinked energy systems. Thus, they could provide economic and capacity assumptions (power demand, generating capacity, electricity cost) for future years to operational models [90].

Model-coupling is a complicated and time-consuming task, and raises several technical issues, *e.g.* convergence of iteration steps, nature and process of data transfer between models. Direct integration of constraints has the advantage of maintaining a single model, but their representation should be realistic. A soft-linking approach could help to identify suitable operational constraints which prominently affect model results and eventually integrate them into the long-term model itself. This improvement will significantly improve outcomes and reduce computational burden.

Recognizing these facts, there is a need for an energy system modeling framework that incorporates power system operational features and enables optimization using high temporal and spatial settings. But, unfortunately, available model generators do not offer comprehensiveness to the problem. There is a profound interest recently to develop such a modeling platform. Despite the existence of several approaches, their usefulness is not verified and also, associated computational costs are often not justified [90].

2.5.1 Challenges and Possible solutions

It is, therefore, important to identify an appropriate strategy to address flexibility in long-term energy system models. Both endogenous and exogenous approaches have advantages and disadvantages, and it is up to the modeler to decide the strategy to be adopted. Here, methodological improvements that can be done via both approaches are summarized.

Possible Solutions with Exogenous Approach

Unidirectional soft-linking approach does not offer chronological optimization of system portfolio over a planning horizon. Instead, it only provides a detailed picture of a target year. As the capacity of that particular year is calculated by system model only, power sector model often finds that techno-economically sub-optimal from a reliability point of view. But, there is no way for system model to rectify that. Therefore, bidirectional approach has clear advantage over unidirectional one, as it performs continuous optimization throughout the model horizon. But these hybrid modeling approaches have following considerations.

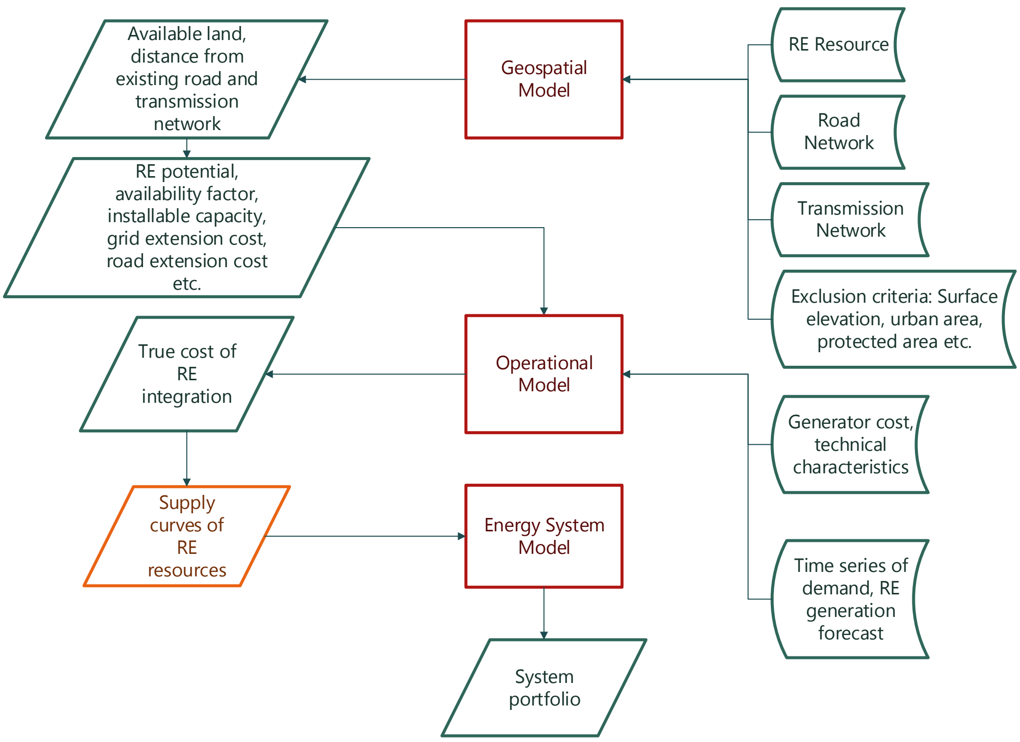


Figure 2.10 Reflection of RE integration cost in Energy System Model

To best utilize the ability of power system model, planning models should have a certain level of endogenous improvement over coarse representation of short-term RE variability. As technology capacity calculation is done by planning models, any endogenous modeling improvement will improve capacity related inputs for the operational model. These improvements can be done by adopting finer model settings, or incorporating additional technical constraints described in the previous section. High temporal resolution can help model to capture underlying variability of input demand data and RE generation. Multi-regional model structure and consideration of intra-regional RE resource variability can also strongly help to capture finer geographic potential variation and generation variability [131]. These methodological improvements can be undertaken as far as computational capacity permits. Though hybrid approaches aim to capture operational effect of various technical constraints with the help of separate models; any endogenous inclusion of suitable constraints within the planning models, though stylized can improve input results for operational models [25, 121]. It also ensures fast convergence, fewer iterations and quick data updation between models.

Apart from actual capacity transfer, coupling is also possible via cost implication. Variability of RE resources leads to additional integration cost, apart from its generation cost. This cost of additional grid infrastructure, balancing capacity, reduced utilization of existing thermal generators, system inflexibility, *etc.* can be calculated by separate models [140]. For example, cost related to new grid expansion could be quantified using geospatial tools depending on high resolution resource potential, land availability, suitability and existing infrastructures (transmission, road network, *etc.*) [131]. Again, cost due to additional balancing and flexible resource requirement, reduced utilization of thermal generators could be quantified using production cost models [141]. Using generation cost, RE resource potential and corresponding integration cost, new supply curves of RE resources can be developed for energy system models to better reflect the capacity and investment needed to support spatial and temporal variability of RE resources [142, 143]. This methodology is illustrated in Figure 2.10.

Possible Solutions with Endogenous Approach

Endogenous approaches have low data requirement, easy model calibration, small model building time and low maintenance effort. It also saves a user from setting up complicated data transfer procedure, as compared to bidirectional soft-link process. But, endogenous modeling improvement necessitates following considerations.

Temporal and spatial resolution aggregation is often inevitable in large-scale planning models to limit computational requirement, but various steps can be adopted to increase the effectiveness of aggregation by retaining details, and managing computational traceability. Instead of traditional way of constructing time slices, typical or representative days extracted from historical RE time series may lead to higher result accuracy [16]. The representative days' selection may depend on the method used, as well as the nature of variability. Single year's data may not be enough and long-time hourly or sub-hourly time series of historical RE generation is required to capture inter-annual variability. Careful methodology selection is important to derive desired number of time sets, as inappropriate method can significantly effect model outputs [144]. Among different methods like down-sampling and statistical clustering, heuristics can be an effective and stable way in this regard [145].

Capturing intra-regional variability of RE is required even in large-scale multi-regional models, where regions are often countries/ states. Increase in number of regional definition is often prohibitive beyond certain logical numbers for a particular study. Separate dedicated resource regions can be considered based on the sub-regional RE classes [146, 131]. Sophisticated GIS tools can be used to quantify intra-regional class wise RE capacity, and generation potential. These key parameters can further be utilized in planning model to better represent RE intermittency.

Endogenous representation of additional constraints often doesn't complement primary focus and objective of the actual model. Low spatial and temporal resolution in these models restrict addressing operational level uncertainty and fluctuations. So, representation of these constraints often becomes stylized and it does not complement related effort. Therefore, additional analysis is required to identify specific constraints which affect result prominently and represent them in a way to reflect system operation. This task may be challenging as it involves multiple simulations for sensitivity analysis. The actual cost of not including these constraints in planning model could be learned from a comprehensive soft-linking approach.

2.6 Energy System Planning and Challenges in India

2.6.1 RE Integration Targets

India has expressed aggressive renewable energy expansion plans to fulfill its sustainable development targets, *i.e.* reducing dependency on imported fuel, meeting climate change obligation, and ensure 100% access to electricity for its people. Several policy mechanisms, like state wise Renewable Portfolio Obligation (RPO), Renewable Energy Certificates (REC), Accelerated Depreciation, and Feed in Tariff have been promulgated to promote RE generation [147–150]. Recently, India announced its targets to achieve 40% cumulative non-fossil fuel-based electric power generating capacity by 2030 [151]. It includes the target of 175 GW of RE capacity by 2022, in which solar and wind are expected to be the major contributors [152]. Share of electricity from renewable energy sources is expected to rise from 6% in 2012 to 16% by 2030. At the same time, share of generation from fossil fuels based generators is projected to reduce from 77% to 61% by 2030 [153]. To meet these targets, National Tariff Policy 2016 has proposed to increase solar RPO target from 3% to 8% by 2022 (excluding hydropower) [154]. Thus, with various central and state initiatives, India is currently focusing strongly on renewable energy sources (mainly solar and wind). Even though no firm RE capacity targets have been set beyond 2022, steady growth is expected which can overtake conventional generation capacity addition rate.

2.6.2 RE Curtailment

With increasing solar and wind energy penetration, generation curtailment is becoming a concern for India as well. Countries like USA, China, and Germany with better grid management protocol and infrastructure witnessed substantial curtailment in near past, and a similar scenario is likely to be repeated here if appropriate mitigation strategies are not adopted. RE curtailment has already been witnessed in states like Rajasthan and Tamil Nadu due to inadequate transmission capacity and unwillingness of distribution companies to buy costlier RE power. In Tamil Nadu, solar PV plants currently face curtailment up to 50-100%, due to profile mismatch between generation and demand. Other states like Telangana, Karnataka, Andhra Pradesh, and Jharkhand face imminent curtailment challenges due to current PV capacity expansion plans [155, 156]. Though inadequate transmission capacity is often cited as the major cause for curtailment in India, other factors, such as inflexibility of coal-based thermal generators, improper operation strategies, as well as planning protocols, are increasingly becoming prominent.

2.6.3 Identification of Appropriate Flexibility Resources

Flexibility options for India can be unique from other developed countries. For increasing flexibility in Indian power system, areas that require immediate attention include rapid exploitation of hydro and pumped hydro storage potential, retrofitting existing coal-fired power plants, and developing adequate transmission infrastructure. Improved system operation protocol such as better area coordination, and accurate RE generation forecasting could significantly enhance flexibility within minimum time and cost. Fresh additions of firm capacity (*e.g.* coal based plants) need to have higher part-load efficiency, ramp rates, and lower start-up time. With adequate regulatory support in place, DSM and energy storage system, both at supply and demand side (*e.g.* MW scale battery, and EV) can turn out to be attractive flexible options in long-term, to mitigate large scale RE fluctuations.

2.6.4 Need of Modeling Improvements

Long-term energy system planning studies in India still do not employ a proper methodology to address RE variability [157–162, 158, 163]. Spatial and temporal definitions in these studies are not suitable to address the intra-regional geographical variability of capacity as well as generation potential of RE sources. Impact of operational scale RE variability on long-term system flexibility planning is also ignored in these studies. There are instances of applying advanced modeling technique like GIS in national and regional RE potential estimation (*e.g.* biomass [164], wind [165–167], and solar [168]) in India, but official estimates often do not facilitate the adoption of high temporal or spatial definitions in planning studies. Due to this, earlier studies in India have either excluded the planning of flexibility options such as storage, or results reported by them are unrealistic considering the large scale RE penetration targets. It is not guaranteed that system resources planned by these models could be operated in a flexible and reliable manner in real time. As variable renewable sources would play a major role in future generation portfolio, a drastic revision of the current planning methodologies is required.

2.6.5 Study Area

Present work is equally focused on developing methodologies to consider short-term RE variability in long-term planning and analyze long-term system RE penetration scenarios in India. Due to data, computational resource, and time limitation, study focuses on a particular region covered by North Indian power grid. India has one interconnected power grid with five regional control areas namely northern, eastern, north-eastern, southern, and western. Among these, northern region is the largest in geographical area (31%), and has 30% of the country's population [169, 170]. This region has diverse generating options; state like Uttarakhand is rich in hydro resources, while Uttar Pradesh is mostly dependent on coal-based thermal generation. High RE potential in north India will continue its capacity expansion. Likewise, states in north India, like Uttar Pradesh, face high transmission and commercial loss, energy access, and power quality issues. These facts make north India a well representative region to study the challenges associated with future energy system evolution of India.

2.7 Summary

After analyzing the current state-of-the-art of energy system planning, following summary has been drawn:

- Large-scale integration of variable RE sources like solar and wind has a profound impact on power system operation and planning. Additional system flexibility is needed to manage large-scale system variation caused by RE.
- There is an urgent need to revise existing planning approaches, as traditional long-term models are unable to consider short-term RE variability in the planning paradigm.

- Planning methods need to evolve to identify suitable flexible technologies and accurately quantify their capacity in long-term.
- Methodological improvements in existing energy system optimization models can be done within the models, *i.e.* endogenously or by using separate models, *i.e.* exogenously.
- Planning approaches need to consider intra-regional RE resource variability (generation and capacity potentials) and its impact on system operation at suitable spatial and temporal granularity.
- GIS and other statistical tools can quantify intra-regional RE variability. Dedicated power sector models can develop insights of system operation which could be utilized by the planning model.
- Certain level of endogenous improvement is needed in the planning model to facilitate the incorporation of granular information from other model/ tools. It may require additional assumptions/ declarations in this regard.
- The methodological improvements are crucial for countries like India where rapid integration plans of large-scale RE capacity have been set up.
- Variation of RE penetration levels, generation & capacity mix, role of storage and transmission lines etc. should be analyzed for large number of parametric scenarios using the improved methodologies.

Chapter 3

North-Indian Multi-Region TIMES Model (NIMRT)

This chapter outlines the development of a long-term planning model used in the present study. It begins with a description of the TIMES modeling framework on which the present model is built [112]. It discusses the mathematical structure, broad in/ outs, and data handling tools of TIMES. Afterwards, development of the North Indian Multi Region TIMES (NIMRT) model, along with a detail description of various settings, data, and assumptions are explained.

3.1 Overview of TIMES

TIMES is a technology-rich bottom-up dynamic energy system model generator developed by the Technology Systems Analysis Program of the International Energy Agency (IEA-ETSAP). It is widely used by several institutions in nearly 63 countries to perform energy, economic, and environment-related analysis for designing long-term least-cost energy system pathways [171]. TIMES family of models have been used extensively for different kinds of systems, ranging from global to regional energy sector [172–174]. TIMES and its predecessor MARKAL have also been used prominently to analyze future energy sector evolution of India [160–162, 175, 176]. Taking the input of present resource stock, current and future technology description, and projected demand, it determines optimum future system portfolio at minimum cost, subject to several techno-economic and policy related constraints. These facts make TIMES the obvious choice for addressing some methodological challenges related to long-term energy system planning.

3.2 Economic Rationale of TIMES

Adopting a bottom-up approach, TIMES based models are technology explicit. In TIMES, Each processes/ devices (energy supply, transformation, transmission, and end-use) can be defined using several techno-economic and environmental parameters. A moderate to large-scale TIMES based model can contain thousands of technologies in various energy sector in each model region. But, ultimately it is the choice of the user to decide the technological detail to be considered. The choice may be driven by data availability, nature of the system and computational infrastructure, *etc.* A user can easily control the number of processes (technology aggregation: plants instead of units) and their technological specifications solely by input data specification, without altering any model equations.

TIMES based model can be multi-regional to track inter-regional energy, emission, and material trading and its effect on system design. As the regions are geographically integrated by several trade-links, decisions taken in one region affect others also. Again, level of regional dis-aggregation (number) of the planning area is dependent on the user. TIMES based planning model cover long-term planning horizon which is divided into a number of time-periods according to the user's choice. The initial period is often single year but multiple yeas are also considered for better data calibration. A year of a time period may further be subdivided into small divisions, namely time slices. Time slices can be annual, seasonal or diurnal. Intra-annual and intra-day time slices are useful to define realistic characteristic of various processes and commodities, *e.g.* solar and wind power plants, electricity, and heat. Defining time slices is also useful to ensure that intra-year peak demand of a commodity is satisfied.

TIMES based models compute a partial equilibrium in energy market without take into consideration the whole economy. At market equilibrium, the total cost is minimized and simultaneously total economical surplus (consumer and producers) is maximized, which leads to social welfare maximization. In every time-period, the model calculates production, consumption and price of the commodities, such that each supplier produces commodity as much as it is demanded (Figure 3.1). The price of producing a commodity affects its demand, while at the same time the demand affects its price. TIMES normally assumes a perfect foresight of market behavior while calculating this equilibrium. It assumes that every market agent has perfect knowledge of present and future market condition (*e.g.* future demand, resource availability, and technology parameters). However, it is possible to deviate from this assumption in TIMES and address future uncertainties either by adopting a myopic foresight or by stochastic programming. However, these model variants are at a cost of higher computational time and data requirement.

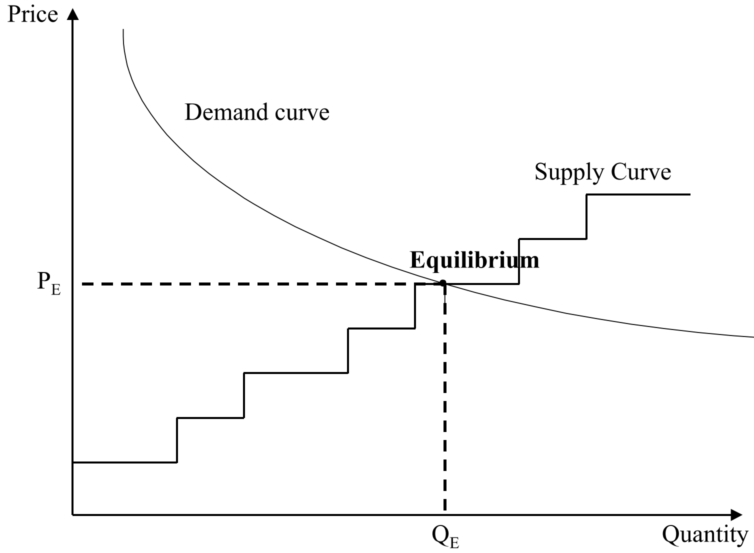


Figure 3.1 Supply demand equilibrium

3.3 TIMES Reference Energy System

To generate a system model, TIMES needs various data inputs from the user pertaining to technology, commodity, and commodity flow. Broad inputs and outputs for a TIMES based model are outlined in the Figure 3.2. Commodities can be various energy carriers (electricity, heat, *etc.*), materials, monetary flows, and emissions. Technologies are the representation of various physical processes which either produce a commodity (mining, import, *etc.*) or transform some commodity into others (power plants, vehicles, demand devices, *etc.*). Finally, commodity flow is the amount of commodity consumed or produced by a process; in other words they are the links between process and commodities. The input data to TIMES can be either qualitative (list of various types of commodities and processes) or quantitative (techno-economic parameters).

Technical parameters associated with processes are efficiency, availability factor, technical life, construction lead time, commodity consumption per unit of activity, *etc.* Economic parameters include various costs related to investment, operation and maintenance, and dismantling. Other than these parameters, taxes/ subsidies and various bounds related to investment, capacity, and activity of a process for a period/ region can be defined. Technical parameters for commodities can be overall efficiency/ loss, and declaration of traceable time slice. For final demand commodities, additional annual demand projection is needed over

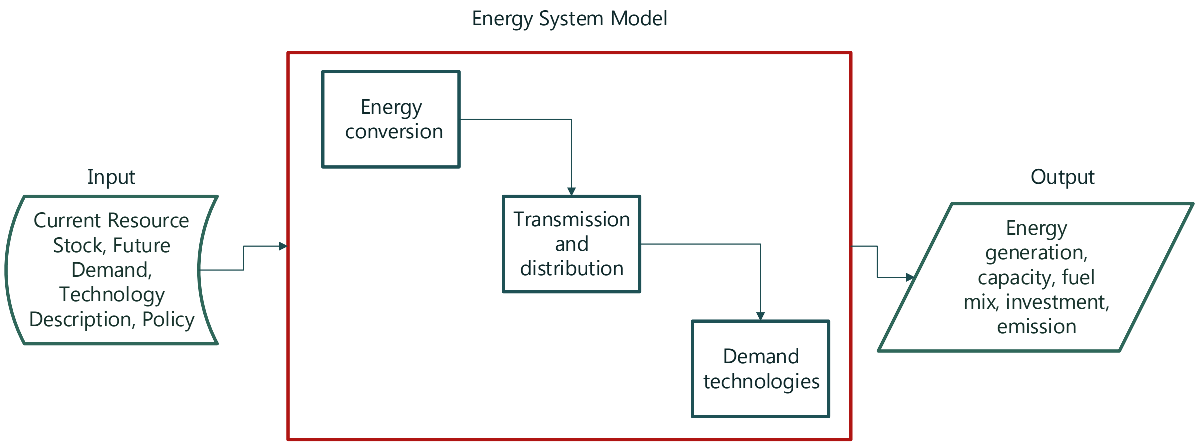


Figure 3.2 Input-outputs of a TIMES based energy system model

the model horizon. If the demand commodity is associated with intra-annual time slices, user need to provide the corresponding demand curve pattern also. Economic parameters associated with a commodity flow are additional costs, taxes, and subsidies on the production of a commodity. Technical parameters are share of a particular commodity within a input/ output commodity flow group, efficiency, emission rate by fuel, *etc.*

The inter relationship between the commodity, processes, and commodity flow creates a directed graph which is termed as RES (reference energy system). In a TIMES RES, commodity flows are links between process and commodity. Though a RES can portray the whole picture of an interconnected energy system starting from resource extraction/ procurement to end use, it can also exclusively focus on a specific sub sector. In general, RES diagrams can be helpful to track the material or commodity flow between various processes.

3.3.1 TIMES Optimization Framework

TIMES based models minimize the discounted sum of the annual costs (investment, operation & maintenance, energy import, export, and delivery, resource extraction, tax, and subsidies, *etc.*) while satisfying several constraints over the modeling horizon. To calculate the net present value of the system cost, the model first calculates regional yearly total system costs over the modeling horizon. Further, the costs are discounted to the base/ reference year for every region (Equation 3.1).

$$NPV = \sum_{r=1}^{R} \sum_{y \in years} (1 + d_{r,y})^{REFYR-y} * ANNCOST(r,y) \tag{3.1}$$

where,

NPV is the net present value of the total cost for all regions (the TIMES objective function)

$ANNCOST_{r,y}$ is the total annual cost in region r for year y

$d_{r,y}$ is the general discount rate

REFYR is the reference year

R is the set of regions

YEARS is the set of cost incurring years (including past investment and dismantling costs, Salvage Value)

TIMES follows linear programming principle. By minimizing the objective function outlined above, it calculates the optimum values of several decision variables, such as new capacity addition, total installed capacity, activity level of technology, quantity of commodity consumed/ produced by a process, price of commodities, *etc.* Minimization of the objective function and calculation of decision variables values is subjected to satisfying several physical and logical constraints. Details of TIMES modeling platform with descriptions of each set, parameters, variables, and equations are available in the documentation [177]. Some of the key model constraints are described bellow.

- Commodity balance: In each time period, for every region, total commodity production plus imports must balance region's consumption plus export.
- Use of capacity: Activity of a technology per time slice/ annually may not exceed its available capacity, as specified by the availability factor.
- Commodity constraints: Commodity production/ extraction limits such as emission cap or annual fossil fuels extraction bounds
- Growth constraints: Yearly growth rate of process capacity within certain bounds to avoid excessive abrupt investment in new capacity
- User constraints: User defined constraints involving any TIMES variable. Specially suitable to model policy scenarios such as, nuclear capacity phaseout, renewable portfolio standards, *etc.*

There has been some recent development in TIMES modeling platform to enable modelers to incorporate unit commitment and dispatch related constraints of power plants and DC power flow for electricity trading [121, 178]. Consideration of these constraints and features may lead to more accurate dispatch decisions of generators and regional power exchange. But, effectiveness of various constraints in planning model and their impact on computational complexity are subjected to scrutiny [16, 179]. There is need to identify specific constraints to incorporate in the planning model based on trade-off between additional computational complexity and result accuracy [19, 180]. In the present study those constraints have not been considered in the planning model. But, detailed unit commitment and dispatch constraints are considered in a separate operational model with which results of the planning model is compared.

TIMES based models are suitable to analyze long-term system development via scenarios or 'what-if' analysis. Scenarios are different from forecasts as they follow logical story lines involving various assumptions of future trajectories of several drivers. In TIMES, a scenario consists of various data inputs pertaining to demand and supply curves, policy definition, and descriptions of technologies. The base, or Business As Usual (BAU) scenario corresponds to the data provided for the current system development trajectory. After optimization, the model calculates the values of decision variables of BAU as well as other cases specified by the user. The decision regarding feasibility and suitability of future scenarios are taken by comparing them with the base case results.

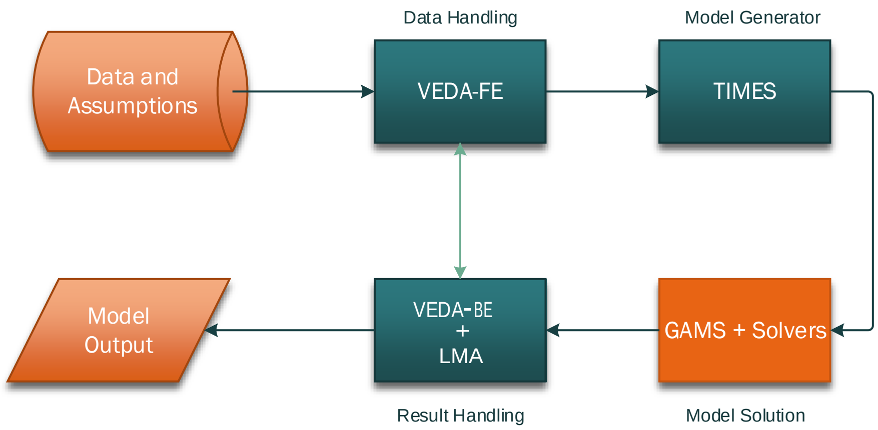


Figure 3.3 TIMES model work-flow

3.3.2 Working With TIMES

The source code of TIMES model generator is written in GAMS (General Algebraic Modeling Language), a high level modeling language to formulate large-scale optimization problems. As high volume of data and assumptions are involved for the model building, separate tools/ software are developed which can work as a interface between user and GAMS. Therefore, user do not need to specify their data and assumption to GAMS source code directly, but utilize these tool to efficiently build, run, and analyse TIMES model results. In the present study, VEDA (Versatile Data Analyst) family of tools are used for the ease of data entry and result analysis [181]. VEDA-FE is used to populate data and specify user constraints, model assumptions, and scenario definitions. Upon user's request, it calls GAMS to compile the source and data, generate the system model, which subsequently calls mathematical solvers for optimization [182]. GAMS also has a report writer utility to assemble the results of the model runs for analysis by a back-end tool called VEDA-BE. The choice of solver depends on the nature of the model. In the present work, formulated TIMES based model is linear and it is solved by CPLEX solver. For result analysis, VEDA-BE and a cloud-based tool called Last Miles Analytics (LMA) are utilized [183]. VEDA-BE is used to create user-defined sets of processes, commodities, and tables to efficiently perform result analysis. The overall process is depicted in Figure 3.3.

3.4 North-Indian Multi-Region TIMES Model (NIMRT)

3.4.1 Model Structure

Key settings/ structures of a TIMES model are the temporal and spatial definitions which include planning horizons, inter-annual time slices, regions, *etc.* Other than that, description of currency units, discount rate, *etc.* are also described in the following subsections.

Spatial Settings

In the present study a TIMES based long-term energy system planning model namely NIMRT is developed for North Indian power sector. NIMRT is a multi-region model. Each state and Union Territory (UT) of North-India is considered as a model region; namely: 1) Chandigarh (CH), 2) Delhi (DL), 3) Haryana (HR), 4) Himachal Pradesh (HP), 5) Jammu & Kashmir (JK), 6) Punjab (PB), 7) Rajasthan (RJ), 8) Uttar Pradesh (UU), and 9) Uttarakhand (UT). Higher spatial resolution allows to reflect spatial variation of resources, specially RE. It also allows region wise capacity calibration of technologies for the base years and helps in state wise tracking of system pathways, inter-regional transmission capacity and energy flow from one state to another.

Temporal Settings

Time Horizon: NIMRT model covers 38 years (2012–2050) of planning horizon with 2012–2017 as the base years[1]. The model has 11 time periods of unequal length. Period length of the model has different time spans (1 – 4 years in the beginning and five years afterward). Short period length in the initial years helps to calibrate existing technology capacity whereas longer time spans in the later stages are sufficient with increasing data related uncertainties. The middle year of a time period is termed as milestone or result reporting year (Table 3.1). In TIMES modeling framework it is possible to alter the number of time periods without specifying additional data. Using internal interpolation algorithm, TIMES automatically calculates values for the new period years.

Table 3.1 Time periods and milestone years of NIMRT model

Period	Start Year	End Year	Milestone Year	Period Length
1	2012	2012	2012	1
2	2013	2013	2013	1
3	2014	2015	2014	2
4	2016	2018	2017	3
5	2019	2022	2020	4
6	2023	2027	2025	5
7	2028	2032	2030	5
8	2033	2037	2035	5
9	2038	2042	2040	5
10	2043	2047	2045	5
11	2048	2052	2050	5

Time slice: Other than the information of time horizon and time-period definitions, model needs information of intra-annual time slices. Choice of the number of time slices/ division within year are solely on the user. Adoption of higher time resolution comes with additional data and computational requirement. In TIMES there can be three type of intra-annual time slices, *i.e.* seasonal, weekly, and daynite. Flexibility of TIMES allows to map a process/ commodity to any time slice; default being annual. As NIMRT model aims to model various large-scale RE integration scenarios, the model adopts a large-number of inter-annual time slices. To consider the seasonal variability of RE generations and load curve, it considers each month of a year as a 'season' and one day per month as the representative. Further, to capture the daily variation patterns, each day is split into 24 hours. Thus, it is possible to

[1] The Indian financial year stretches from 1st April to 31st March. Hence, the year 2012 is representative of 1sst April 2011 to 31st March 2012

incorporate hourly variation of RE generation and load curve for the selected days of each season. Therefore, the model represents 8760 hours of a year by 288 time slices, with their corresponding annual fractions. In the present study, no specific methodology (as mentioned in Chapter 2) is followed to construct the time slices. The main motivation is to capture the seasonal as well as daily variation of the RE generation and its impact on system operation and planning. Further, availability of data and computational resources are also taken into account to consider the 288 time slices.

Other Settings: System-wide 6% discount rate with discounting year 2017 has been considered throughout the model horizon [2]. The discount rate is applied to calculate the annuity on capital expenditure and system costs. All energy flows, technology capacity, and costs are tracked in Peta Joule (PJ), GigaWatts (GW), and million Indian rupees (MINR) respectively. Overall technical and commercial loss of electricity has been assumed to be around 18% in 2012, and expected to gradually decrease to 8% in 2050.

Table 3.2 Fuel wise emission factors (Kt/PJ)

	Coal	Gas	Lignite	Diesel
CO2	92.104	50.294	92.626	66.559
CH4	0.010	0.001	0.010	0.003
N2O	0.002	0.000	0.002	0.001

Emissions

The model also tracks emission from the processes (in Kilo tons) using commodity based conversion factors. It considers carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) emissions from fuel combustion in power plants [184] (Table 3.2). In the present study emission factors of plants are assumed to be constant throughout its lifetime. It has been inherently assumed that the plants will do retrofits to keep their efficiency and thus emission in check. As the model focuses only on electricity consumption in the demand sector, no emission is considered. Emission is also not considered in fuel supply sector also.

3.4.2 NIMRT RES

As mentioned earlier, all the technologies and commodities from resource extraction to final demand of a TIMES model can be represented in the form of a RES diagram. NIMRT model

[2]Rate of interest payable by the nationalized banks in India in the year 2017 on fixed deposits was around 6% (varies slightly from bank to bank)

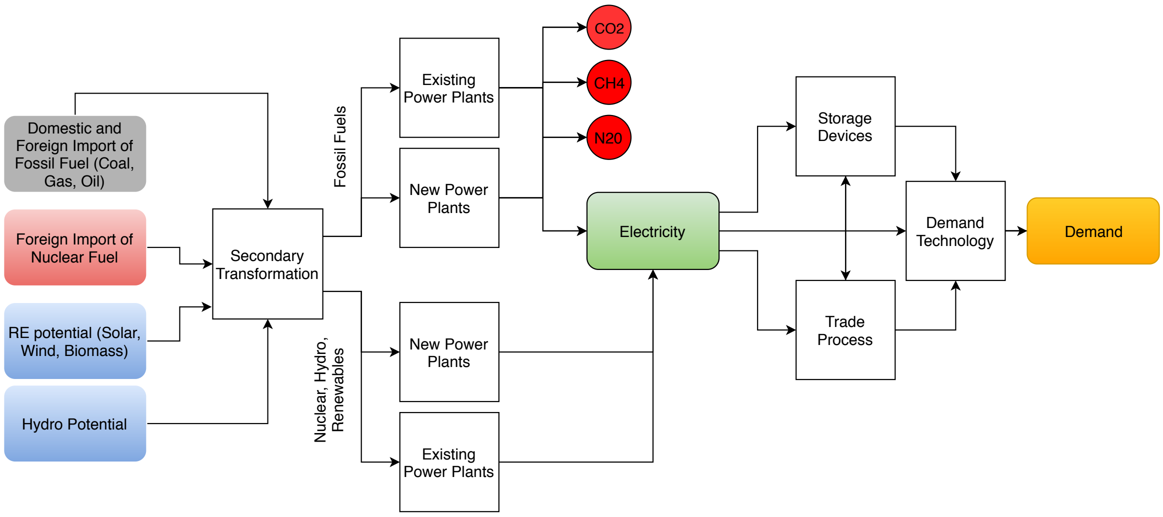


Figure 3.4 RES diagram of NIMRT

focuses only on the power sector. The model has around 800 processes, 30 commodities, and several commodity flows between processes which describe the whole power system. The technologies in the model includes power generation technologies (power plants), storage technologies, interconnections, *etc.* Commodities include various energy resources (coal, gas, hydro, *etc.*), emissions and electricity demand. The overall RES diagram is depicted in Figure 3.4. As it can be seen, primary sources of fuel are domestic or imported fossil fuels, hydro and renewables. By utilizing these resources power plants generate electricity, which then can be transmitted to demand devices for consumption, traded between regions, or stored for later use. The power plants produce emissions which are also tracked. The following subsections outline various RES components.

Resource Supply

For fossil fuel requirement, North India is primarily dependent on imports (domestic (outside NI) or foreign) as there is no significant mining resource within study area. For coal, gas, and oil both domestic and foreign import options are considered. Only domestic mining is considered for lignite while only foreign import is considered for nuclear.

As domestic coal supply will be an important energy resource option, detailed modeling of domestic coal supply is done considering transportation cost of coal from mine to a particular region. Six coal mining regions are considered (only non-coking coal mining districts) namely Odisha (ODI), Jharkhand (JHA), Chhattisgarh (CHH), Madhya Pradesh (MAD), and West Bengal (WES), and Uttar Pradesh (UTT) (Figure 3.5, Table 3.3).

Table 3.3 Coal mining states, districts, and calorific values

State	Districts	Average GCV (KCal/ Kg)
Chhattisgarh (CHH)	Koriya, Korba, Surguja, Raigarh	4150
Jharkhand (JHA)	Ramgarh, Hazaribagh	4600
Madhya Pradesh (MAD)	Sidhi, Singaruli, Shahdol,	4450
Odisha (ODI)	Jharsugdha, Angul	3700
Uttar Pradesh (UTT)	Sonbbhadra	4450
West Bengal (WES)	Puruliya, Bankura, Bardhman	3550

Due to unavailability of specific data regarding the allocation of mine wise produced coal to states, some assumptions are taken to develop the dataset. Historical data of 2006-2017 are used to project future production rate using simple trend line analysis [185] [3]. For each region (excluding CH) import process are defined connecting each mining zone (total 48 processes) with associated transportation cost. For calculating transportation cost, instead of considering the distance of each power plants from the coal mine, centroid of the model region is used as the representative location of all power plant of that region. Railway freight cost for different distance range is used to derive transportation cost/tonne for each coal importing process [186]. Thus it is left for the model to trade-off between distance of mine from the power plant and calorific value (CV) of the concerned coal.

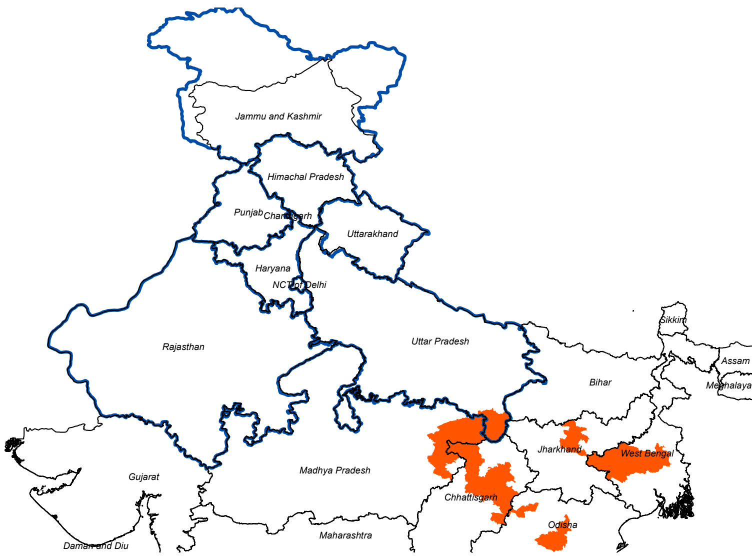


Figure 3.5 Non-coking coal mining region considered in the model

For foreign coal import, Kandla port in the western coast and Vijag in the eastern coast are considered. Kandla port is assumed to import South African coal of CV 6226 Kcal/Kg

[3] For each mine, certain percentage of total production is assumed to be available for the NI region: Chhattisgarh 25%, Jharkhand 30%, Madhya Pradesh 25%, Odisha 15%, Uttar Pradesh 100%, West Bengal 10%

and Vijag port is assumed to import Indonesian coal of CV 4271 Kcal/Kg [187]. Current import price at the port is considered with their increasing trend similar to domestic coal. Costs of transporting coal to each region from the port is calculated in similar way as the domestic coal.

Pit head price of coal for 2013 and 2017 are taken from Coal India Limited [188, 189]. Further, average calorific value of different grades of non-coking coal of mine is used to calculate mine wise coal price as well as transportation cost in terms of MINR/ PJ [185]. Coal price increase in 2040 compared to 2013 level is taken from India Energy Outlook 2015 report [190]. Price of 2050 is calculated further with basic trend analysis. Price projection trend of other fuels, *e.g.* gas, oil, are collected from Indian Energy Security Scenarios V2 (IESS, 2047) ([191]). Detailed modeling of the supply curves of these fuels is avoided as they constitute a small fraction of generation mix.

Power Plants

NIMRT model has detail techno-economic description of several processes of the existing power system. It also has a database with details of future power plants with their technical and cost characteristics. In this subsection, description of these technologies are presented. Details of RE power plants are described in the next chapter.

Existing Power Plants: The model has detailed techno-economic description of existing utility-scale generating units (hydro, lignite, gas, coal, diesel, and nuclear) in North-India. Under-construction and sanctioned thermal, hydro and pumped hydro storage power plants are considered in the reference model database as proposed plants, with their expected year of commission. Critical attributes of generating units, such as efficiency, and annual capacity factors are calculated from past generation and CO_2 emissions [192].

For proposed plants, standard data is used. Region-specific average availability factors of existing hydro power plants is utilized as availability factor of proposed hydro and small hydro plants. Due to unavailability of exact specification of existing hydro plants, units with a capacity less than 25 MW have been considered as small, and others are treated as large hydro. Due to unavailability of unit-specific cost data (fixed operation & maintenance (OM), variable OM), fuel wise generalized assumptions (present and projection up to 2050) are utilized from domestic, as well as international sources [191, 193, 194]. The existing solar and wind energy plants are represented class wise (discussed in detail in Chapter 4), whereas a single aggregated technology is considered for biomass plants per region. It is assumed that current installations of solar and wind plants correspond to the highest resource class. Year

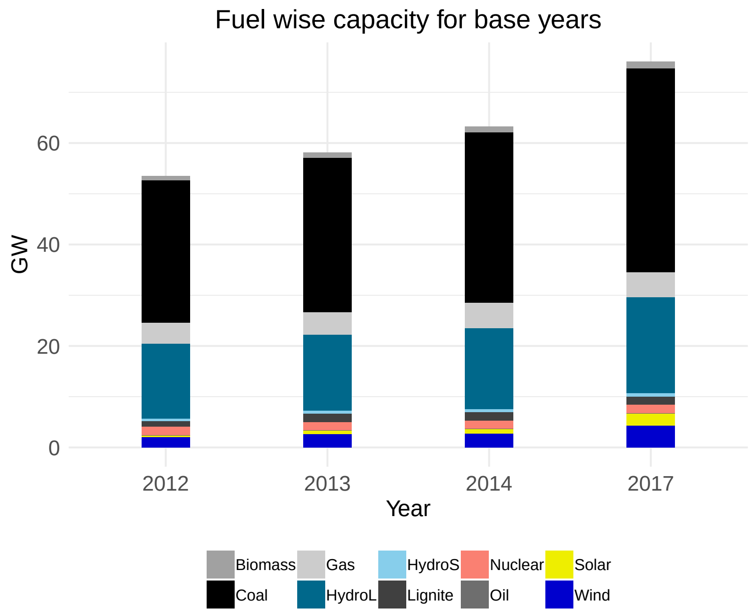


Figure 3.6 Fuel wise capacity for base years in NIMRT model

(2012-2017) and fuel wise power plant capacity calibration has been performed to ensure model consistency, as outlined in Figure 3.6 [195].

Future Power Plants: Existing and proposed power generating technologies are expected to retire when they reach their lifetime. No additional capacity investment in the existing power plants is considered. Instead, new power generating options are defined in the model to meet additional demand of future years. New technology fleet includes those which are not presently available/ commercially viable, with their expected year of becoming mainstream.

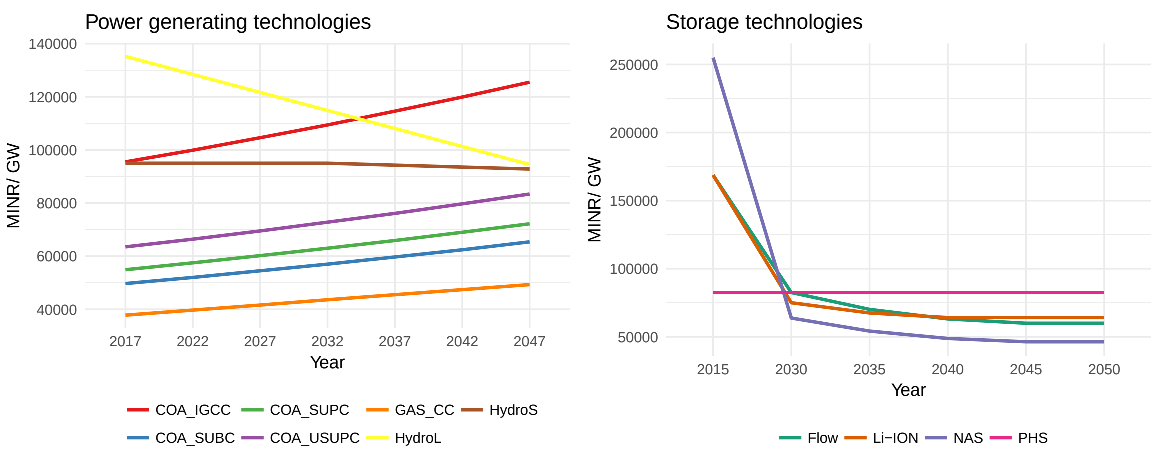


Figure 3.7 Technology investment cost

Apart from other techno economic attributes, investment cost projections are also specified for new technologies (Figure 3.7). In this model, new generating options include various thermal (Supercritical, ultra-supercritical, internal combustion combined cycle (IGCC)), gas (combined cycle), hydro (small and large), renewable (solar PV, wind, and biomass) and energy storage (pumped hydro, lithium-ion, sodium sulfide (NAS), and Flow batteries) technologies, which have future potential of installation. Due to political and security concerns, nuclear power expansion in India is currently volatile; thereby its capacity expansion is not considered.

Various techno-economic attributes of new technologies pertaining to future years, like investment, OM costs, efficiency and annual capacity factor are taken from the IESS-2047 documentation, CERC tariff reports, and other international reports [196, 197, 191]. The cost trend of storage for 2015–2030, and their techno-economic attributes are considered from World Energy Council Report [198]. Further cost reduction trend up to 2050 is based on assumption.

Trade Technologies

Bi-directional electricity trade processes (transmission lines) between model regions are defined following existing high voltage lines between states. The lines do not simulate real transmission line operation or mimic physics of power flow, but provide a way to import/ export energy from/to one region to/ from another, as needed to balance energy demand and supply. For simplicity, distance between the geographical centroid of the regions is taken as effective transmission line length. Transmission line investment cost has been taken as $2032/ kW/ 1000 miles or approximately 132 MINR/ GW/ km [199]. Future cost trend has been taken from IESS-2047 [191]. Transmission lines considered for the NIMRT model are outlined in the figure 3.8.

As the present study focuses on the future evolution of North Indian power grid, detailed modeling of lines connected to other states is avoided. But, for each region, single exogenous line is specified such that it can import energy from a dummy external region to meet demand as a last resort. This has achieved by specifying higher electricity price for each of these dummy transmission link per region. The result shows that model uses these lines to import a portion of the demand in the base years, similar to actual practice. But, for future years, model utilizes existing resources and makes new investments to meet its demand, rather than importing required energy from the external dummy region.

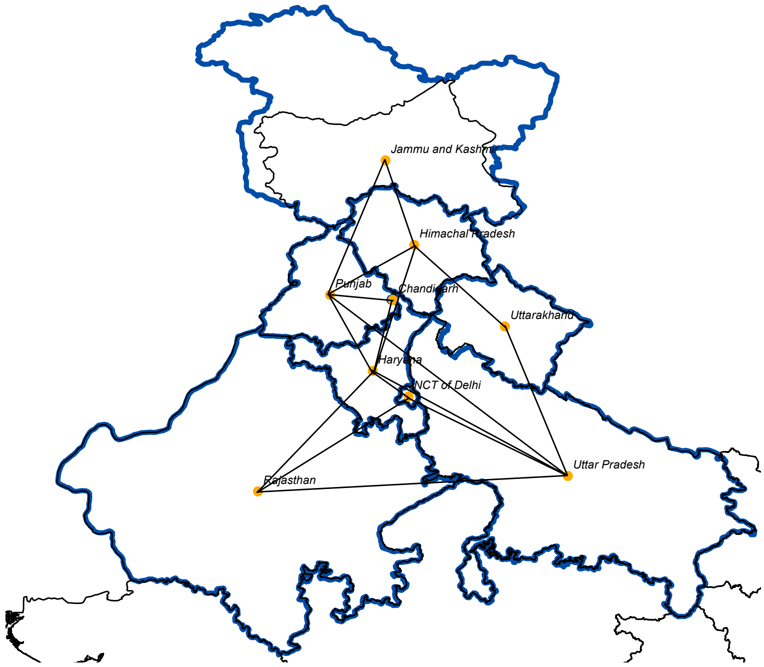


Figure 3.8 Transmission lines between regions considered in the study

3.4.3 Demand Projection and Load Curve

Demand Projection

The model needs region wise yearly energy demand projection for the entire planning horizon. The 19th Electric Power Survey Report of Central Electricity Authority (CEA) covers year wise electricity demand projection for 2016-17 to 2026-27, and 2031-32 and 2036-37 for all the states/ UTs [200]. As study horizon of this article extends beyond 2037 and yearly estimation is required, the future energy demand has been projected. A multiple linear regression model is developed for this purpose using R [201]. The fitted equation for demand projection is shown in equation 3.2, where ELC_tot is the projected electricity in TWh, POP_B is the population in billion and GDP_T is the GDP in trillion USD [4].

$$ELC\_tot = 157.549 - 145.179 \times POP\_B + 231.401 \times GDP\_T \tag{3.2}$$

Population and gross domestic product (GDP) are taken as exploratory variables. As the year and state wise data of population and GDP were unavailable, the projection has been performed for the whole country, and then historical state wise demand share is used to calculate dataset for individual state/UT. The 'train data' for the regression model is constructed using population estimates and projections of World Bank (1990–2017), and

[4] Appendix A1 outlines further the details of the model summary, code and state wise demand projection

GDP (2010 USD PPP) from OECD GDP long-term forecast (1990–2017), and Per Capita Power Consumption Time Series of World Bank (1990–2014) [202–204].

Average share of power consumption in North India for the years 2001–2014 is approximately 29% [205]. Demand for 2015–2017 is calculated applying 29% share for Northern region (World Bank data is up to 2014). State wise share of power consumption is calculated using 'State-wise Power Requirement' data from Handbook of Statistics on the Indian States from the Reserve Bank of India (RBI) [206]. Sum of state shares (North-India) are further adjusted to 29%, as share of RBI does not add up to the actual national total. Energy demand has been projected for 2018–2050 (Figure 3.9). Test data has utilized population projection of the World Bank and long-term GDP forecast of OECD [202, 203]. The model has been checked for consistency and accuracy by various diagnostics tests, as well as 10-fold cross validation using DAAG package in R [207].

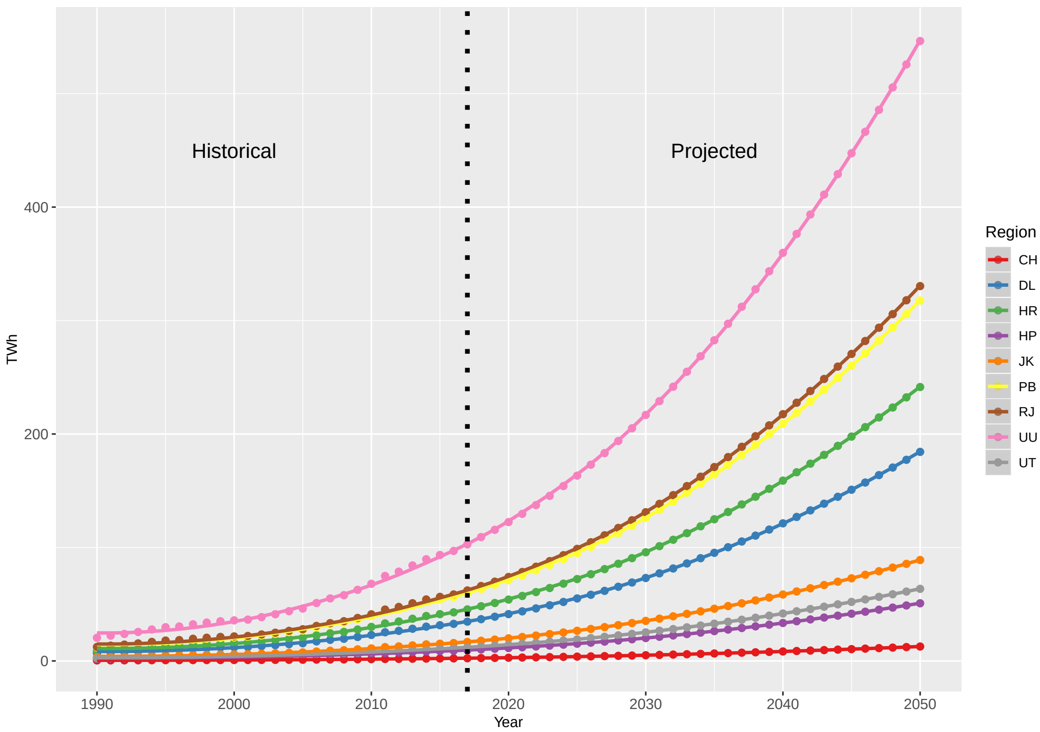


Figure 3.9 North-Indian state wise demand projection

Load Curve Pattern

Apart from demand projection, the model requires information of region wise load curve pattern corresponding to the time slices. In TIMES modeling framework, load curve is defined by specifying demand fractions corresponding to each time slice. It is desirable that historical hourly/ sub-hourly load curve for every region is used to derive demand fraction for every time slice. But, due to data scarcity, national load curve pattern for the years 2010 and 2011 has been used for all the regions. Due to unavailability of sector-specific load curve data (industrial, commercial *etc.*) and focus of the present work, detailed modeling of demand side has been avoided, and a single aggregated demand technology is considered for each region.

3.4.4 Scenarios

NIMRT model is utilized to simulate and analyze a large number of cases corresponding to various futuristic parametric scenarios. Compared to previous studies which analyze specific RE penetration targets etc., present exercise considers the parameters as key divers for RE expansion. Three individual scenarios of five parameters, *i.e.*, coal price, CO_2 price, cost of solar PV, wind, and energy storage are considered. Combination of these three scenarios, *i.e.* Reference, low, and high, results in 243 model cases which outline various futuristic RE penetration cases. Details of the chosen parameters, scenarios, and corresponding assumptions are discussed in detail in the Chapter 5.

Chapter 4

Intra-Regional RE Spatial and Temporal Variability Modeling Using GIS

4.1 GIS and Energy System Planning

As described in Chapter 1 and 2, traditional long-term energy system planning models do not address intra-regional RE variability at a suitable spatial and temporal scale. The number of study regions in these models are often determined by the administrative boundary, and any increase is often prohibitive beyond specific logical numbers. As the regional dimension of global and national scale planning studies are often country or state, capturing intra-regional variability is becoming essential to quantify optimal capacity and identify suitable investment locations. Region-specific capacity potential and annual capacity factor are two key modeling attributes of RE technologies. Normally, a single representative/ aggregated annual capacity factor value of a RE technology is used for a particular region, with associated capacity potential. With large-scale integration plans of solar and wind, consideration of intra-regional RE variability is becoming important.

Geographic information system (GIS) is a framework designed to collect, mange, manipulate, analyze, and visualize various geographical data. GIS tools and methods have been applied in various fields of study for diverse applications. It includes the application of GIS for natural resource management, energy system planning, power system design, *etc*. Regarding RE sources, GIS has been used worldwide to quantify geographical as well as the technical potential, identifying a suitable location for installation, and environmental impact assessment [208–212].

Sophisticated geospatial tools can be used to develop the data related to intra-regional RE generation and capacity potential, and eventually be utilized in energy system planning models. There are recent attempts to utilize GIS tools and methodology to generate suitable data sets for long-term power system planning. These studies consider dedicated RE resource regions to develop realistic supply curves [146, 131, 213, 214]. In this chapter, a detailed geo-spatial methodology is presented to quantify intra-regional RE capacity and generation potential to be used in a planning model. The capacity potential is estimated at geographical grid-cell level. For each grid-cell, RE capacity factor is estimated for each time slice. Further, this information is passed to NIMRT model to consider the RE variability at sub-regional level, while calculating future system portfolio.

4.2 GIS Based RE Potential Calculation for North India

The geo-processing task involves developing a tool which can automate the task of working with several data sets and generating required information. In this section, description of individual data layers/ time series *etc.* is discussed, followed by the overall methodological approach.

4.2.1 Data

Data used for overall GIS analysis can be classified into two categories. Various spatial data layers are used to quantify suitable land availability for RE installation. Historical RE time series data are used to calculate annual and time slice specific capacity factor values. GIS is utilized to process several geographical and socio-economic data sets, such as road, rail network, water bodies, protected areas, land cover, and elevation. Following is a short description of the various GIS related data sets, followed by their description in Table 4.1.

Road and Rail Network: RE installation cannot take place on the existing road or rail network. There should be suitable buffer distance from the road/ rail lines for the land to be suitable for large scale RE farms (100% excluded) (Figures 4.1b, 4.1a).

Water Bodies: Major water bodies like river, lake, wetlands, and dams are not considered for RE installation to preserve natural wealth (100% excluded) (Figure 4.1e).

Protected Area Protected areas includes national/ world heritage areas, sanctuary, national parks, monuments, biodiversity areas, reserve forests, restricted areas (*e.g.* military) *etc.* which need to be preserved (100% excluded) (Figure 4.1c).

Urban Area: Densely populated and urban areas are kept out of the purview of large-scale RE installation. Large-scale wind farms should be installed outside the residential areas to avoid vibration and noise. The study excludes the potential of roof-top solar PV installations and focuses only on large-scale grid connected PV plants (Figure 4.1d).

Land Cover: The land cover GIS layer has several geographical classifications. For suitable location for RE installation, a subset of classes is chosen following the assumption adopted in [215]. Selected areas are: bare areas, closed to open shrub-land, closed to open herbaceous vegetation, mosaic cropland / vegetation, post-flooding or irrigated croplands, rain-fed crop lands, sparse vegetation (Figure 4.2).

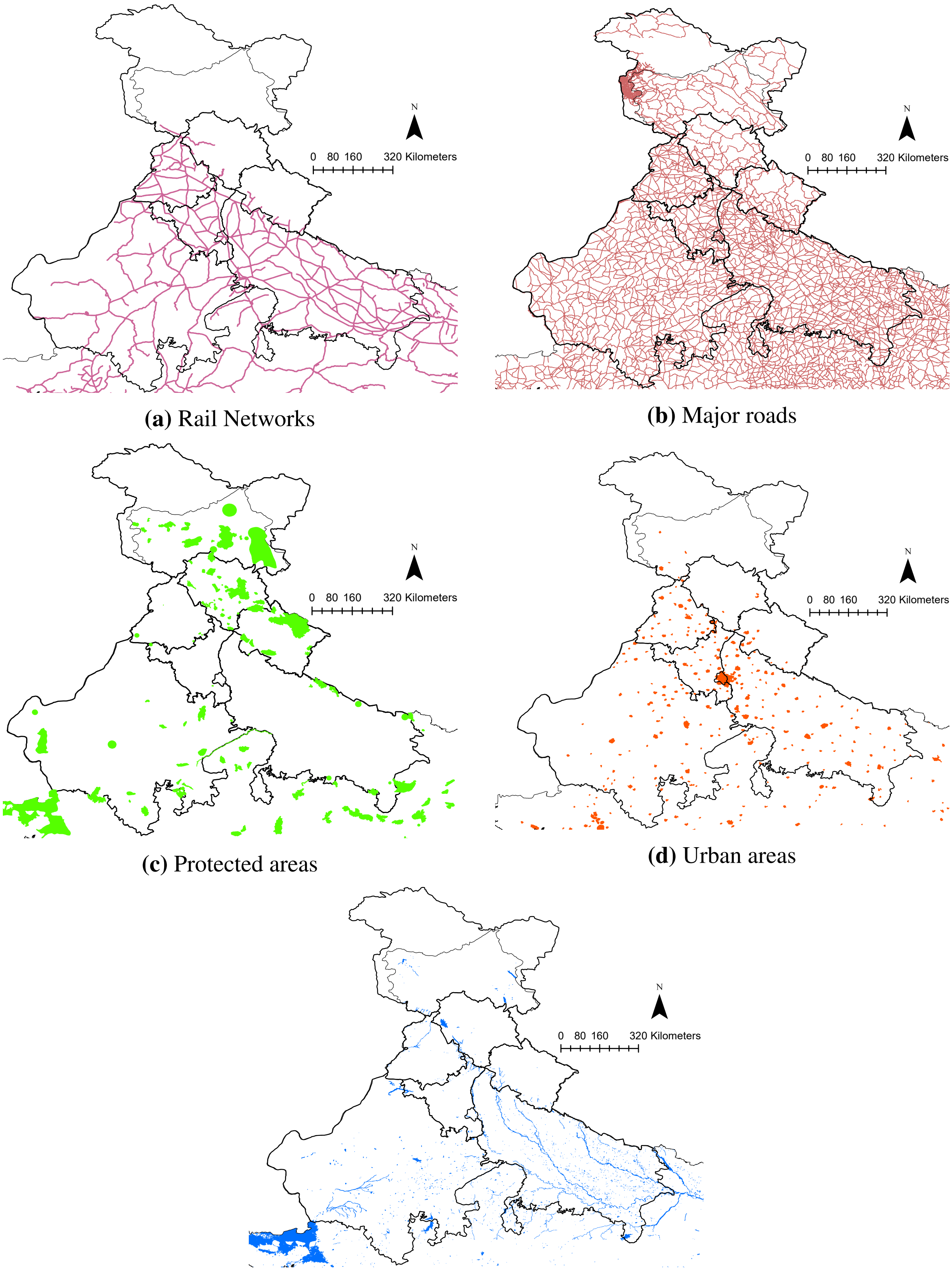
Terrain Condition: RE plants can only be set up at places having favorable altitude and slope. Digital elevation model data layer is used to calculate slope and altitude [216]. Height over than 2000 meter and slope over 10 degree are considered unfavorable for large-scale plant installation (Figures 4.3).

Wind Speed: Due to unavailability of ground measured wind speed data at desired spatial distribution, satellite-derived global data sets are used for the study. Thirty-seven years (1980-2016) historical hourly wind speed data of MERRA V2 (Modern-Era Retrospective analysis for Research and Applications, Version 2) has been utilized [217].

Solar Radiation: Ground measured historical multiple years' solar radiation data for India is not available in open domain. Hence, hourly typical meteorological year (TMY) data from PVWatts tool of NREL is used [218].

Table 4.1 Data source and assumptions for GIS based calculation

GIS Data	Type	Buffer (meter)	Spatial Resolution	Source
Administrative Boundary	Vector	-	-	GADM [219]
Grid Mesh	Vector	-	1^0 by 1^0	SWERA [220]
Protected Areas	Vector	1000	-	WDPA [221]
Land Cover	Raster	-	0.3 km by 0.3 km	Globecover [222]
Road Network	Vector	500	-	SEDAC [223]
Urban Areas	Vector	1000	-	Natural Earth [224]
Rail Network	Vector	500	-	Natural Earth [224]
Elevation Model	Raster	-	1 km by 1 km	GTOPO 30 [216]
Water Body	Vector	300	-	GLWD, WWF [225]
Wind speed	Time series	-	approx. 50 km	MERRA V2 [217]
Solar Radiation	Time series	-	approx. 10 km	PVWatts [218]



(a) Rail Networks

(b) Major roads

(c) Protected areas

(d) Urban areas

(e) Water bodies

Figure 4.1 Exclusion areas for RE installation in North-India

Present GIS study has not focused on the analysis of other detailed GIS data sets such as terrain roughness, shape, aspect, *etc.* Other socio-economic/ infrastructure related restrictions are also avoided, as the study is focused on long-term system planing. Future change in land usage pattern, *e.g.*, urbanization are also not considered. Project specific feasibility studies could look for these information in minute details. The capacity potentials calculated here are geographic potential rather than technical or economic potential. It implies that the study excludes the analysis of technological, structural, and legislative restrictions related to large-scale RE installation [226]. All the locations identified as suitable for RE installation do not have similar potential and some places may be un-economical for large-scale installation. But, the present study takes a generalized approach, and leaves that decision on the planning model. These aspects are further elaborated in the following methodological discussion.

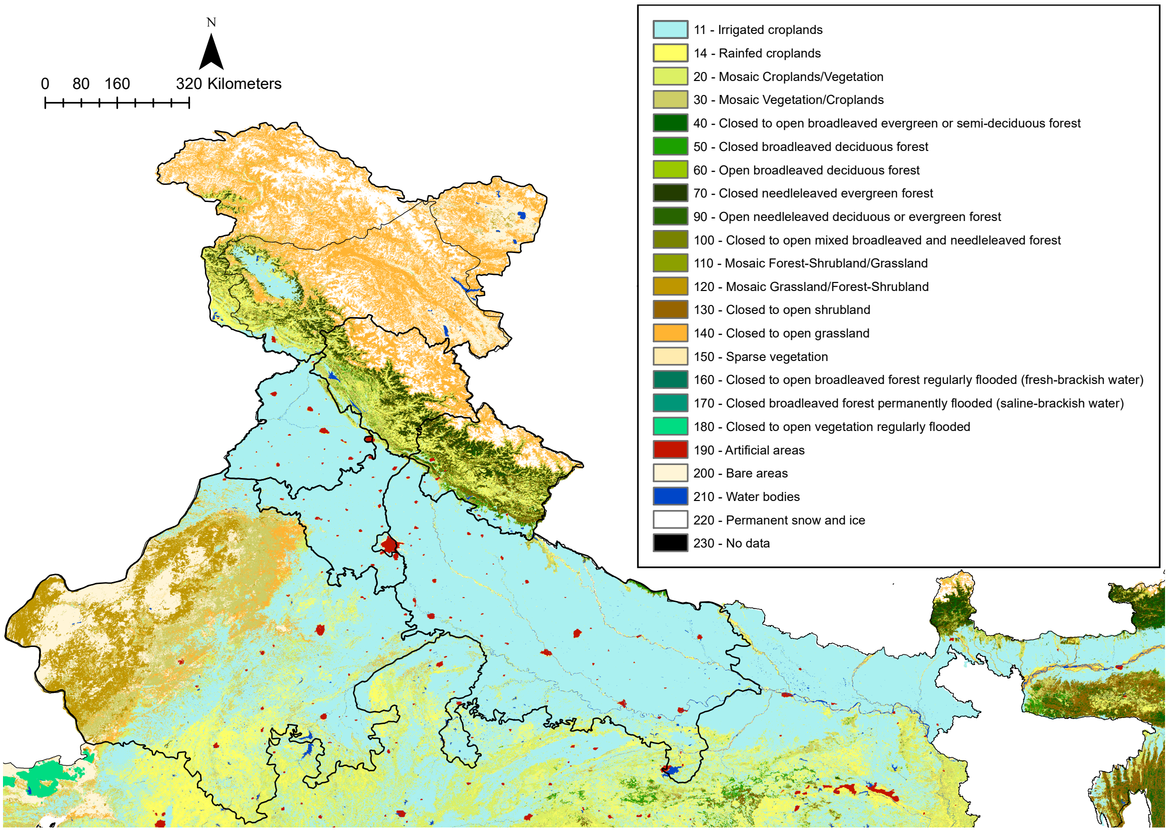
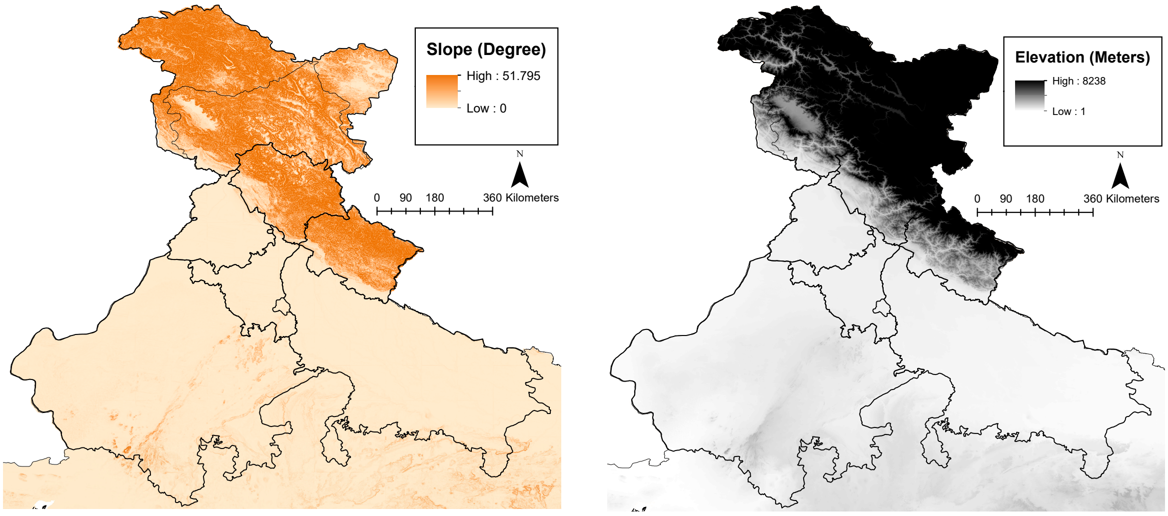


Figure 4.2 Land cover map

4.2.2 Methodology and Outputs

Official estimates of RE potential available in open domain for India are geographical values. These values are often calculated assuming a certain percentage of land/ wasteland available



(a) Terrain Slope **(b)** Terrain altitude

Figure 4.3 Slope (degree) and altitude (meter) of North-India

for future RE installation [227–229]. Also, a selected threshold of wind power density or solar radiation is considered to be only suitable for RE installation. But, it is a matter of fact that a high RE resource region may not be the first choice for investment, if integration related costs at that location are substantially higher [141]. Though the present model does not consider those costs; it assumes that these infrastructures (transmission lines, road network, *etc.*) will be developed in future.

In the present approach, the study area is first divided into a number of 1-degree by 1-degree [1] geographical grid cells. Capacity and generation potentials are then developed for each grid-cell. The grid-cells have been classified into ten equal range of solar and wind resource classes, based on their annual capacity factors (discussed in Subsection 4.2.2). The methodological discussion is divided into two parts *i.e.*, quantification of capacity potential and generation potential respectively, as outlined in Figure 4.4.

Quantification of RE Capacity Potential

The overall geo-spatial study to quantify RE capacity potential involves identifying land (in km^2) suitable for large-scale plant installation. Standard area to capacity conversion factors are then applied to calculate actual capacity potential (in GW). Terrain conditions, altitude, land cover type, and several exclusion criteria are considered for this purpose, as described in Subsection 4.2.1. Land cover selection assumptions are similar to [215].

[1] maximum dimension, size of each grid cells varies due to the shape of map

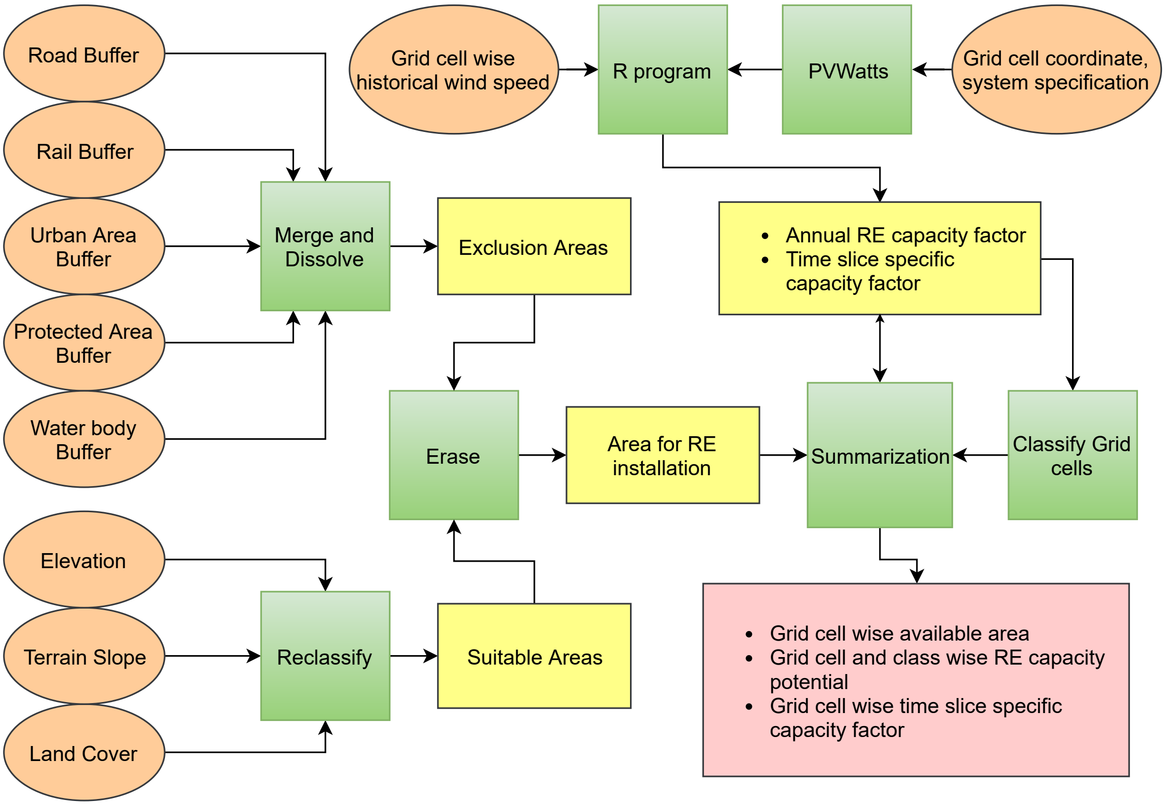
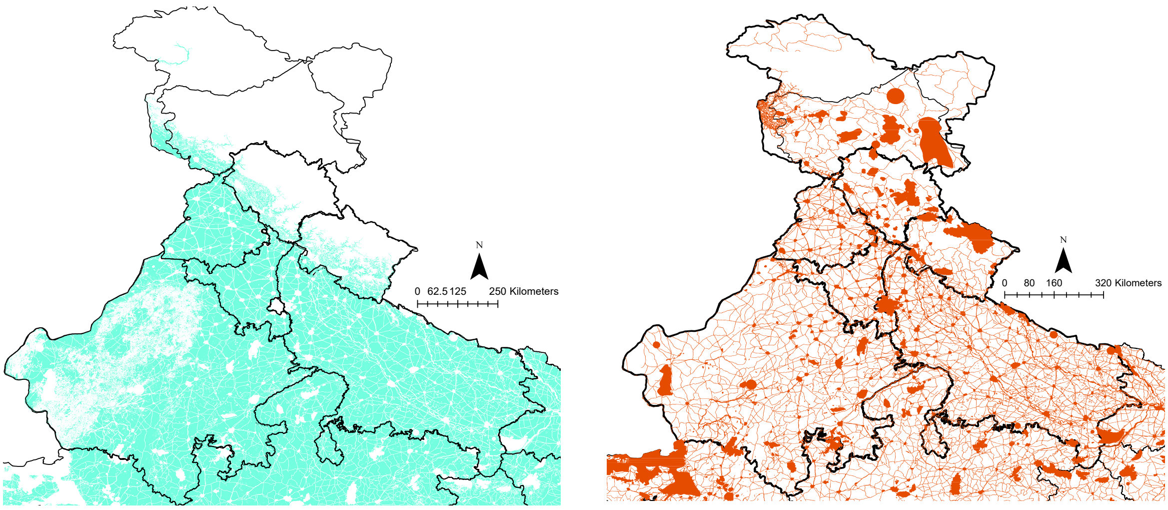


Figure 4.4 Overall geospatial analysis methodology



(a) Suitable area

(b) Area excluded

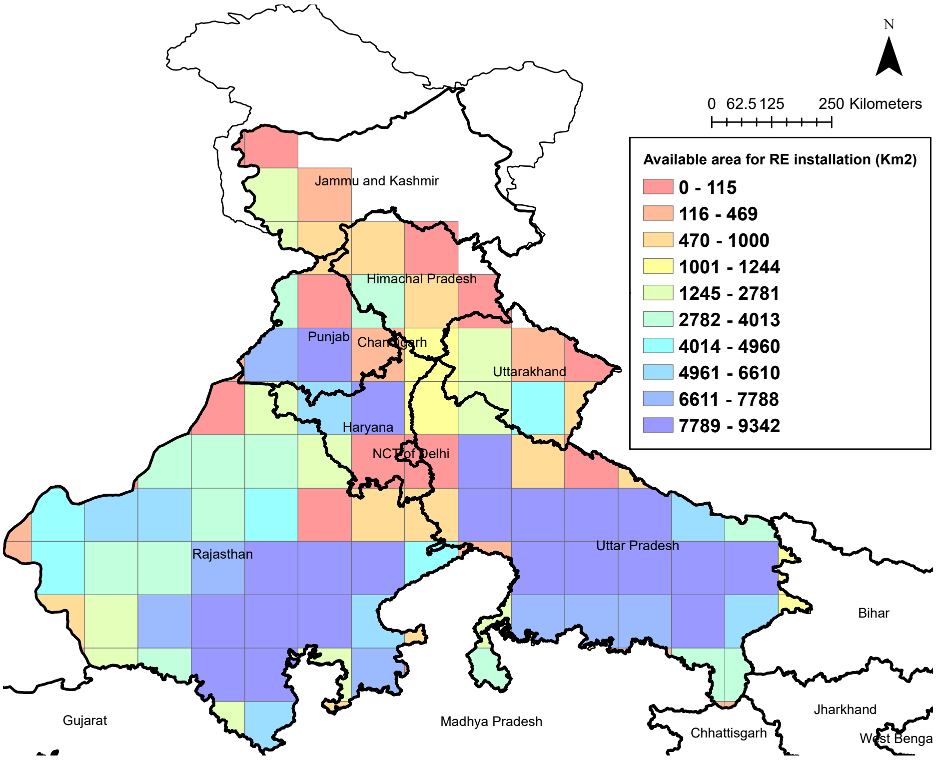
Figure 4.5 Suitable and excluded area for RE installation in North-India

Model builder facility of ArcGIS software is utilized to develop a tool for the overall geo-spatial analysis and data aggregation. ARcGIS is complemented by other spatial/ statistical calculations in R to determine RE capacity factors. The exclusion layers with suitable buffer distance are merged and dissolved to form a single layer of non-suitable area (Figure 4.5b). Slope of the terrain is calculated from digital elevation model data set. Raster data related to altitude, slope and land cover is reclassified to only select the areas with suitable geographic conditions for RE installation (Figure 4.5a). Non-suitable area layer is erased from the suitable area layer to obtain the final layer favorable to large-scale RE installation. The capacity potential of solar and wind for each grid-cell is calculated by a factor of 8.9 Acre/MW and 85 Acre/MW for solar and wind respectively [230]. Grid-cell wise suitable area is then further aggregated to regions, to calculate region and class wise available area to be considered for the NIMRT model (Figure 4.6). The developed GIS tool is a generic one, and it can be used to calculate RE capacity potential of any geographical coverage having similar data sets. Consideration of additional assumptions/ exclusions can be adopted by incorporating additional GIS data layers. The tool can be automated to work on multiple areas of interest via iteration, using the model builder feature of ArcGIS.

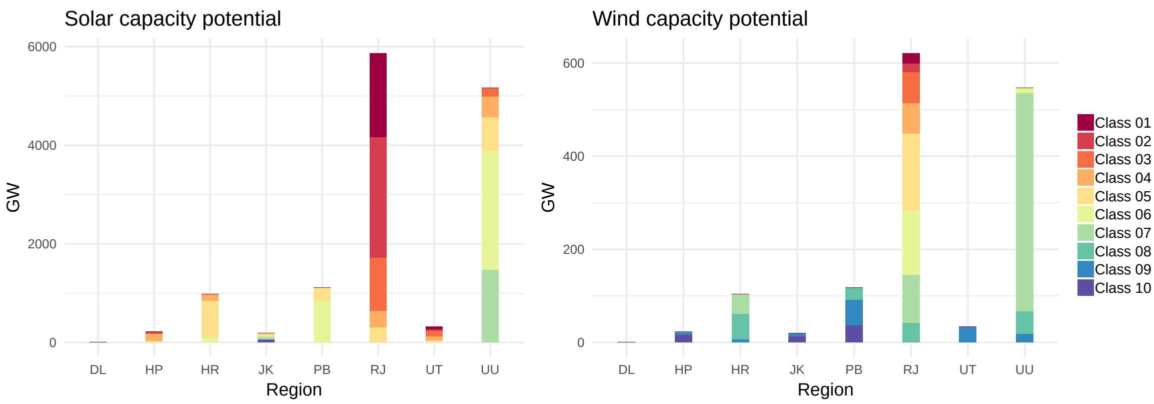
Quantification of RE Generation Potential

Due to the intermittent nature of solar and wind power, consideration of only single annual CF value in planning models gives false information about the intra-annual generation variability. As RE intermittency has seasonal, daily, and hourly dimensions, consideration of annual CF value neglects the impact of over/under generation of RE technologies in intra-annual scale on the overall system portfolio. To handle this issue, time-slice specific CF for solar and wind for every grid-cell in each region has been developed. Annual CF values for each grid-cell are also calculated and classified (Figure 4.7).

Time Slice Wise Solar PV CF: For calculating time-slice wise solar PV CF, an online tool PVWatts of NREL is utilized [218]. The coordinates of all the grid cells centroids along with system specification values, are provided to PVWatts, which in turn calculates hourly PV power generation for the whole year. To simulate the output of existing PV plants, considered system configuration are 4 kW capacity, poly-crystalline type (15% efficient, -.47% / ^{0}C temperature coefficient of power), tilt angle equal to latitude, 14% system loss and 96% inverter efficiency. New PV plants are assumed to have premium grade modules with 19% efficiency and -0.35 % / ^{0}C temperature coefficient of power. The output files of PVWatts have been processed, and hourly generations are aggregated to time slice specific generation and capacity factors for all grid cells. Plot A) of Figure 4.8 illustrates the time slice wise

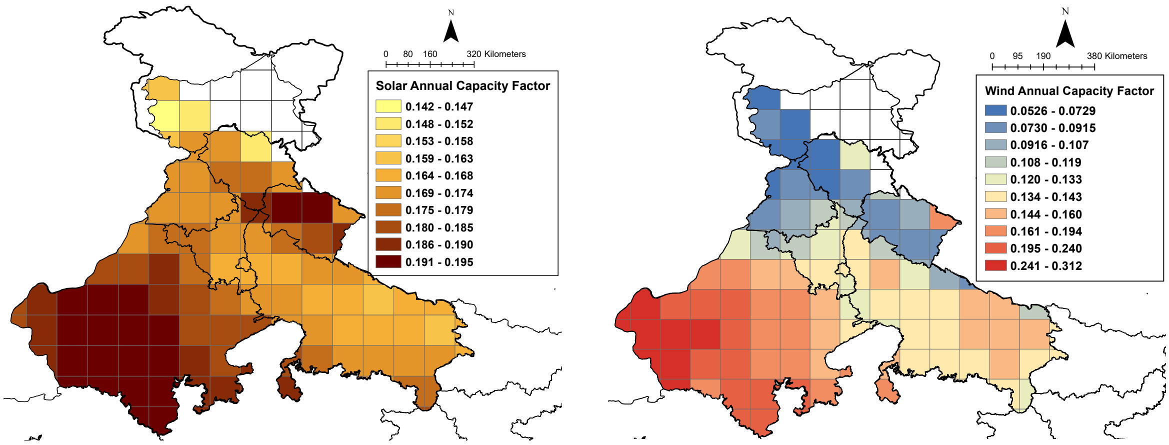


(a) Suitable area per grid-cell



(b) Region and class wise solar and wind capacity potential (GW)

Figure 4.6 Available area per grid-cell and RE capacity potential



(a) Solar annual capacity factors

(b) Wind annual capacity factors

Figure 4.7 Region and grid-cell wise distribution of solar and wind annual capacity factors

variation of CF values for existing and new solar PV power plants, corresponding to class 1 solar resource in RJ.

Time Slice Wise Wind CF: The wind speed in collected data is for 10 meter height above ground, which has been extrapolated to 90 meter hub height using the formula $S_2 = S_1 * (H_2/H_1)^{\alpha}$, where S_1 is wind speed at 10 meters, S_2 is wind speed at 90 meter, H_1 is 10 meter, H_2 is 90 meters, and α is wind shear coefficient with a considered value of taken as 1/7. A standard wind turbine specification has been used for calculation. Hourly wind generation P is calculated using standard formula (Eq. 4.1) where r_p is rated power = 2.1 MW, c_i is cut-in speed =3 m/s, c_o is cut out speed = 21 m/s, c_r is rated speed = 10 m/s, a is swept area of the blade=9817 m^2, ρ is wind power density = 1.225 Kg/m^3, c_p is wind turbine power coefficient = 0.35 [231]. The existing wind turbines are considered to be of height 90 meters, whereas new installations are assumed to be of 120 meters.

$$P = \begin{cases} r_p & \text{if } c_r < v < c_o \\ 0.5 * \rho * a * c_p * v^3 & \text{if } c_i < v < c_r \\ 0 & \text{otherwise} \end{cases} \tag{4.1}$$

Hourly past wind generation is then aggregated to one year, and finally to time-slice specific generation and capacity factors for all grid cells. Time slice wise variation of wind capacity factors for existing and new technologies for class 1 wind resources in RJ are illustrated in plot B) of Figure 4.8.

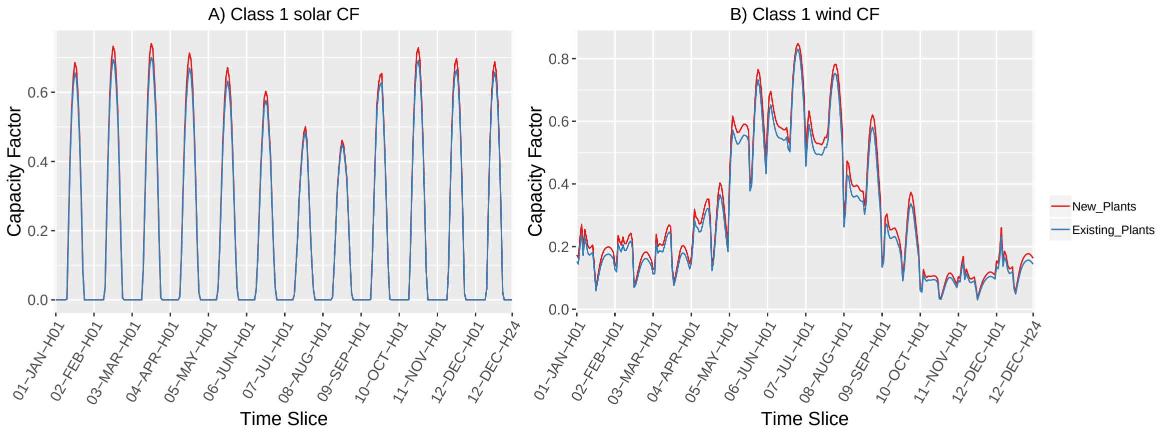


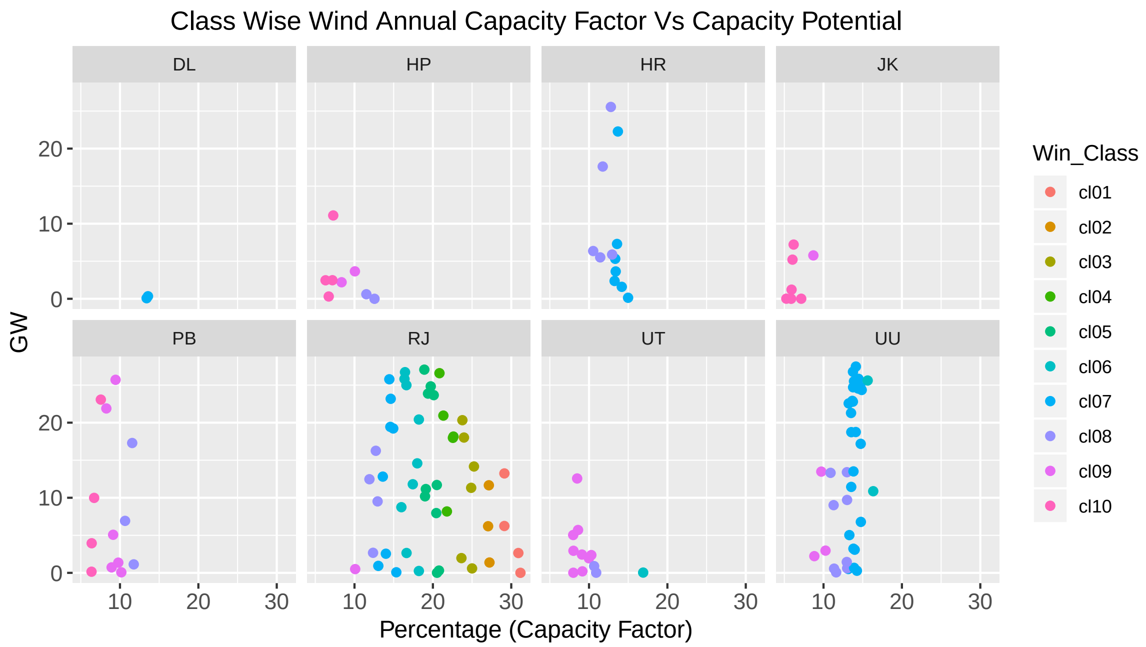
Figure 4.8 Time slice capacity factors of existing and new PV plants for class 1 solar and wind classes in RJ

Figures 4.9 outlines the RE capacity potential available in every region for various annual capacity factor ranges. For that, potential of each grid-cell is plotted with respect to its annual capacity factor. The grid-cells are faceted into regions and colored by class. For solar, it can be seen that, RJ has more number of grid cells corresponding to higher classes. The grid-cells in RJ which correspond to higher solar class, also have high capacity potential. The range of solar CF values is approx. 17%–19.5% in RJ. For wind, again RJ has maximum capacity potential of higher wind classes, followed by UU. The wind CF values of RJ vary between 10%–31%. Variation of class wise grid-cell capacity potential and CF values is further summarized and illustrated in Figure 4.10.

Solar and wind time slice wise CF calculation is automated by programs written in R, as the number of grid-cells is large. The program loops through each grid-cell's data files, calculates hourly CF values, and finally aggregates them to time slice definitions. The program can be readily extended/ applied to any geographical region depending on data availability.

4.2.3 Representation of RE Information in NIMRT Model

As mentioned earlier, all the geographical grid-cells are classified into ten equal range of solar and wind resource classes based on their annual capacity factors (CF). Each RE class is considered as a separate technology; both existing and new. For each RE class, region wise capacity potential (upper bound) and time slice specific availability factors (generation bound) are further incorporated into the NIMRT model, without prejudice over their suitability *a priori*. It is up to the planning model to invest in a suitable solar/ wind class depending on



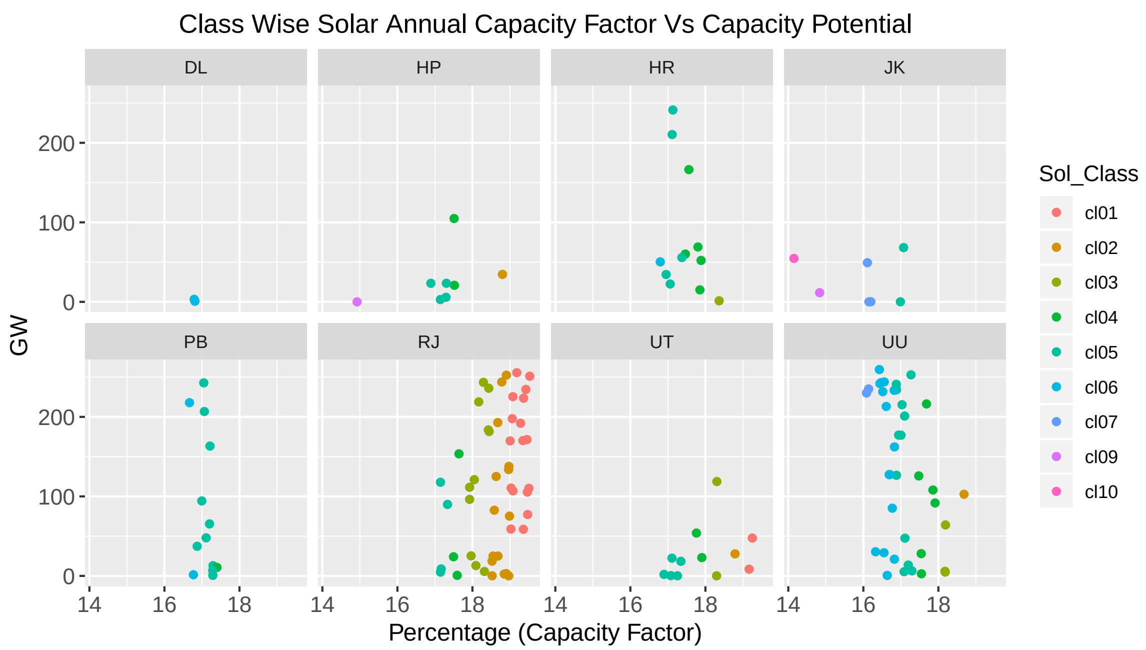


Figure 4.9 Region wise RE capacity potential vs capacity factors

the generation (CF), capacity potential (GW) and other techno-economic conditions over long-term.

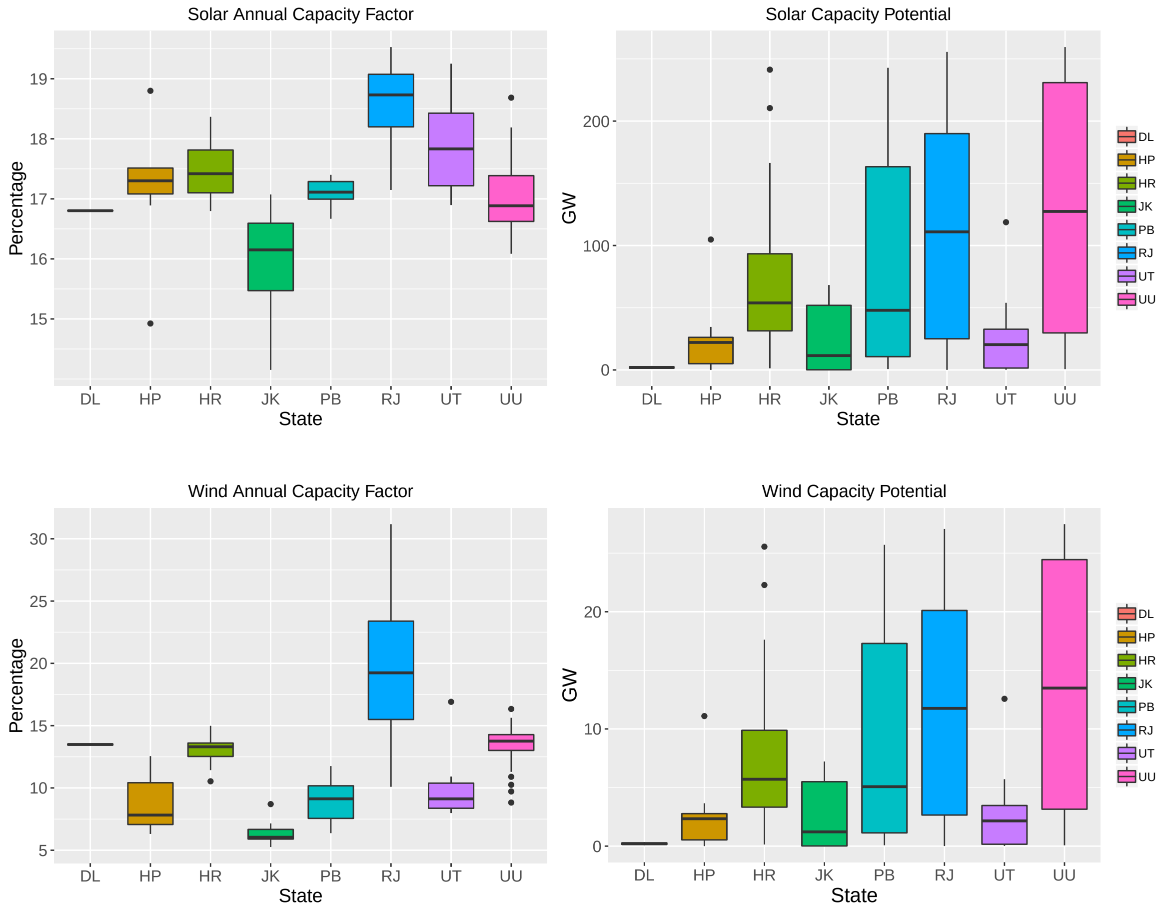


Figure 4.10 Region and grid-cell wise distribution of solar and wind annual capacity factors

Other than RE technologies, dummy commodities and processes are created to report solar and wind curtailment. The availability factors of each RE class are incorporated in NIMRT as fixed bounds, *i.e.* the generators work with utilization factor in a particular time slice. Depending on system resource, load curve, *etc.*, system may or may not absorb the total RE generation. When the system is unable to absorb the total RE generation, RE technologies produce dummy curtailed solar and wind commodities which are exported to a dummy region through dummy uni-directional export processes. Suitable export prices are specified so that production of these commodities are restricted otherwise.

Within a region, for a particular RE class, time slice specific CF data of a single grid-cell is taken as a representative *i.e.*, time slice wise CF values of every grid-cell corresponding to a class within a region are not considered. The region specific RE capacity bounds are specified to the model by creating user-constraints pertaining to each RE class. The bound is applied on the sum of existing and future capacity calculated by the model. As total existing RE installation is not substantial, current regional capacity is mapped to the highest RE class of that region for simplicity.

As the land calculated for RE is considered to be common for solar and wind, additional constraint has been applied, so that sum of RE capacity (solar and wind) calculated by the model for a region does not violate the maximum available area for that region. Suitable growth rates are also applied such that rate of yearly change of total solar and wind capacity does not violate any logical numbers. Throughout the planning horizon, generation potential of (annual and time slice wise CF values) a RE class is assumed to be constant.

Chapter 5

Long-Term Scenario Analysis with NIMRT Model

This chapter outlines the results from NIMRT model having intra-regional RE variability information, corresponding to various parametric scenarios. Definitions of scenarios are described first, afterwards, the numerical results are presented. Result related to variation of RE penetration levels, nature of power dispatch, technology capacity, role of inter-regional energy exchange and storage, coal supply, and CO_2 emission are discussed. Due to the difference of resource potential, technological suitability, and demand, each region's (*i.e* state's) generation mix is unique. Hence, regional interpretations of results are also drawn. Due to a large number of cases considered in this study, only those which present interesting observations, are outlined.

5.1 Scenarios

The present study is primarily focused on exploring the effects of scenario sensitivities on future system portfolio. Therefore, modeling of exogenous policy related inputs (*e.g.* specific government RE penetration targets/ emission intensity reduction percentage) is avoided. So, the model is free to invest in new capacity or retire existing assets, as it finds cost-effective and technologically optimal.

Table 5.1 outlines various model parameters and their parametric variation. Corresponding to the parameters, description of each scenario is further elaborated in the following paragraphs. As mentioned in the previous chapter, five parameters *i.e.*, coal price (L), CO_2 price (C), cost (investment and annual operation & maintenance) of solar PV (S), wind (W), and energy storage (T) are considered for the scenario analysis. For each parameter, three scenario variations *i.e.*, Reference (R), low (L), and high (H), are taken. Combinations of these three scenarios results in 243 model cases and considered for this study. Reference scenario of every parameter indicates the value used to build the base case of the model. 'H' and 'L' cases are constructed using available literature and assumptions (for coal, base, high, and low scenarios are termed as LL, LH, and LV respectively as discussed in the following paragraphs). Table 5.2 outlines various model cases and assumptions associated with it.

Table 5.1 Parametric scenarios considered for long-term scenario analysis using NIMRT model

Parameter	Description	Scenarios
CO_2 price	Additional price on producing CO_2	Reference scenario: No CO_2 price. Low and high scenario: Two additional CO_2 price projections.
Coal price	Coal production rate increase	High scenario: Present coal production trend. Two production rate increase cases: one is taken as reference and other as low price scenario.
Solar Cost	Solar investment and operating cost reduction.	High and low scenarios: Flat and steep cost reduction trends respectively compared to reference cost reduction trend.
Wind Cost	Wind investment and operating cost reduction.	High and low scenarios: Flat and steep cost reduction trends respectively compared to reference cost reduction trend.
Storage Cost	Storage investment and operating cost reduction.	Low and high scenarios: Certain percentage change (lower and higher) compared to the reference costs reduction trend.

The parameters considered for this study have the potential to impact overall future energy system portfolio. One of the major challenges for large-scale RE capacity expansion is their higher cost compared to other options like coal-fired power plant. Costs of these technologies are decreasing steadily due to technological advancements. Energy storage device is a key enabler for integrating variable RE power e.g. solar. Though the present cost of utility-scale storage is not favorable for large-scale deployment, available projections indicate drastic cost reduction in coming years. India is still largely dependent of coal for power generation. Current initiatives to improve coal production rates can ensure better utilization of existing coal-based power generation capacity and encourage new installations. Finally, CO_2 prices act as a driver for RE capacity expansion. Though detailed modeling of learning curves related to cost reduction of technologies, or CO_2 price implementation is not attempted, data from available literature has been compiled. In case of unavailability of India specific data, either international sources are used or assumptions are taken.

Previous studies related to long-term scenario analysis of Indian power sector using similar kind of models focus primarily on CO_2 tax implementation, specific CO_2 emission reduction, or RE integration targets, as discussed in Chapter 2. Earlier works have also not analyzed future energy system evolution using a large number of cases, similar to the present study. In the present exercise, the chosen parameters are treated as key drivers of RE expansion, irrespective of any external policy inputs. Therefore, results from scenario analysis could help in policy formulation considering the effects of these drivers. Due to uncertainty related to values in the future, three scenarios are considered for each of these parameters. The number of scenarios chosen is according to the scope and focus of the present research work. Any future exercise can focus on larger number of scenarios and to analyze the impact of a specific parameter on system development.

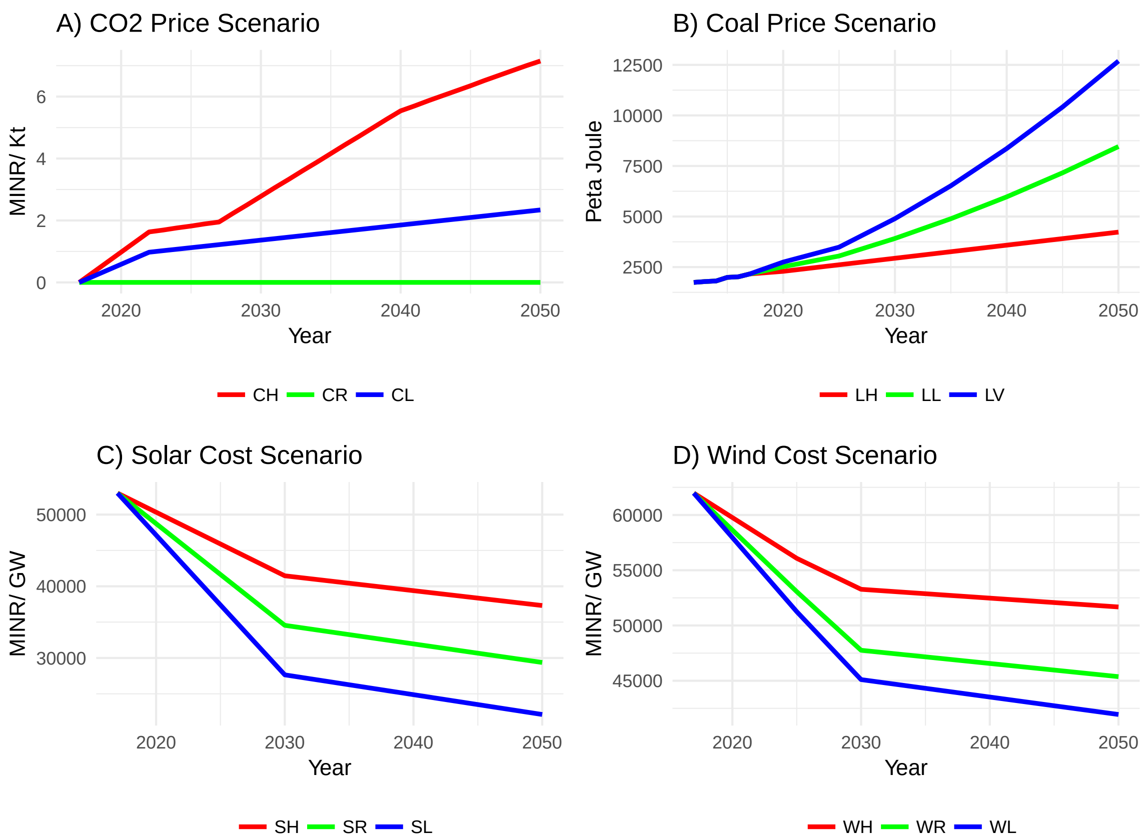


Figure 5.1 CO_2 price, coal price, solar cost, and wind cost scenarios

Coal is a major energy resource in the Indian power generation portfolio. The recent government decision to rapidly increase domestic coal production rate and restrict foreign import will decrease the price of non-coking coal and encourage new installation of coal power plants. Therefore, a variation of coal supply is an interesting parameter to look for in

Indian case, considering the RE penetration targets. The coal price scenarios in this article reflect domestic coal production rates. State-wise historical coal production (available to North-Indian states) rates of 2006-2017 are used to calculate future production rates using simple trend line analysis [185]. Calculation shows that present production rate will increase from 1743 PJ in 2012 to 4230 PJ in 2050. This scenario is termed as high coal price scenario (LH). Two increasing cases are considered for future coal production increase. In low coal and very low price scenarios (LL, LV), coal production rates are assumed to increase by two and three times respectively in 2050, as compared to the LH case (plot B in Figure 5.1). LL scenario is taken as the reference scenario for coal price.

Table 5.2 Scenario Matrix

Sl. No.	Case	CO_2 Price	Coal Price	Solar Cost	Wind Cost	Storage Cost
1.	CR.LH.SR.WR.TR	Ref	Hi	Ref	Ref	Ref
2.	CL.LH.SR.WR.TR	Lo	Hi	Ref	Ref	Ref
3.	CH.LH.SR.WR.TR	Hi	Hi	Ref	Ref	Ref
4.	CR.LL.SR.WR.TR	Ref	Lo	Ref	Ref	Ref
5.	CL.LL.SR.WR.TR	Lo	Lo	Ref	Ref	Ref
..	....	..	..	...	...	...
..	....	..	..	...	...	...
242.	CL.LV.SH.WH.TH	Lo	Vlo	Hi	Hi	Hi
243.	CH.LV.SH.WH.TH	Hi	Vlo	Hi	Hi	Hi

Imposing exogenous CO_2 price encourages model to choose cleaner generation options. Here, two cases are explored. In the Ref (CR) case, there is no imposition of CO_2 price. In CH case, price of CO_2 is expected to increase from 1.6 MINR/ Kt in 2022 to 7.2 MINR/ Kt in 2050 [232]. In CL case, the values are 1 and 2.3 respectively (plot A in Figure 5.1). Level of CO_2 price and its imposition in India is quite uncertain. In the present study, consideration of CO_2 price scenarios are primarily to simulate high RE penetrated system portfolio.

Due to technological progress, capital costs of PV, wind, and storage technologies are gradually reducing. For PV and storage, this reduction will be drastic in the coming years. Therefore, the impact of different cost reduction trends of these technologies compared to Ref case and their impact on generation portfolio is interesting to explore. As data for the alternate cost scenarios are not readily available in literature, own assumptions are taken. Motive was to build three scenario which portrays three plausible values for future years. While constructing the cost scenarios, technological learning is kept in mind so that cost decline in the recent years are much steeper than later. Cost reduction trends of solar and wind are depicted in plots C) and D) of Figure 5.1 respectively. Cost of solar and wind for the years

2015 and 2017 has been taken from CERC [196, 197]. Future cost reduction trend is taken partly from literature and rest from assumptions [233]. In SH and SL cases, PV investment cost is expected to reduce by a factor of 0.54 and 0.32 respectively in 2050 from the 2015 level, as compared to 0.42 times in base case. Wind is a mature technology compared to PV and its cost reduction trend is not that steep as of PV. Wind cost is expected to reduce to 0.86 and 0.7 times in WH and WL scenarios in 2050 from 2015 level, as compared to 0.8 times in base case. In the case of storage, reliable data for future cost variation is scarce. It has been assumed that in high storage cost (TH) cases, pumped hydro and other storage cost will increase by a factor of 1.05 and 1.2 respectively for all future years, as compared to the base case (outlined in Figure 3.7). In low storage cost (TL) cases, the values are 0.95 and 0.8 respectively.

Generating and managing a large number of model cases is difficult (243 in this case). An automated approach is therefore taken involving VEDA-FE tool. Instead of generating each model case manually and run them in single/ batch mode, a master workbook is created with all scenario definitions and their combinations (cases) (Table 5.2). Given an instruction, VEDA-FE automatically generates the model cases on the fly and initiate runs.

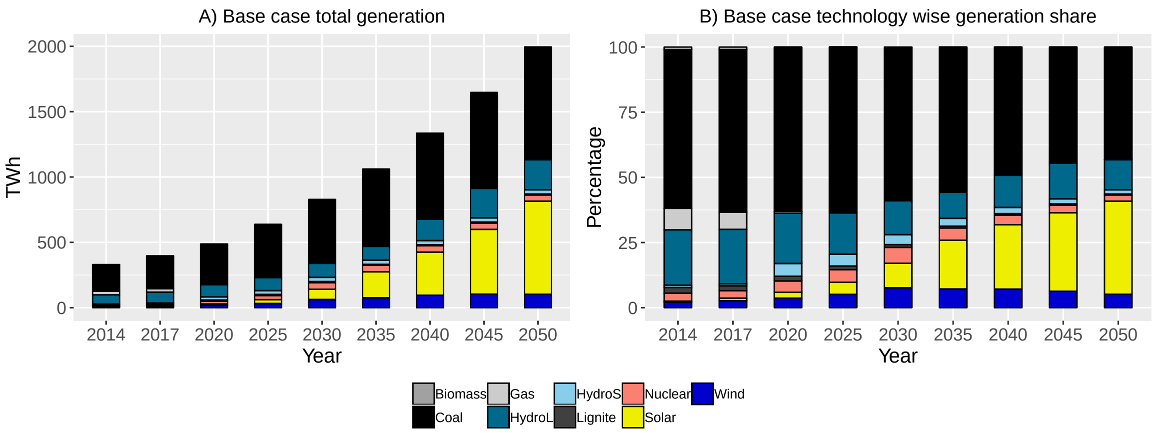


Figure 5.2 Annual generation mix of base case for 2014-2050

5.2 Numerical Results

5.2.1 RE Penetration and Curtailment

Base case generation mix

Figure 5.2 outlines base case generation mix. Base years' generation is dominated by coal (60%) and large hydro (20%) based generation. The share of coal increases to 64% in 2025;

and reduces to 43% in 2050 as solar PV based generation increases steadily from 2017. In 2050, the contribution of coal and solar PV is about 860 TWh and 712 TWh respectively. PV penetration in 2050 (36%) is much higher than wind (5%) due to higher cost reduction potential. Overall RE penetration (excluding hydro; in terms of percentage) increases by approximately 16 times from 2014 to 2050. The contribution of hydro is around 263 TWh (13%) in 2050, utilizing full capacity potential. Around 2% generation in 2050 comes from nuclear power plants.

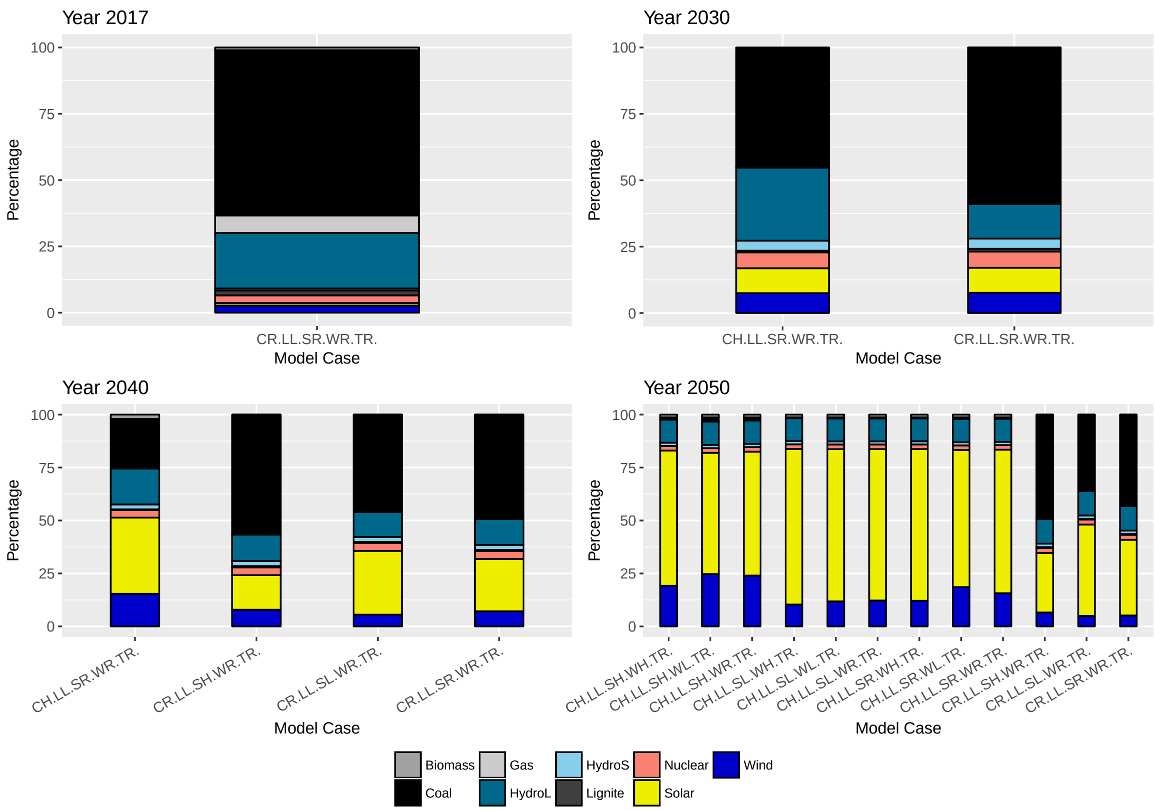


Figure 5.3 Technology wise generation share for various CO_2 price, solar and wind cost scenarios in different years

Year and scenario wise variation of generation mix

Annual generation mix varies considerably in different model cases throughout the planning horizon. Figure 5.3 outlines scenario wise generation share variation of power producing technologies for 2017, 2030, 2040, and 2050. To illustrate results, two scenarios of CO_2 price (CR, CH), and all the three scenarios of solar and wind cost are chosen; coal price and storage cost are set to Ref.

In 2017, every case has a similar generation mix as expected. Hence, generation mix of only the base case is illustrated. Among fossil fuel based generators, coal has the dominant share (62%). Gas and lignite contribute 7% and 2% respectively. Wind penetration (3%) is more than solar PV (1%). Large hydro is also a significant contributor, having approximately 21% generation share. Nuclear power contribution is around 3%. In 2030, a noticeable change is observed only in coal and large hydro generation share, between the two CO_2 price scenarios. Hence, two cases (base and a case involving CH scenario) are chosen to outline the results. In CH cases, share of coal-based generation reduces to 45% while hydro-based generation share increases to 27%. On the other hand, for CR cases, share of coal and hydro-based generation is around 59% and 13% respectively. Total RE penetration is around 17% (8% wind, 9% solar) irrespective of CO_2 price variation. Nuclear based generation increases to 6% due to completion of proposed plants in HR and RJ. Small hydro power contributes 4% of total the generation in all cases.

In 2040, all CH cases have similar generation mix; hence a single case is considered to outline their results. Total RE penetration is around 50% in these cases (solar 35%, wind 15%). The share of coal and large hydro-based generation reduce to 23% and 17% respectively. In CR cases, variation of generation mix is primarily observed between three solar cost scenario groups. Therefore, three cases involving the three solar cost scenarios are illustrated to discuss the results. Total RE penetration for SR, SH, and SL scenarios are 30%, 25%, and 36% respectively. The share of coal-based generation varies inversely in the range of 46%-57%, according to solar cost variations. Large-scale hydro generation share goes down to 12%. Nuclear based generation share is constant at 4%, irrespective of CO_2 price scenarios.

In 2050, clear diversification of generation mix is observed between two CO_2 price cases. Effect of wind cost on wind generation is prominent in CH cases. Variation of generation mix in CR cases is seen in the solar cost scenario groups. Therefore, for illustrating results, all model cases involving CH scenario and three CR cases representing three solar cost scenarios are considered. In CH cases, total RE penetration is around 83% (solar 57%-73%, wind 10%-25%). As in all CH cases, share of firm generation is low (around 5%), system balancing is mainly done using storage charge-discharge operation and inter-regional power exchange, which is further elaborated in following subsections. Inter-case variation of solar and wind penetration is directly linked to their cost assumptions. In CR, or no CO_2 price cases, coal-based generation is higher as expected. Coal supplies approximately half of total energy demand in high solar cost cases with RE contributing around 35%. In low and ref solar cost cases, PV penetration increases to around 47% and 41% respectively. Variation of wind generation share is not prominent for any CR case (4%-7%). Hydro generation share is almost constant at 11% in all cases irrespective of CO_2 price, due to the full utilization of capacity potential.

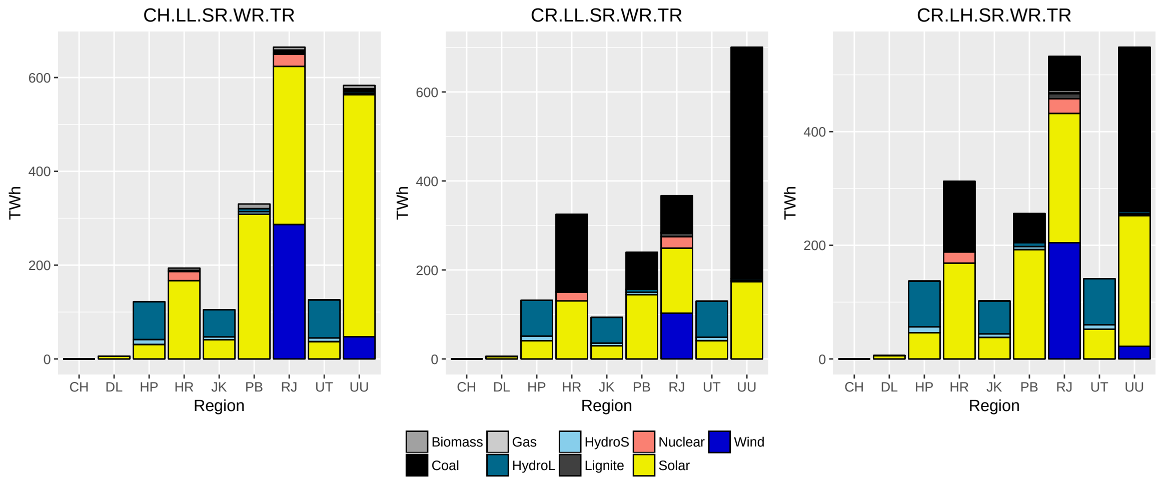


Figure 5.4 Region wise variation of technology activity in various RE penetration scenarios in 2050.

Regional generation mix in three RE penetrated scenarios

Due to the difference in RE resource potential, existing capacity, and demand level, generation mix of each model region varies substantially. In Figure 5.4, regional interpretation of annual generation mix is presented for 2050. Three selective model cases are chosen indicating three different RE penetration levels (base: CR.LL.SR.WR.TR, mid: CR.LH.SR.WR.TR, high: CH.LL.SR.WR.TR).

It is observed that coal-based generation is highest in UU region. In base and mid-RE cases, it produces almost 60% and 55% of total coal-based generation. Solar PV based production mainly comes from UU, RJ, HR, and PB. In base and mid-RE cases, each of these regions has almost 18%-24% contribution in total PV generation. In high-RE case, PV generation from HR drops to 12% while UU increases its contribution to 36%. It is mainly due to the increase of energy import and imposition of CO_2 price respectively for HR and UU. In the base case, wind-based generation is only seen in RJ; but for other two cases (high, mid), UU also contributes 14% and 10% share respectively. In RJ, the increase of wind generation is almost 2 and 2.8 times respectively in mid and high-RE cases, as compared to the base case. HP, UT, and JK are major hydro power producing regions contributing 91 TWh, 88 TWh, and 63 TWh respectively for all three RE cases. In hydro-rich states like HP, UT, and JK, hydro-based generation is constant for all three cases.

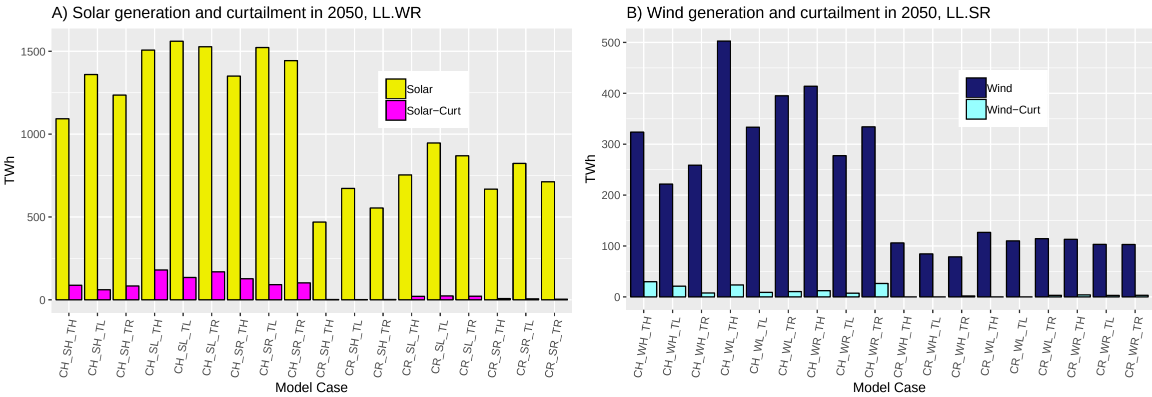


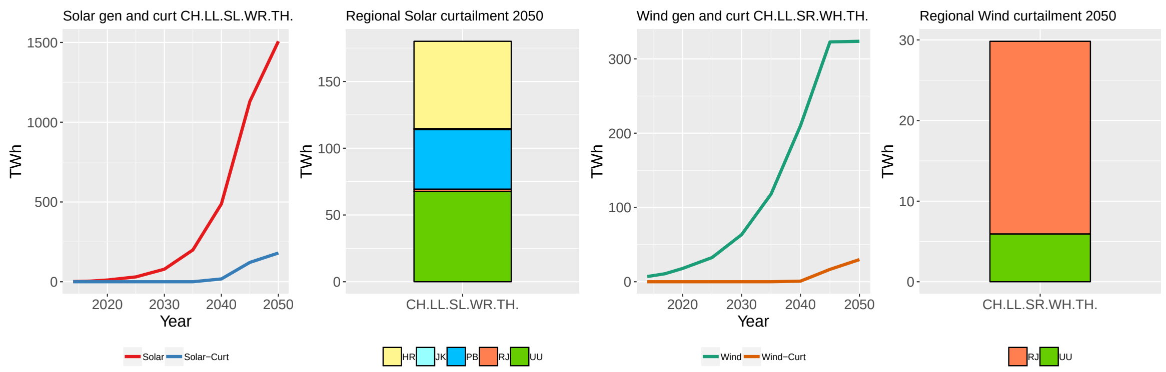
Figure 5.5 Annual solar and wind energy curtailment in various scenarios

RE Curtailment

Renewable energy curtailment is a major operational concern for high RE penetrated power systems. The present study captures possible solar and wind energy curtailment in all model cases. Current and subsequent subsections respectively present annual and time-slice wise interpretation of RE curtailment levels.

Figures 5.5 A) and B) outline annual solar and wind energy curtailment respectively in various scenarios for 2050. Two cases of CO_2 price (CH, CR) and all the three cases of solar, wind and storage cost are considered. Coal price is set to LL in all the cases. For outlining solar energy curtailment, wind cost is set to reference scenario and vice versa. For both solar and wind, curtailment is only prominent in CH cases. Maximum 3% curtailment is seen in CR cases for both solar and wind. Solar and wind curtailment varies in the range of 4%-11% and 3%-9% respectively in CH cases. For the same cases, solar and wind penetrations are in the range of 52%-73% and 11%-28%. In CR or negligible curtailment cases, solar and wind penetration is around 24%-47% and 5%-7% respectively.

Figure 5.6 outlines year wise variation of solar and wind penetration and curtailment for two selective high solar and wind curtailment cases. Regional interpretations of curtailment for both solar and wind is also drawn. Curtailment is prominent from 2040, for both solar and wind when their penetration is around 36% and 15% respectively. UU, HR, PB, and RJ report higher solar energy curtailment. Despite high solar penetration in RJ, curtailment is considerably less. Higher energy export and storage activity are the major reasons behind this. RJ reports considerable wind energy curtailment due to its higher penetration.



(a) Solar generation and curtailment **(b)** Wind generation and curtailment

Figure 5.6 Yearly variation of solar and wind generation and curtailment in various regions

5.2.2 Power Dispatch

Overall daily and seasonal power dispatch

By virtue of high temporal and spatial resolution adopted in the NIMRT model, it is possible to analyze region wise power dispatch pattern, along with the activity profile of inter-regional transmission lines and energy storage, with respect to seasonal and diurnal variation of demand and RE generation. In this subsection, these issues are elaborated for two selected cases, base (CR.LL.SR.WR.TR) and high-RE (CH.LL.SR.WR.TR) for 2050. Overall dispatch pattern for North-India and four selected regions namely, UU, RJ, HR, and PB are also presented.

Timeslice wise power dispatch, activity of storage, and inter-regional transmission lines in 2050 for the two cases are outlined in Figure 5.7. Hourly activity profile of a typical day in June is also presented to better illustrate intra-day variation. From daily activity profile of June, it is evident that thermal and hydropower plants act as balancing resources, and RE generation pattern determines their activity level. At times of high RE penetration, these generators decrease their output level to accommodate incoming RE and during periods of low RE availability they ramp-up their generation. Charging of energy storage devices occurs at daytime when excess solar energy is available, while discharging occurs at other time slices. Net power import/ export volume is also substantial, which highlights the importance of inter-regional power exchange. In high RE case, due to unavailability of firm generators, energy storage activity contributes strongly to system balancing along with inter-regional power exchange. Solar and wind energy curtailment happen at the noon time. Wind curtailment occurs mainly to accommodate cheaper solar power.

Seasonal variation of dispatch pattern is also prominent from Figure 5.7. Higher solar penetration is seen in February-April and October-December. On the other hand, wind

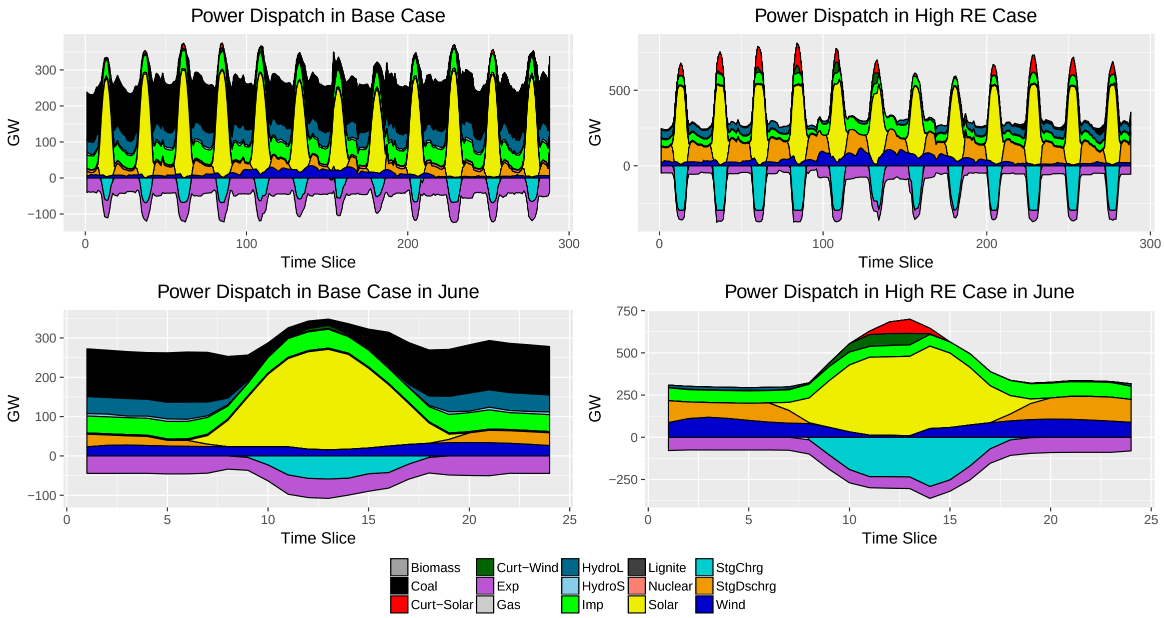


Figure 5.7 Overall generator dispatch pattern and activity profile of energy storage and inter-regional transmission lines in 2050 in base, and indicative high RE penetration scenarios

penetration increases substantially in May-August. In both cases, RE curtailment is observed in high RE penetrated time slices. It is mainly reported when the system cannot accept additional RE, despite lowering/ stopping generation of other generators and/ or store it. In the base case, highest solar energy curtailment (5%) is observed in April and March in H12 and H13 time slices respectively. In high RE penetrated case, highest solar curtailment is in April-H12 time slice, and in June-H13 for wind. Curtailment for wind and solar energy in these two time slices are 88% and 22% respectively. Highest total RE curtailment of 37% is observed at April-H12 time-slice. Storage mainly works as daily energy arbitrage device as it is charged by available excess RE power (mainly solar) and is discharged when RE generation is not available. Compared to base case, storage activity is much higher than power exchange in the high RE scenario. Impact of seasonal variation of RE production is prominent on seasonal variation of storage charging/ discharging and energy export/ import pattern.

Regional daily and seasonal power dispatch

Regional picture of dispatch pattern is different from the overall one and worthy of inspection. Dispatch patterns of four regions RJ, UU, HR, and PB are illustrated in Figure 5.8. In UU, base case dispatch is heavily dominated by coal. Due to the absence of other firm generators, heavy cycling of coal-based power plants is seen. UU is a net power exporter in the base case.

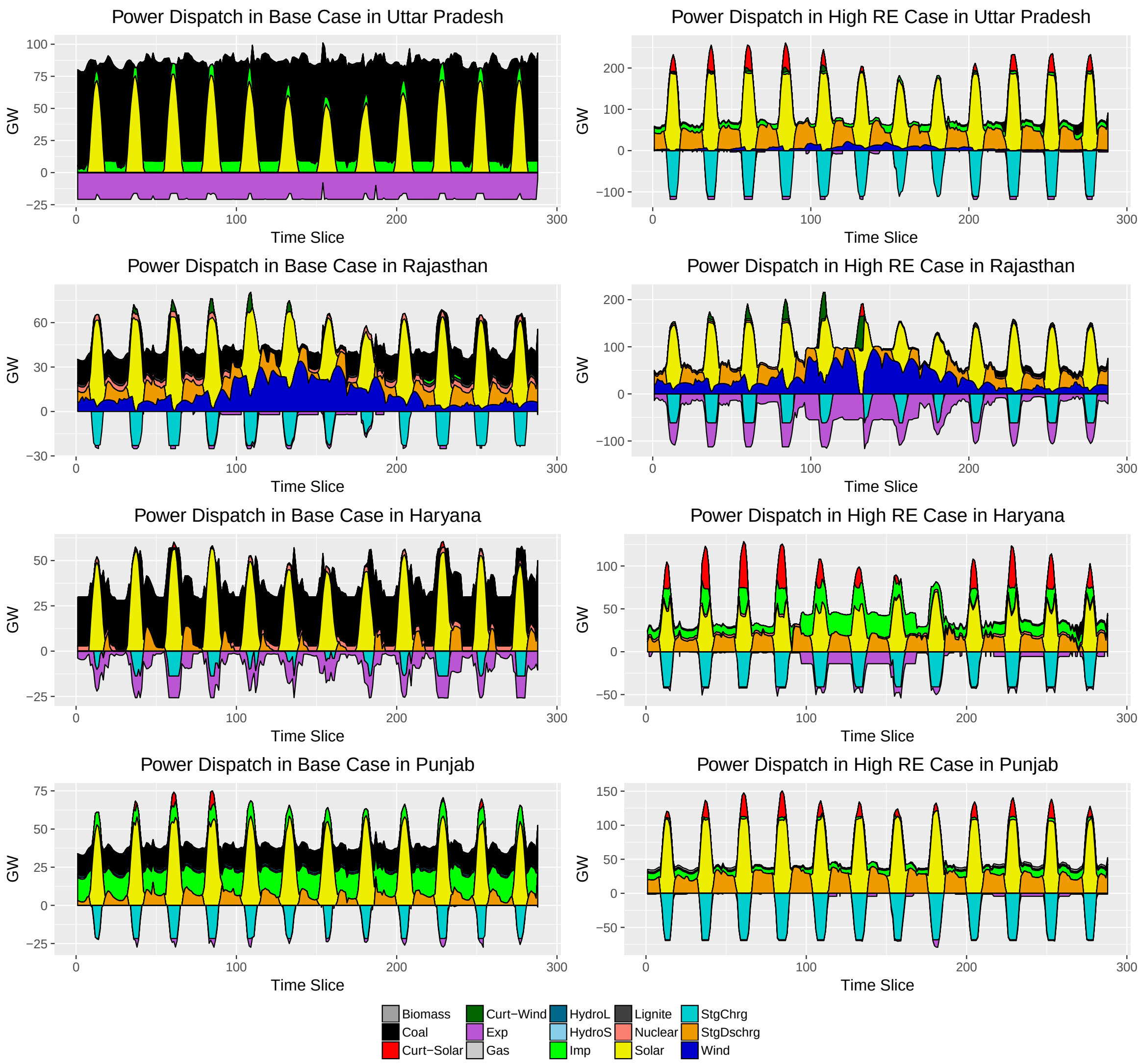


Figure 5.8 Regional generator dispatch pattern and activity profile of energy storage and inter-regional transmission lines in 2050 in various RE penetration scenarios

All solar generation is absorbed without any storage or curtailment activity. In high RE case, coal-based generation reduces drastically. Solar generation gradually increases from January to April, and then reduces to its lowest in July. Afterward, it again increases till December. High solar penetrated time slices are involved with higher generation curtailment. Highest solar curtailment (26%) is observed in the 13th hour of February. Wind dispatch is higher in rainy season, but interestingly curtailment is low in these seasons. Rather wind energy curtailment is as high as 100% in some time slices, like May 12. From this it is evident that wind generators are backed down to accommodate cheaper solar power. In high RE case, quantum activity of storage is observed compared to base case when storage is absent. Clearly, storage follows solar seasonal as well as daily dispatch pattern and acts as a daily arbitrage device.

In RJ, renewable play a major role in power dispatch, both in the base and high RE case. Coal, gas, and lignite are the firm resources supporting the balancing operation in base case. Nuclear power also supplies a significant portion of energy demand. In both cases, a decline in solar energy production is seen in monsoon, along with considerable wind generation increase. In the base case, solar energy curtailment is negligible; rather 100% wind curtailment is seen in some time slices. In high RE scenario, the highest solar curtailment percentage is around 23%, during June H13. In this case, wind curtailment is as high as 100% in some time slices. In the months of February-June, wind energy curtailment is prominent. Wind energy curtailment occurs mainly in the daytime to accommodate solar energy penetration. In the base case, daily as well as seasonal variation of storage charge-discharge follows solar dispatch pattern. Most of the generation is consumed within the region with very little export in the base case. In high RE penetration case, export increases substantially.

In HR, coal and nuclear power plants are main firm generating options in the base case. HR is a net power exporter in base case, but in high RE case, it is a net power importing region. Inter-regional power trading contributes significantly to daily system balancing. In high RE case, solar curtailment is prominent in almost all months. Solar curtailment level as high as 57% is seen in some time slices.

PB is heavily dependent on energy import in the base case. Energy import provides as high as 50% energy requirement in some time slices. Considerable storage activity is also seen to support solar penetration. Though solar PV curtailment is seen only in some seasons in the base case, all seasons in high RE case are associated with solar curtailment. Highest solar energy curtailment in the base case and high RE case are around 19% in APR-H12 and 26% in APR-H13 respectively. Dependency on energy import decreases in high RE scenario, with an increase in storage activity.

5.2.3 Technology Capacity

New capacity requirement for power generation, storage, and transmission are some of the major outcomes of the current planning study. In this section, capacity evolution of prominent power generating resources is outlined; while energy storage and transmission lines are discussed in next subsection.

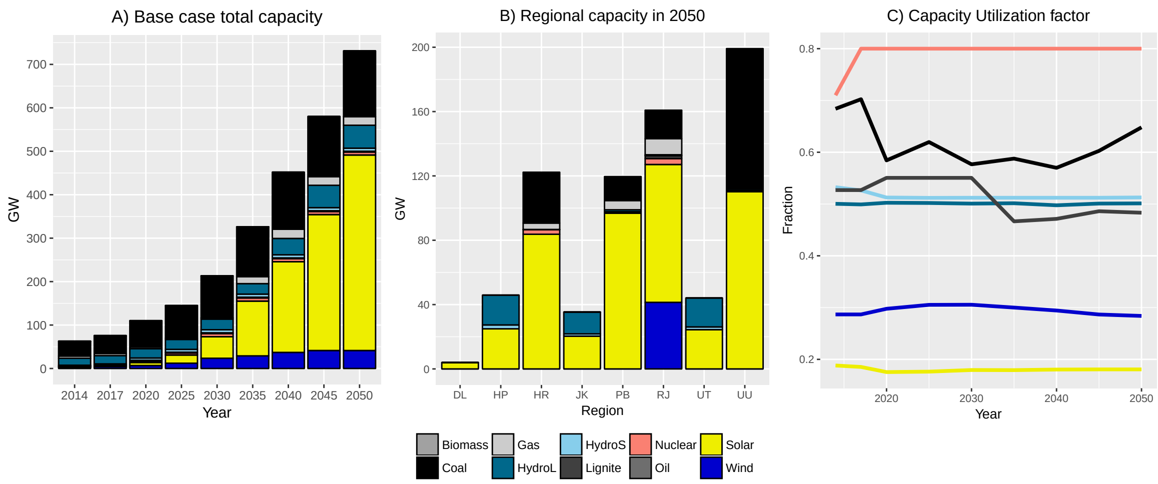


Figure 5.9 Year wise technology capacity, regional capacity distribution of 2050, and capacity utilization factors in base case

Base case generation capacity mix

Figure 5.9 A), B) and C) respectively outlines year wise total installed power generation capacity, regional capacity distribution in 2050, and their capacity utilization factors for the base case. Steady capacity addition in coal-fired power plants is observed up to 2040 (132 GW); later due to increased RE penetration, its growth rate is slowed, and total capacity reaches 152 GW in 2050. UU has the highest installation of coal-fired plants (87 GW), which is almost 58% of the total coal capacity in 2050. HP, UT, and JK are the regions endowed with a considerable share of hydro power in their capacity portfolio. Total hydro capacity (small and large) reaches 60 GW in 2050, utilizing full potential. Total gas based capacity is 20 GW in 2050 from 5 GW in 2017. Gas based plants' installation is seen in RJ (51%), HR (20%), and PB (29%). RE capacity addition occurs at a steady rate from 2017 to 2050. Investment in wind is seen only in RJ, though in other high RE penetrated cases, wind installation takes place in UU and HR. In 2050, total wind capacity is 41 GW. Major solar installation takes place in UU (110 GW), RJ (86 GW), HR (84 GW), and PB (97 GW). Total installed capacity of solar PV in base case is 450 GW in 2050. Over the modeling horizon, nuclear plants operate at the highest annual capacity utilization factors (CUF) (80%) followed by coal (57%-70%). Hydro power plants' CUF is around 50%. Wind and solar power plants operate at about 30% and 18% annual CUF respectively.

Year and scenario wise variation of capacity mix

Generation share of power producing technologies for 2017, 2030, 2040, and 2050 in various cases is illustrated in Section 5.2.1. Figure 5.10 outlines capacity implication of those technologies in the same cases. The number of cases for illustrating results of a year is similar to that detailed in the Section 5.2.1. In 2017, each model case has a similar capacity mix as expected. 53% of total capacity is constituted of 40 GW of coal followed by 19 GW of large hydro (25%). Gas and wind each having 4 GW capacity, have 6% share. Solar PV capacity is around 2.3 GW (3%).

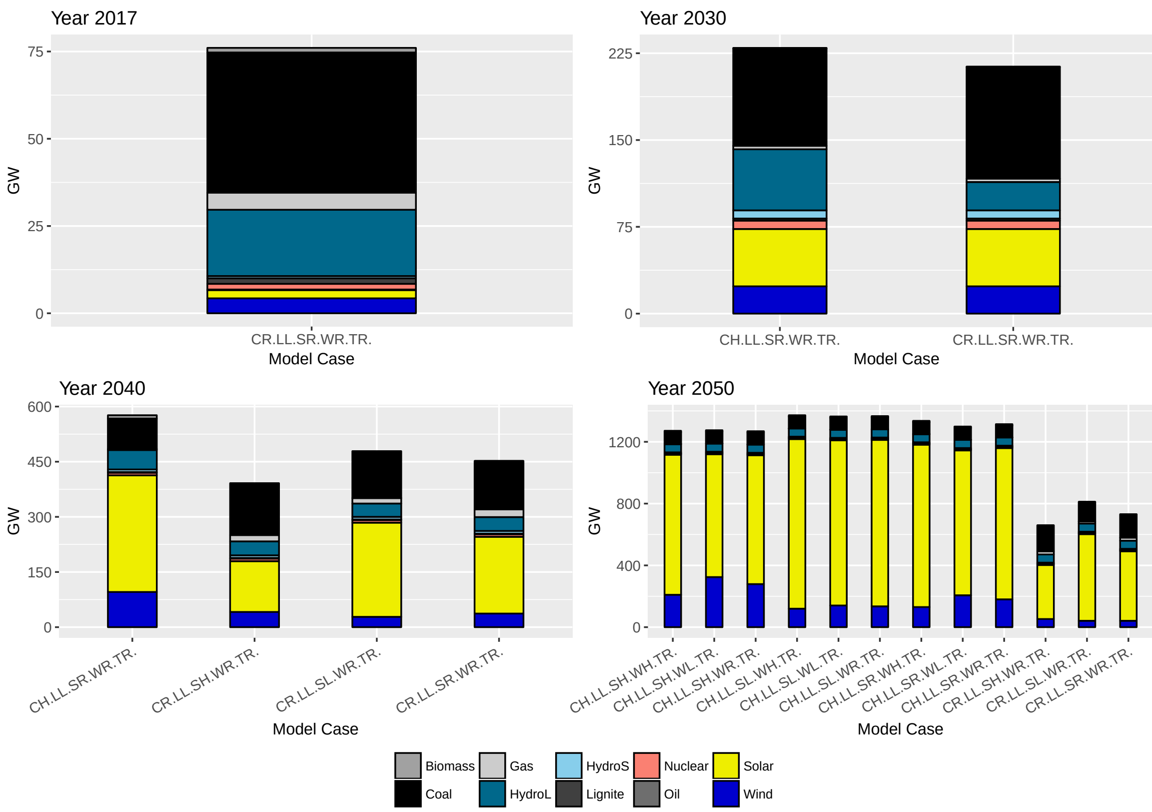


Figure 5.10 Capacity mix in 2017, 2030, 2040, and 2050 for various CO_2 price, solar and wind cost scenarios

In 2030, ref or no CO_2 price cases have almost 13% higher coal-based capacity (96 GW) than high CO_2 price cases (84 GW). Large-hydro capacity increases to 53 GW in CH cases and 25 GW in CR case, from 19 GW in 2017. The capacity of solar (50 GW) and wind (24

GW) are constant irrespective of scenario variation. In 2030, an increase of solar and wind capacity is almost 25 and 6 times their values in 2017. Around 7 GW of nuclear and small hydro capacity installation is also observed in all the scenarios.

In 2040, solar and wind-based generators share 55% (317 GW) and 17% (96 GW) of capacity respectively in CH case. On the other hand, the capacity share of RE technologies in CR cases varies from 46%-60% (180-285 GW) according to solar cost scenarios. The share of wind and solar based capacities are in the range of 5%-11% (24-41 GW) and 35%-52% (138-250 GW) respectively. Large hydro-based generation capacity is around 53 GW and 36 GW in CH and CR cases respectively. Coal contributes 83 GW capacity (14%) in CH scenario, whereas in CR cases its capacity ranges from 128-141 GW. Nuclear and small hydro-based generation capacity is constant at 7 GW respectively in all scenarios.

In 2050, the share of RE capacity (solar and wind) is around 88% in CH cases, as compared to 61%-74% in CR cases in the overall capacity portfolio. Among high CO_2 price cases, the highest wind capacity observed is 324 GW when solar cost is high and wind cost is low. On the other hand, highest solar capacity is 1098 GW when solar cost is low and wind cost is high. In no CO_2 price cases, solar capacity reaches approximately 357 GW in SH scenario and 560 GW in SL scenario. The capacity of wind is almost 57 GW when wind cost is low and the solar cost is high, and 28 GW when solar cost is low and wind cost is high. The capacity of coal is higher for no CO_2 price cases as expected. For high CO_2 price cases, coal capacity is almost 76 GW, whereas it varies from 127 GW to 169 GW depending on RE capacity penetration levels in CR cases. Total hydro capacity is constant in all cases at 60 GW. CO_2 price does not encourage building new gas power plants as RE technologies are more effective to reduce CO_2 emission intensity. Gas based capacity is seen to be mere 1-2 GW in CH cases, as compared to 11-20 GW in no CO_2 price cases. Total installed generation capacity for CR cases is lower than CH cases, due to higher utilization of coal-based generator and low capacity factor of RE plants.

Year and scenario wise variation of solar, wind and coal capacity

Coal, hydro, solar, and wind are important energy sources for future power generation. There is no prominent scenario wise variation in hydro capacity. Therefore, capacity evolution of solar, wind, and coal is illustrated in detail in Figure 5.11 A), B), and C) respectively, for various model cases. For illustration, three scenarios of CO_2 price, solar cost, and wind cost are chosen. Coal price and storage cost are set to their reference values. Result for each technology is presented in three separate graphs, indicating high, low, and ref CO_2 prices respectively.

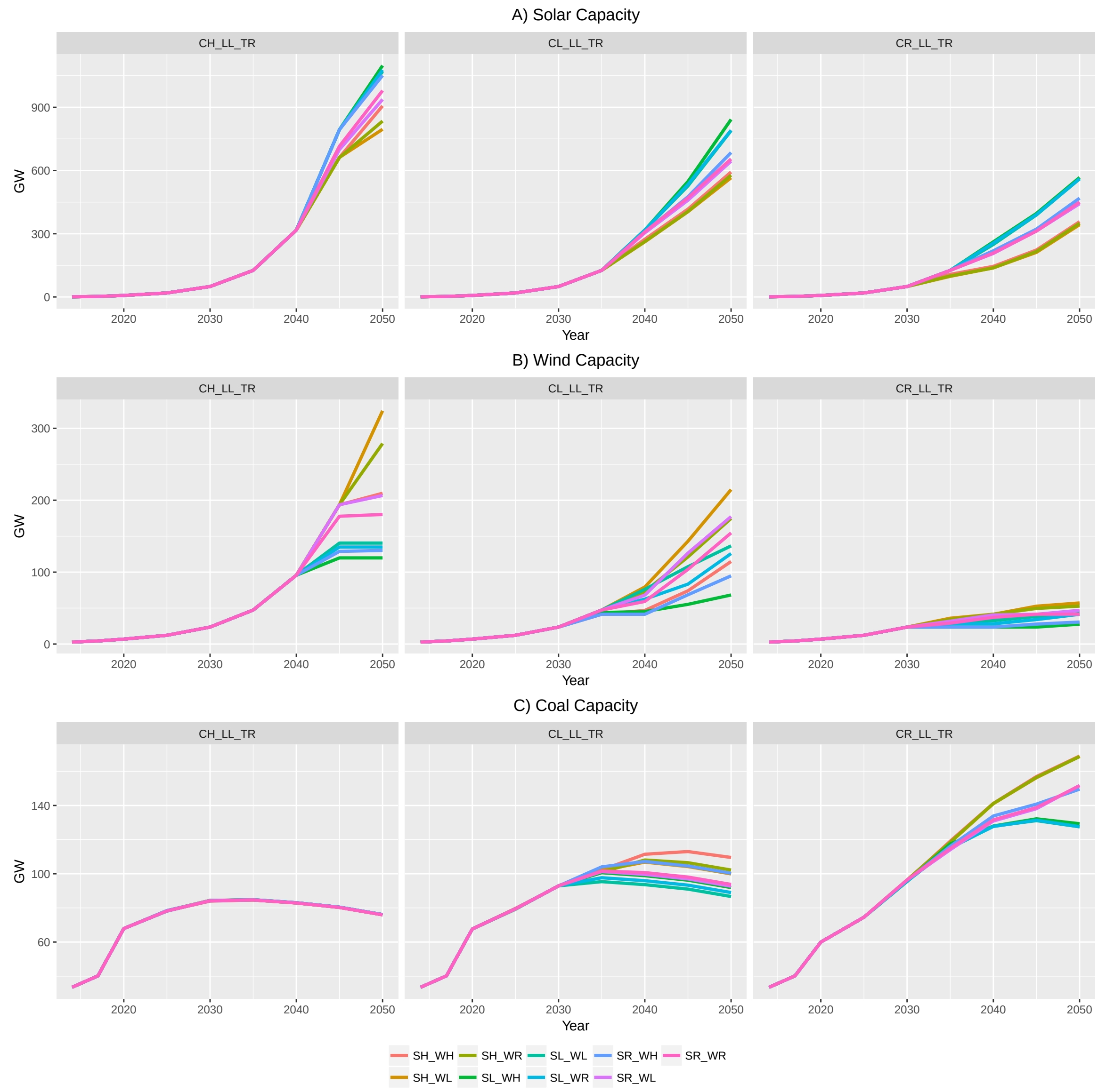


Figure 5.11 Scenario wise evolution of solar, wind, and coal capacity in CO_2 price, solar, and wind cost scenarios

In reference CO_2 price scenario, solar capacity reaches 50 GW in 2030, irrespective of scenario variations. Afterward, low solar cost takes capacity to approximately 567 GW in 2050. In reference and high solar cost scenarios, solar capacities are around 450 and 343 GW in 2050. Wind cost has a negligible effect of changing solar capacity addition. In all high CO_2 price cases, solar follows similar capacity addition trend up to 2040; reaching 317 GW. Subsequent effect of solar and wind cost on solar capacity investment is seen in 2050. In SR, SL, and SH scenarios, solar capacity in 2050 ranges from 937-1051 GW, 1070-1098 GW, and 796-907 GW respectively according to variation in wind cost. Finally, for low CO_2 price cases, the system installs 126 GW of solar capacity in 2035 in all cases, following a similar increasing trend. Without any alteration of solar cost, capacity goes up to 685 GW in 2050, when wind cost is high. In high and low solar cost scenarios, solar capacity varies in the range of 566-842 GW (Figure 5.11 A).

Wind capacity reaches 24 GW for all reference CO_2 price cases in 2030. Total capacity increases to 57 GW in 2050, with low wind cost and high solar cost. Around 41 GW of capacity is seen in reference wind cost cases in both SL and SR scenarios, but capacity increases to 53 GW when solar cost is high. High wind cost and low solar cost restricts wind capacity to 28 GW only. High CO_2 price leads to an exponential increase of wind capacity to 96 GW in 2040 for all cases. Further, 1.5-3.4 times increase in capacity is observed for low wind cost cases. Total wind capacity varies in a range of 120-279 GW for various cases under the influence of solar and wind cost in 2050. In all low CO_2 price cases, wind capacity reaches 24 GW in 2030. For reference wind cost, it increases further to 175 GW in 2050 with high solar cost. For low and high wind cases, capacity varies in the range of 137-215 GW and 68-115 GW, reflecting the influence of solar cost (Figure 5.11 B).

Coal capacity increases steadily in all scenarios to around 96 GW in 2030, when there is no CO_2 price imposed on the system. Afterward, for high solar cost cases, capacity increases to 170 GW in 2050. Coal capacity is approximately 130 GW and 150 GW respectively, when solar cost is at the ref and high levels. For all high CO_2 price cases, coal capacity increases to 85 GW in 2035; afterward, it decreases gradually to 76 GW in 2050. There is no scenario wise variation in the installed coal capacity in this scenario. On the other hand, for low CO_2 price cases, after reaching 93 GW in 2030, a variation of 23 GW (87-110 GW) is observed in various cases for 2050. (Figure 5.11 C).

Year and region wise variation of generation capacity

Figures 5.12 A), B) and C) illustrates the impact of solar, wind, and coal costs on their own capacity development respectively. They also outline the regional distribution of capacity evolution of technologies for future years. In all solar cost cases, major solar installations

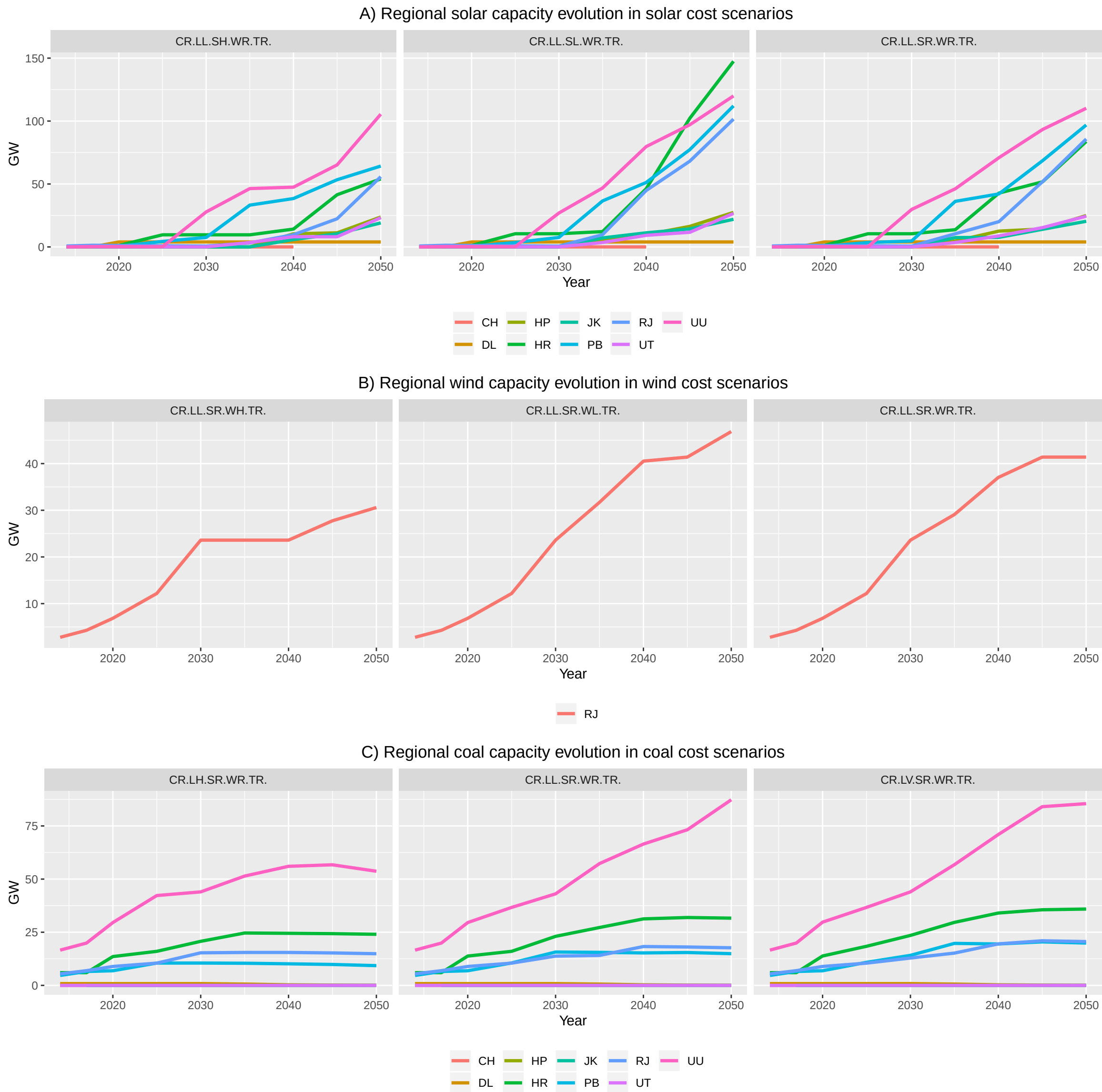


Figure 5.12 Region wise evolution of solar, wind and coal capacity in respective cost scenarios

regions are UU, RJ, PB, and HR. Solar capacity addition in UU starts from 2030, and it varies from 105 GW in SH scenario to 120 GW in SL scenario for 2050. Though UU has highest installed solar capacity in SH and SR scenario, in SL scenario, maximum capacity is installed in HR (147 GW). In RJ, solar capacity addition rates are higher in later years, contrary to the other three regions. In all three wind cost scenarios, installation is only seen in RJ. Total wind capacity for WH, WR and WL scenarios are 30 GW, 41 GW and 46 GW respectively. Wind capacity addition rate in RJ is higher than solar in initial years. Highest coal capacity is in UU, followed by HR, RJ, and PB. Due to limited coal supply in LH scenario, total coal capacity is almost constant from 2035 in all regions, except UU. Capacity in UU reaches 57 GW in 2045 and goes down to 54 GW in 2050 in LH scenario. In LL and LV cases, coal capacity in UU is around 85 GW. In other regions, similar coal capacity increase is observed for LL and LV cases after 2040.

5.2.4 Energy Exchange and Storage

It is evident from generator power dispatch related results in Subsection 5.2.2, that storage activity and power exchange between regions strongly helps to maintain daily system balance. In this subsection, overall and regional interpretation of storage and energy exchange activity and capacity are discussed.

Role of Energy Exchange

Figures 5.13 and 5.14 outline inter-regional annual energy exchange and transmission capacity in three RE penetrated cases (base, mid, high) in 2050. The cases are same as discussed in Section 5.2.1, to outline regional RE penetration.

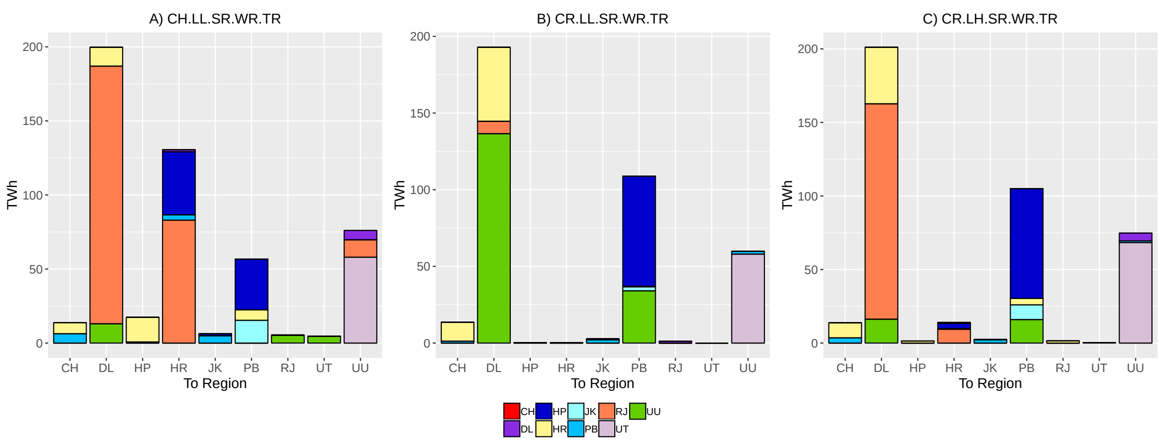


Figure 5.13 Inter-regional annual energy exchange in base, indicative mid, and high RE penetration scenarios

As outlined in Figure 5.13, for all three cases, DL is a significant energy importer among all regions. In base case, it imports almost 193 TWh of electricity annually from HR (25%), UU (71%) and RJ (4%) to satisfy its need. But in the other two scenarios, the source regions from where DL imports its required energy gets changed. RJ provides 73% and 87% of total import of DL in mid and high RE cases respectively. HR is a net energy exporter in base as well as mid RE case. But, for high RE case it becomes net energy importer due to surplus RE available from RJ. In high RE case, HR imports a significant portion of its energy need from RJ (64%) and HP (33%). PB is another major energy-importing region. In base case it imports almost 109 TWh of electricity from mainly HP (66%) and UU (31%). In mid RE scenario, though total import of PB is almost similar, share of HR (4%) and JK (10%) becomes prominent. In the high RE scenario, total import of PB reduces by almost half, and all the imported power comes from HP(60%), HR(12%), and JK (27%). UU is a major energy exporting region in base case, where it exports its surplus energy to DL (80%) and PB (20%). In both mid and high RE cases, it becomes net energy importer. A significant share of UU's import comes from hydro-rich UT region in all the three cases (around 60-70 TWh). RJ is main energy exporting region for high and mid RE cases, where it mainly supplies energy to HR and DL regions. HP plays a crucial role in providing power to PB in all cases. CH is entirely dependent on import for fulfilling its energy demand, by importing energy from HR and PB.

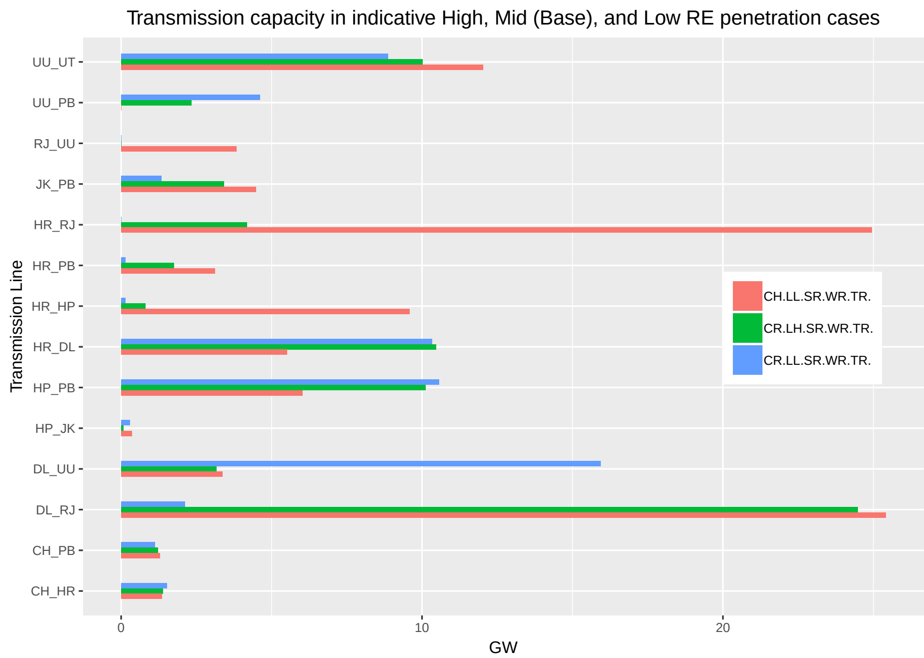


Figure 5.14 Inter-regional transmission capacity in base, indicative mid, and high RE penetration scenarios

Capacity interpretation of energy exchange can be seen in Figure 5.14, where scenario wise variation of transmission line capacities are outlined for three RE penetration cases (similar to the previous paragraph). It can be observed that capacity variation of transmission lines is different in three scenarios depending on which regions they are connected to. The DL_RJ line which mainly imports energy from RJ to DL has a capacity of around 25 GW for the high and mid-RE scenario, compared to only 2 GW in ref case. The capacity of lines connecting DL to UU decreases drastically for mid (3 GW) and high RE (3 GW) cases from its ref case value (16 GW). The capacity of UU_UT increases gradually from 8.9 GW for the ref scenario, to 12 GW for high RE scenario. There is no transmission capacity reported between RJ and HR for the ref scenario, but for mid and high RE case, reported capacity are 4 and 25 GW respectively. Transmission capacity of HR_DL reduces from base to high RE scenario due to dependency on DL_RJ line for importing energy from RJ. In base case, capacity of HR_DL is 10 GW, but for high RE case, it reduces to 5.5 GW. The capacity of transmission lines connected with PB, such as JK_PB and HR_PB sees a gradual increase in capacity with increasing RE penetration as dependency on these lines increases for energy from/ to PB region.

Role of Energy Storage

Along with transmission capacity, energy storage technologies play an important role to integrate RE based generation, especially solar PV. In Figure 5.15, yearly variation of storage capacities for the three solar and wind cost scenarios are presented, along with its regional interpretation in 2040 and 2050; CO_2 price, coal, and storage cost are set to ref values. As storage capacity variation is primarily dependent on solar cost, three cases representing solar cost scenarios are considered for illustrating regional results in 2040 and 2050.

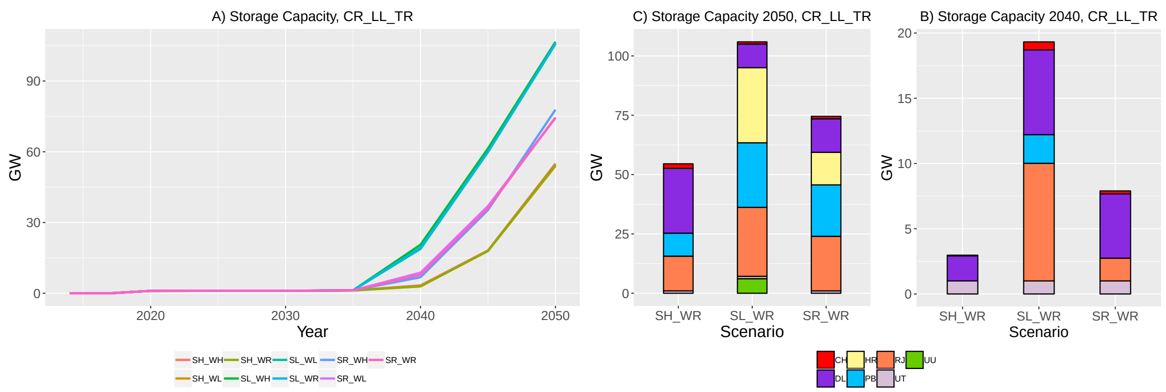


Figure 5.15 Total energy storage capacity in solar and wind cost scenarios

Storage capacity addition is prominent from 2035, and the total reaches 55 GW when solar cost is high. But, at reference and low solar costs, storage capacity in the range of 75-106 GW is seen. In 2040, storage installation is seen in DL for all the cases. Storage capacity in RJ is only seen for SL and SR scenarios. PB only installs storage for SL cases. In 2050, high solar cost leads to 50% storage installation in DL (27 GW), whereas PB and RJ share around 18% and 27% of total capacity. The share of storage capacity in DL for low and reference solar cost scenarios are approximately 9% and 16%. The share of PB and RJ for these two scenarios is around 26%-29% and 27%-30% respectively. Despite that HR does not have storage installation for SH scenario, it shares approximately 30% storage capacity (30 GW) in SL cases. Storage installation in UU is only seen for low solar cost cases (approx 6 GW).

Storage capacity evolution for different CO_2 price, solar, wind, and storage cost scenarios are illustrated in Figure 5.16 A) and 5.17 A). Regional interpretation of the capacities are also drawn for the year 2050 in Figure 5.16 B) and Figure 5.17 B) respectively. Three indicative cases of solar cost are considered for illustrating regional results. Figure 5.16 illustrates results for two CO_2 price cases (CH, CL), setting storage and coal cost to ref scenario, while Figure 5.17 outlines results for two storage cost cases (TH, TL), setting CO_2 price and coal cost to ref scenario.

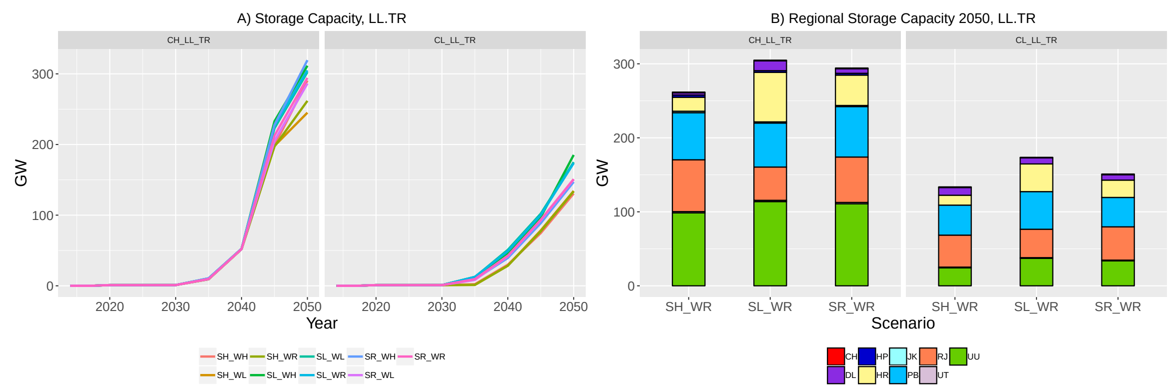


Figure 5.16 Total energy storage capacity in CO_2 price, solar, and wind cost scenarios, along with regional interpretation in 2050

In Figure 5.16 A), storage capacity addition is prominent from 2030 in high CO_2 price (CH) cases, though the effect of scenario variation is not prominent till 2040. In 2040, storage capacity reaches 52 GW in all cases. In 2050, capacity becomes as high as 319 GW in SR.WH case. In the three solar cost cases, storage capacity varies in the range of 245-291 GW (SH), 302-313 GW (SL), and 286-319 GW (SR) respectively. In CL scenario, capacity addition in storage is seen from 2030 in SL and SR cases. For SH cases, capacity addition is prominent from 2035. In 2050, storage capacity is around 130 GW in SH cases, 175-185

GW in SL cases, and 150 GW in SR cases. In 2050, for all high CO_2 price cases, UU has the highest storage installation (37%) (Figure 5.16 B)). Total capacity in UU is as high as 115 GW in SL_WR case. Apart from UU, in SR cases, primary storage capacity contributions are from HR (14%), PB (23%) and RJ (21%). In SL cases, these regions contribute 22%, 20%, and 15% respectively. In low CO_2 price cases, share of storage capacity in UU ranges between 15-23%. RJ, HR, and PB capacity shares are approximately 22%-35%, 10%-22%, and 26%-30% respectively.

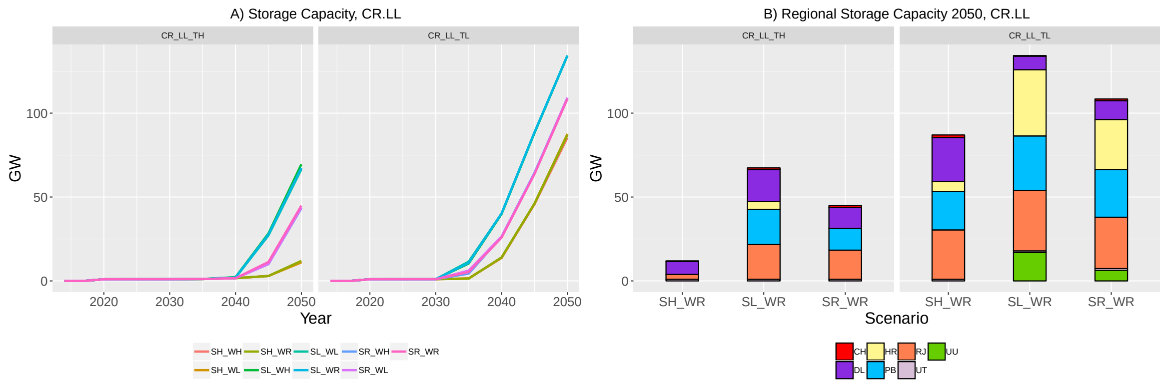


Figure 5.17 Total energy storage capacity in solar, wind, and storage cost scenarios along with regional interpretation in 2050

In Figure 5.17 A), high storage cost cases lead to storage capacity addition from 2040 only. In these cases, total storage capacity in 2050 is as low as 12 GW when solar cost is high. Reference and low storage cost leads to capacity increase in the range of 43-70 GW only. Higher storage capacity is reported in low storage cost scenario as expected. In SL, SR, and SH scenarios, storage capacity reaches 134 GW, 109 GW, and 85 GW in 2050. In TL cases, investment into storage capacity starts as early as 2030 for SL and SR scenarios. In SH cases, capacity starts building up from 2035. In 2050, for TH cases, storage capacity is only prominent in DL and RJ, when solar cost is high (Figure (5.17 B)). In low solar cost, DL, PB, and RJ share around 30% capacity each. In reference solar cost, storage capacity in DL and PB is around 13 GW, whereas RJ installs 17 GW capacity. Low storage cost leads to an increase in storage capacity in all regions. In SH cases, DL, PB, and RJ share about 30% capacity each. The share of DL reduces to 6% (8 GW) whereas HR contributes 30% capacity (40 GW) in SL cases. UU contributes around 13% and 6% of capacity (17 GW, and 7 GW respectively) in SL and SR cases. In SL cases, the contribution of PB and RJ is around 24% (32 GW) and 26% (36 GW) respectively, whereas in SR cases they contribute 26% (29 GW) and 28% (30 GW) respectively.

Energy storage is an indispensable investment required to streamline future capacity expansion of solar PV. One of the major concerns with increasing solar integration is generation curtailment. Energy storage technologies are unique devices to reduce curtailment (via energy time shifting) and help in quick system balancing. Figure 5.18 outlines storage discharge variation with respect to total solar generation for three CO_2 price cases; coal price and wind costs are set to ref scenario. Each point in the plots indicates a model case, and colour of the points denotes solar cost scenario groups. It is observed in the three plots that, storage activity (discharge) increases with increasing solar penetration due to CO_2 price effect in 2050. For each CO_2 price scenario, solar-based generation linearly increases with the decrease in solar cost. Again in each solar cost scenario group, lower storage cost leads to higher solar based generation (storage cost for each point is labeled). Therefore it can be inferred that, if there is existing feasibility of solar energy penetration, energy storage is a key enabling technology for its integration.

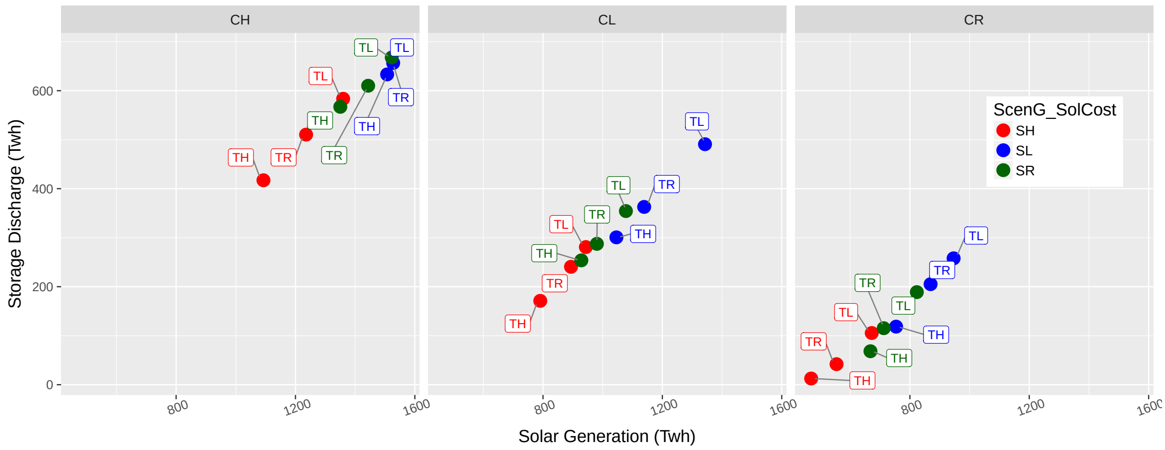


Figure 5.18 Storage discharge vs Solar generation in different CO_2 price and storage cost scenarios in 2050

5.2.5 Coal Supply

Coal being the most important energy resource in India, its evolution in long-term is outlined in this section. Regional coal consumption, supply options, and price are important aspects of future coal capacity expansion. Figure 5.19 outlines total coal consumption in different scenarios of coal price, CO_2 price and solar cost cases. The first graph (Figure 5.19 A)) presents coal supply in different scenario combinations of coal price and solar cost and the second graph outlines coal consumption in scenario combinations of CO_2 price and solar cost.

In the first graph, in high coal price cases (LH) or present annual coal production trend, annual production increases only 1.7 times in 2050 compared to 2017 level. System utilizes

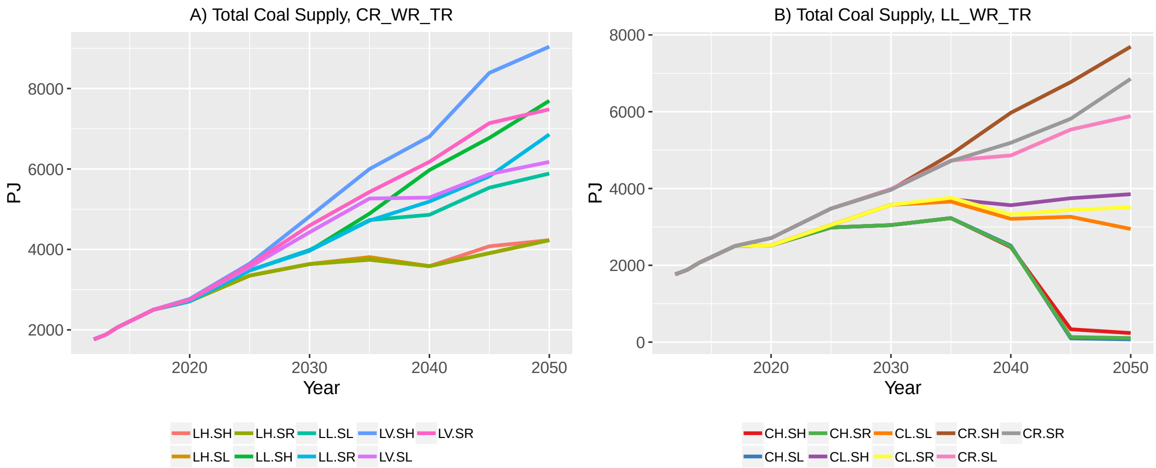


Figure 5.19 Total coal supply in various

full available coal irrespective of solar cost scenarios. This indicates need of ramping up the coal production rate significantly from the current rate. In low (LL) and very low (LV) coal price cases overall coal consumption increases by approximately 1.6 and 1.84 times respectively in 2050 with respect to LH cases when solar cost is at ref level. Effect of CO_2 price is drastic on coal consumption starting from 2035, as outlined in figure 5.19 B). Coal consumption in high and low CO_2 price (CH, CL) cases are approximately 0.015, and 0.53 times that of reference or no CO_2 price scenario in 2050.

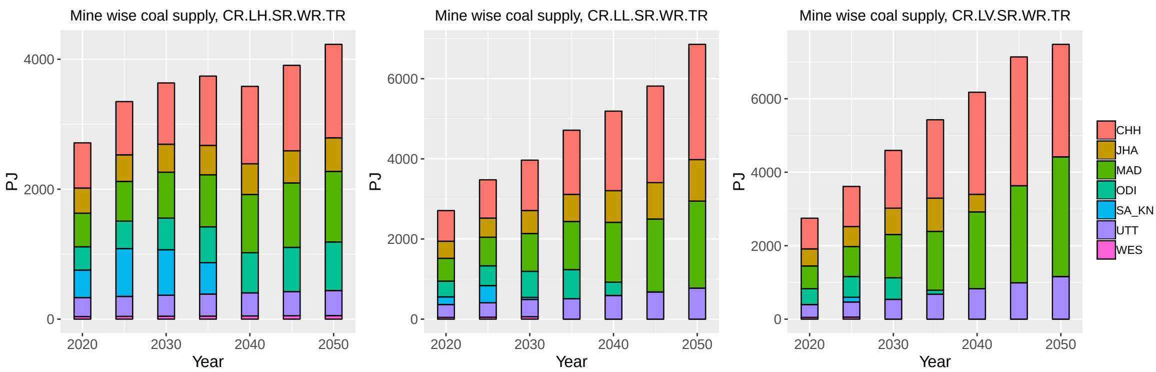


Figure 5.20 Mine wise coal supply in three coal price scenarios

Figure 5.20 outlines mine wise coal production over the planning horizon, and Figure 5.21 region wise consumption for three coal price scenarios when other parameters are set to ref. In both LH and LL scenarios foreign import of coal (SA_KN) is prominent upto 2035, and 2030 respectively. In 2025, foreign imports are respectively almost 22% and 14% in the two scenarios. In LV case, domestic production is sufficient to meet the future coal requirement. In LH case system imports coal from all the available mining regions in all future years.

Among the total domestic production, Chattisgarh, Madhya Pradesh, are the major coal producing states in all the scenarios. In 2050, their share of production in LH, LL, and LV cases are 60%, 74%, and 84%. Rest of the coal demand is satisfied by Odisha, Jharkhand, Uttar Pradesh, and West Bengal in LH scenario, Jharkhand and Uttar Pradesh in the LL scenario, and Uttar Pradesh in LV scenario. Region wise annual coal consumption is according to regional growth of coal based generation capacity and their activity profile. UU, HR, PB, and RJ are the main consumer of coal in all three coal price cases with UU having 54%-60% share in all coal price cases.

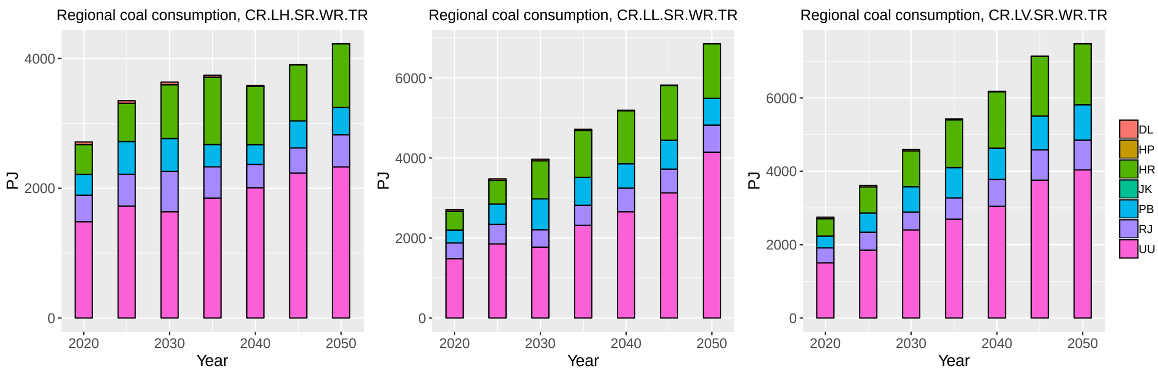


Figure 5.21 Region wise coal consumption in three coal price scenarios

Figure 5.22 indicates coal supply from mines to the regions in 2050 to outline which coal mines supply coal to which region in three coal price cases. In LH case Chattisgarh supplies coal to Rajasthan (496 PJ) and Haryana (942 PJ). Coal for Punjab comes from Madhya Pradesh. Uttar Pradesh procures coal from all the mines except CHH. In LL case Chattisgarh supplies 47% and 24% of its production to Haryana and Rajasthan. The rests is supplied to Uttar Pradesh. Madhya Pradesh supplies 70% of its production to Uttar Pradesh and rests to Punjab. Uttar Pradesh also utilizes its domestic production and import coal from Jharkhand to meet rest of its demand. In LV case Uttar Pradesh procures 57% of its coal demand from Madhya Pradesh and rest from Chattisgarh (14%) and own production (29%).

Coal prices calculated by the model in these three cases for four high coal consuming regions are indicated in figure 5.23 for four selected years (2017, 2030, 2040, 2050). In LH case, an increasing trend of coal price is observed in all scenarios as expected. Increase in price is almost 1.5 times in 2050 compared to 2017 level in all regions. In these cases, the lowest price is observed in Uttar Pradesh (295 INR/ GJ) in 2050 due to closeness to mining regions. Highest coal price is in Punjab (361 INR/ GJ). In LL case, the significant price reduction is observed in all regions post 2030. Compared to 2030, highest price reduction is

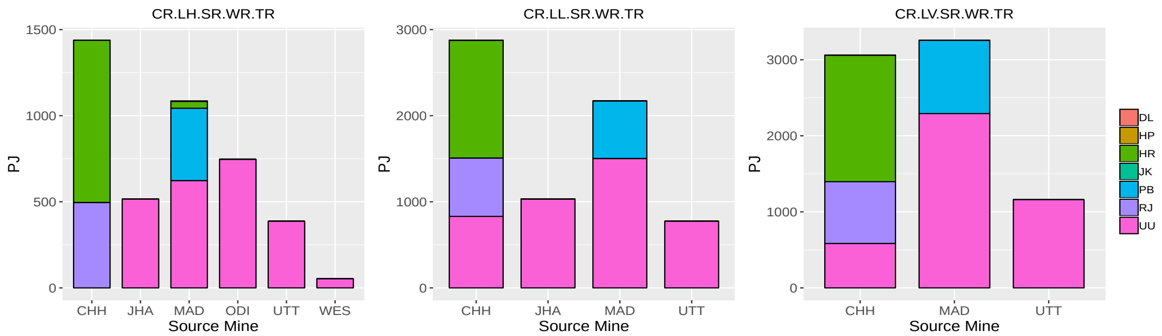


Figure 5.22 Coal supply from mines to regions in 2050 in coal price cases

observed in Uttar Pradesh (36%), while lowest reduction is in Punjab (25%) in 2050. In LV case almost 27% reduction in price observed in 2050 compared to 2017 level in UU; while for Punjab, Haryana, and Rajasthan it is almost 11%, 16%, and 15% respectively.

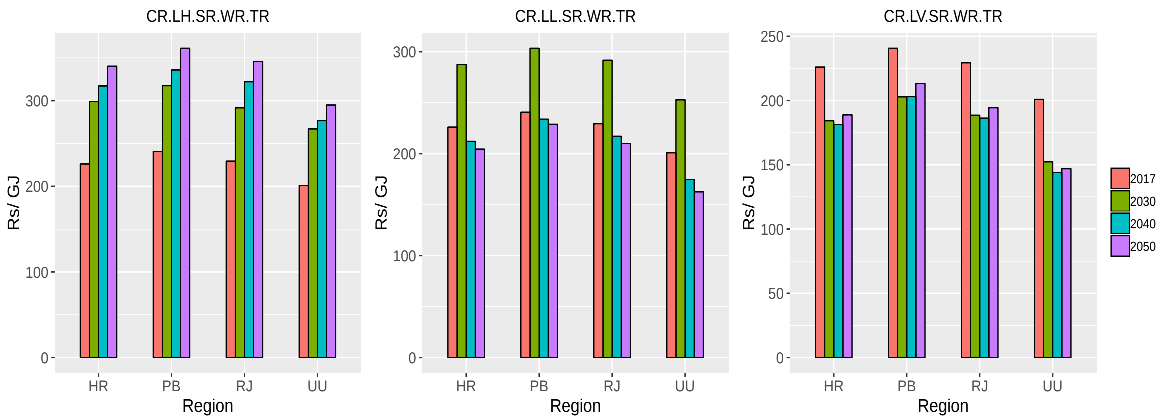


Figure 5.23 Regional coal price in coal price cases

5.2.6 CO_2 emission

Coal fired power plants are main CO_2 emitter due to their high share among all the fossil fuel based plants. Long-term reduction of the carbon emission intensity of power generation is one of the sustainable development related goals of India. In this subsection, variations of total emission as well as power generation emission intensity in different model cases are discussed.

Figure 5.24 outlines year wise variation of total CO_2 emission and emission intensity in CO_2 price and solar cost scenarios. Though total emission increases in various cases due to steady addition of coal based plants, gradual infusion of RE and hydro sources causes net reduction in emission intensity. In CR cases, emission intensity reduction in the level of

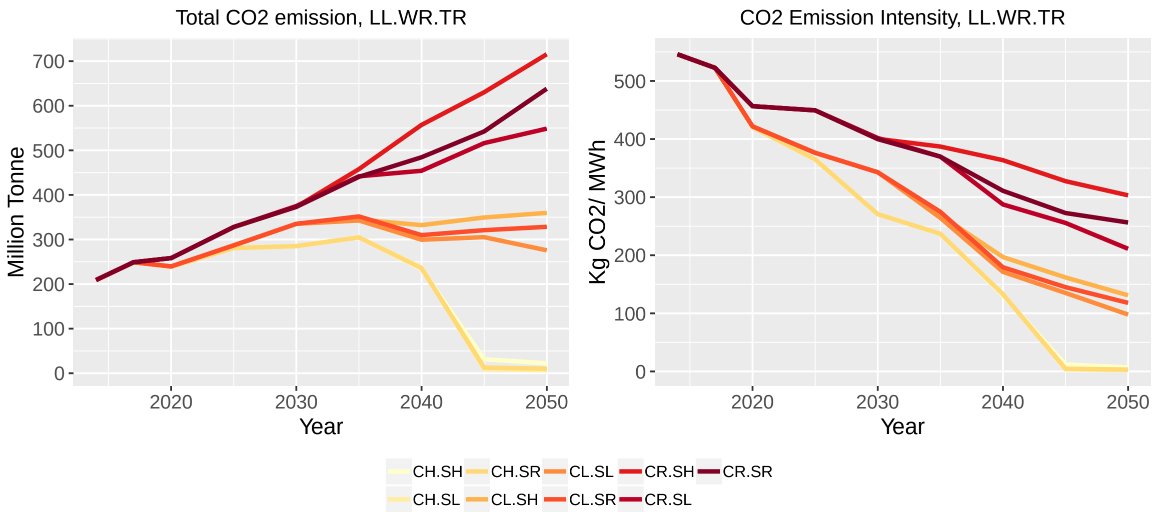


Figure 5.24 Total CO_2 emission and emission intensity in CO_2 price and solar cost scenario

42%-60% is observed in 2050 compared to 2017 level. Reduction potential in CL and CH cases are as high as 80% to 99%.

Effect of CO_2 price is drastic on total emission in the later stage of the planning horizon. In base case, total emission rises to approximately 638 million tonnes in 2050 from 250 million tonnes in 2017. In CR cases total emission goes up to 716 Million tonnes in 2050 (approximately three times of 2017 level) when solar cost is high. Low solar cost leads to 549 million tonne emission when CO_2 price is at ref scenario. In CL cases, CO_2 emission increases by only 1.11-1.44 times in 2050 from 2017 level. In CH scenario, CO_2 emission increases by only 1.2 times in 2035 compared to 2017. Afterward, emission reduction rate is very fast and drastic (approximately 97%) by 2050. It is mainly due to the retirement of existing generators and strong discouragement towards emission.

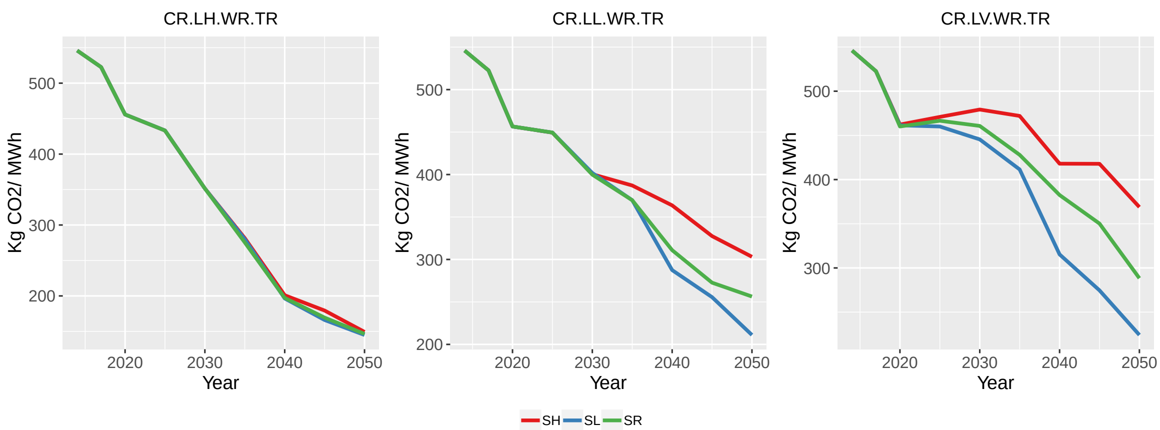


Figure 5.25 Variation CO_2 emission intensity in coal price and solar cost scenarios in 2050

In different coal price and solar cost scenarios CO_2 emission intensity varies considerably (Figure 5.25). In high coal price scenario, solar cost has almost no effect on emission intensity reduction; indicating all scenarios fully utilize available domestic coal production. CO_2 emission intensity in 2050 (149 Kg CO2/ MWh)is around 0.27 times that of 2014 (545 Kg CO2/ MWh) in these cases. In LL cases, effect of solar cost is seen after 2030. In SH, SL, and SR cases reduction of emission intensity is seen to be 44%, 61%, and 53% in 2050. Due to higher availability of coal in LV cases, emission intensity increases after 2020 in all solar cost cases, though it is reduced eventually in later stage. In 2050 emission intensity reduction potential is around 32%, 60%, and 47% in high, low, and ref solar cost scenarios respectively.

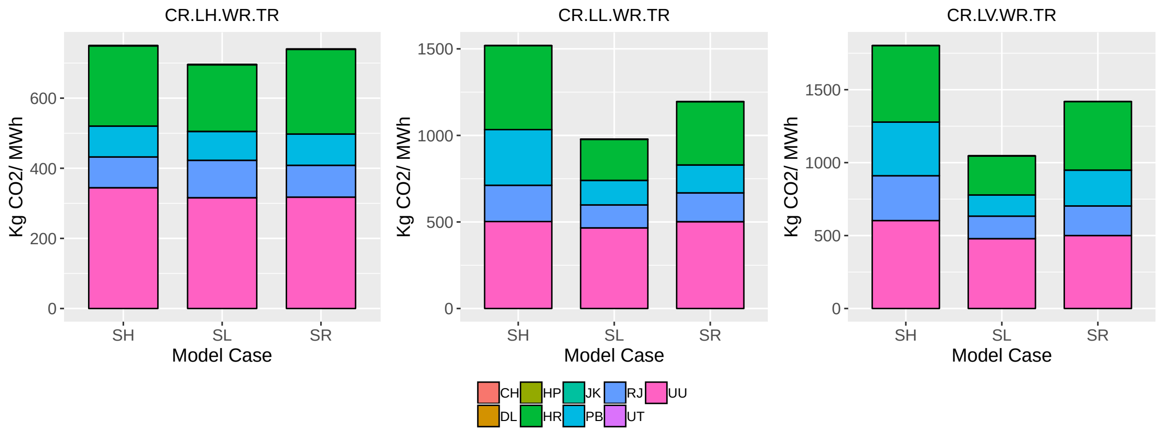


Figure 5.26 Variation of Regional CO_2 emission intensity in coal price and solar cost scenarios in 2050

In figure 5.26, regional interpretation of emission intensity of power generation is presented for coal supply and solar cost cases in 2050. Clearly, UU, HR, RJ, and PB are the regions with considerable emission intensity due to installed coal based generation capacity with UU being the highest. Emission intensity in UU is around 345 Kg CO2/ MWh in LH.SH case and goes up to 603 Kg CO2/ MWh in LV.SH. In case of HR, PB, and RJ increase of emission intensity between LH.SH and LV.SH are 2, 4, and 3.5 times respectively.

Figure 5.27 outlines effect of storage cost on the regional share of total CO_2 emission in 2050 in different solar, and wind cost scenarios. Three sub-figures in figure 5.27 indicates three storage cost scenarios. Total emission varies in the range of 773-663 MT, 626-538 MT, and 657-587 MT in TH, TL and TR scenarios when solar cost is at high, low and ref scenarios respectively and wind cost is set to High. In all the regions, CO_2 emission is higher in higher storage cost cases. For a given storage cost scenario change of regional total CO_2 emission is similar for different solar cost cases.

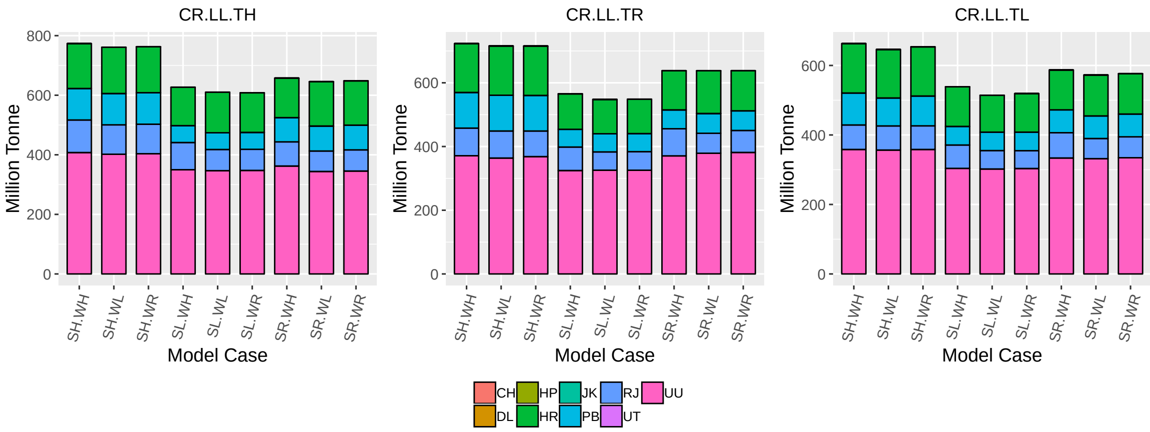


Figure 5.27 Variation of region wise total CO_2 emission in storage cost scenarios in 2050

5.3 Summary

After analyzing the numerical results pertaining to various futuristic scenarios using NIMRT, key findings are as follows:

- Results illustrate the utility of adopting higher spatial and temporal resolution, which helps to incorporate detailed RE related information into the modeling framework developed by GIS methods.
- A large number of model cases help to identify the effect of sensitivities of different critical parameters on system development.
- To our knowledge, it is the first attempt to capture intra-regional spatial and temporal variability using GIS approach in a large-scale, long-term planning model in India.
- Various model cases indicate system transition towards large-scale RE penetrated generation portfolio. In 2050, 41% RE penetration (excluding hydro) is seen in the reference case, which doubles when high CO_2 price is considered.
- Solar energy curtailment is prominent in high RE penetration scenario. Regional RE share and curtailment are higher than overall penetration level in RE rich states.
- Coal-based power plants are important generation options unless high CO_2 price is imposed.
- Storage systems work as energy arbitrage device for integrating solar energy and reducing curtailment. Storage capacity in various model cases is in direct relation to solar capacity development.

- Immediate initiatives are required to integrate new flexible resources like storage, into the system. This will require setting up a better business case, as well as policy mechanisms.

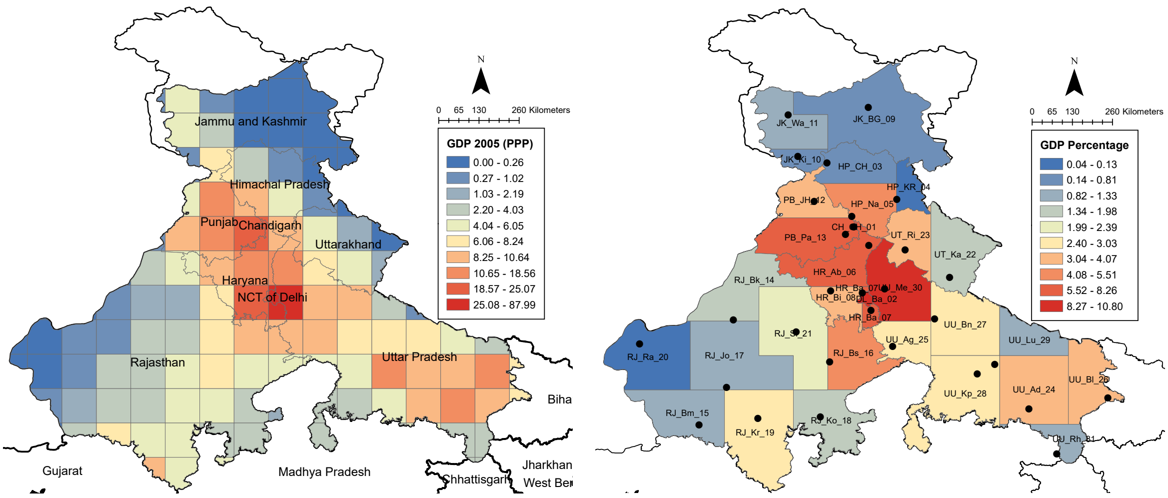
Chapter 6

Linking NIMRT Model with North-Indian Power System Operational Model (NIPSO)

As outlined in the previous chapters (*i.e.* Chapter 1, 2), long-term energy system planning models like NIMRT do not consider power system operational aspects while calculating future investments into various technological options. Consideration of limited number of annual time slices and aggregated spatial definition also do now facilitate tracking system variation realistically. On the other hand, a power system operational model has the capability to look into detailed daily operations such as generator scheduling, dispatch, power flow studies, contingency and security analysis, *etc.* Consideration of operational aspects is becoming relevant with the large-scale integration of variable RE resources.

To get insights of system variation pertaining to large-scale RE penetration, a power sector operational model is developed for the study region (North Indian Power Sector Operational Model (NIPSO)) to optimize daily generator scheduling. The model operates at higher spatial and temporal resolution and has several additional operational constraints compared to NIMRT model. Therefore, it can portray a realistic picture of generator and other devices' activity level corresponding to RE and demand variation. The activity levels of key technologies and other operational aspects are then compared to analyze the possible impact of not considering the operational aspects/ coarse model settings, *etc.* in the planning model. Further, a method is proposed to incorporate by which these operational insights in the planning model to improve the results.

For developing NIPSO model, system capacity related inputs are taken from the NIMRT scenario results pertaining to the model regions (states). The operation model runs for a single targeted year (2030 in this case). Various assumptions, rules and data preparation process are then adopted to develop additional datasets for the NIPSO model which works on sub-regional nodes. Following section describes these processes in detail.



(a) Grid-cell wise GDP in purchase power parity term

(b) GDP share of intra-regional nodes of NIPSO model

Figure 6.1 Intra-regional nodes and demand share for NIPSO model

6.1 Methodology

The objective of NIPSO model is to generate realistic dispatch profiles of generators, as compared to the NIMRT model. Therefore, it, facilitates checking whether the activity profiles of the generators calculated by the NIMRT model are realistic, and in case not, the quantum of deviation. To analyze and illustrate the impact of large-scale RE share on system operation, a single RE penetration case is considered. A particular RE penetration case is developed using NIMRT model. Thereafter, NIPSO is used to analyze the case for a particular targeted year. Following subsection discusses the data development process, followed by the description of NIPSO model.

6.1.1 Data Preparation

Compared to nine regions and 288 annual time slices in the planning model, NIPSO model has 31 nodes (intra-regional) and it works at hourly resolution throughout the year (8760 hours) (Figure 6.1b). Therefore, it requires additional data pertaining to the nodes and time. Detailed data preparation process is involved to prepare the input data sets and develop the assumptions for NIPSO model. A part of the data is prepared from NIMRT model results (pertaining to the scenario), and others by various assumptions/ data compilation. The overall data preparation for the NIPSO model involves statistical and GIS tools like R and ArcGIS. Figure 6.2 outlines overall data preparation process.

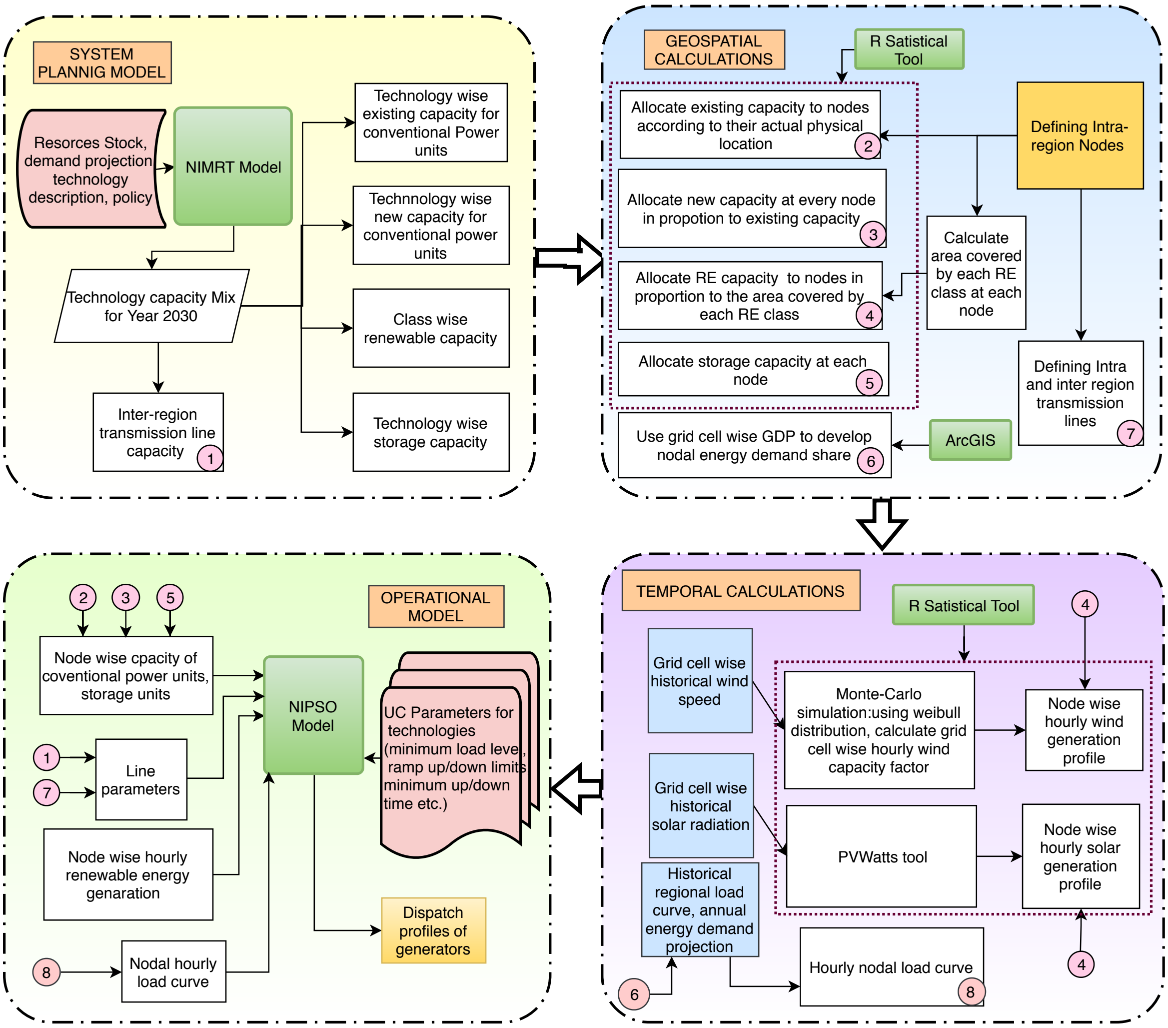


Figure 6.2 Overall data preparation process for the NIPSO model

Extracting Data from NIMRT Result

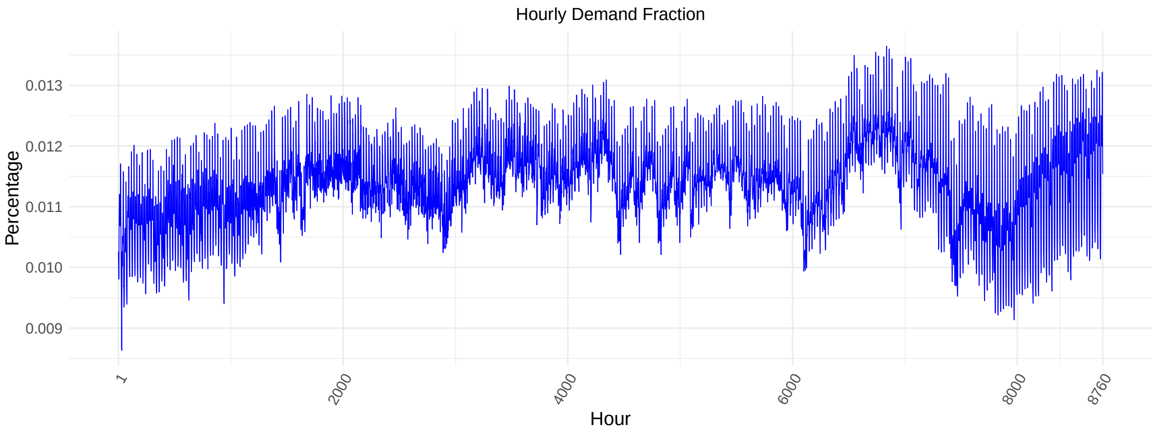
For linking NIMRT to NIPSO model, a specific system portfolio (capacity mix) is considered pertaining to a certain RE penetration scenario. The scenario targets for at least 25% RE penetration (12% solar, 13% wind) in 2025 and 50% RE share (35% solar, 15% wind) in the year 2030, out of the total energy generation. The operational model is used to analyze the activity profile of system components for a single year *i.e.* 2030.

For the milestone years, NIMRT model generates outputs in text based format (.VD), which are further imported to VEDA-BE for result analysis. For preparing the NIPSO model data sets, several calculations and assumptions are needed. Therefore, instead of VEDA-BE, generic programs are developed in R to extract the required information from the raw text files, apply assumptions, and automate the workflow. The key information extracted from the NIMRT scenario provide technology capacity (existing and new, RE and conventional) pertaining to each region. The capacities are further assigned to intra-regional nodes by applying suitable assumptions. Though The overall workflow is automated by several R programs, various manual interventions are still needed.

Preparing Data for Intra-Regional Nodes

Intra-Regional Nodes: Selection of the number of intra-regional nodes and identifying their location is done considering several factors. Due to the difference in area of regions (States), number of intra-regional nodes differs. Each node corresponds to certain geographical spread based on different assumptions (*e.g.* existing thermal generators, 400 kV transmission substation, RE resource class, and demand). The 1^0 by 1^0 grid-cells are merged to prepare the nodes' spatial spreads based on these factors (Figure 6.1b). It should be pointed out that the nodes do not exactly follow the actual buses of transmission system. But, they are 'synthetic' nodes to facilitate the running of NIPSO at intra-regional scale.

Generating Units: List of the existing generators is available from NIMRT model database. Further, it is checked whether any unit is retired due to reaching its lifetime. All the existing and proposed generators which exist in the year 2030, are mapped to their actual geographical location. They are further mapped to the corresponding nodes if it falls within its geographical spread. For new generators, several rules and assumptions are developed to allocate aggregated regional capacity to intra-regional nodes. The new capacity of technologies are aggregated values pertaining to each region. This aggregated capacity value needs to be suitably allocated to the intra-regional nodes. Also it is unrealistic to perform optimization with NIPSO model having aggregated generating capacity. So, the aggregated regional new capacity values of technologies (thermal and hydro) are divided into realistic dummy physical unit sizes. The dummy units are mapped to the nodes according to the current nodal share of corresponding technologies. For RE technologies, aggregated capacity pertaining to each class is used. For a region, the nodal capacity share of a particular RE class is according to the area available for that class for that node (*e.g.* according to the mapped grid-cells for a node). In case of energy storage, pump hydro storage capacity is allocated at the node of installed hydro power plants. Battery energy storage capacity of a region is allocated to nodes according to the ratio of nodal solar capacity.



(a) Hourly historical demand fraction of India for the year 2010 used for NIPSO model

(b) Time slice wise demand fractions for NIMRT model

Figure 6.3 Hourly (NIPSO) and time slice wise (for NIMRT) load curve

Demand and Load Curve: NIPSO model requires hourly load curve data to optimize the daily generator scheduling at hourly resolution. For that, nodal share of annual energy demand and hourly load curve pattern is required for the targeted year (2030). The nodal annual energy demand share is developed using a GIS approach. Spatial data sets related to gridded (100 km by 100 km) GDP data is available for both Market Exchange Rate (MER) and Purchasing Power Parity (PPP) at global-scale for the years 1990, 1995, 2000, and 2005 [234]. The data set has GDP per 100 km by 100 km grid-cell for global scale. For the present study, GDP values of 2005 is used. From the actual GDP values, percentage share/ contribution of each grid-cell ($1^0 * 1^0$) and eventually of each node is calculated (Figure

6.1b). Nodal shares are applied thereafter to the total North-Indian annual energy demand projection for the year 2030, to calculate nodal annual energy demand. To develop the hourly load curve, demand share of each hour is calculated from past load curve data. Nodal annual energy demand is then multiplied by hourly fractions to develop the annual hourly load curve. Similar to NIMRT model, NIPSO have similar load curve pattern for each node which follows historical overall load-curve (Figure 6.3).

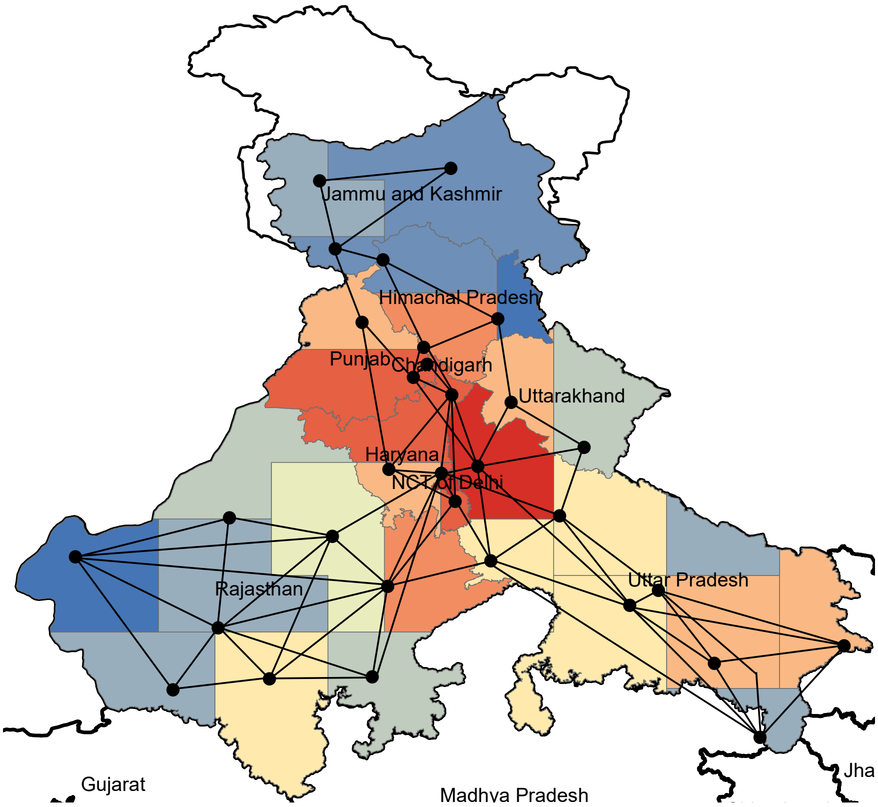


Figure 6.4 Nodes and transmission lines considered for NIPSO model

RE Generation: For calculating nodal hourly solar and wind energy generation, calculations performed are similar to those outlined in Chapter 4. For determining hourly wind energy generation, first historical wind speeds are fitted to Weibull probability density function (PDF) and Monte-Carlo sampling is performed to draw values from the PDF. Sampled hourly wind speeds are then used to calculate hourly capacity factor of wind for a particular grid-cell considering standard wind turbine specification. Due to limited availability of long-term historical solar radiation data at suitable temporal and spatial resolution, PVWatts tools is again used to generate hourly capacity factors for each grid-cell (Chapter 4). Hourly capacity factor values of solar and wind are developed for all the grid-cells. From nodal RE capacity and hourly capacity factors, total hourly generation is then estimated for each node.

Network: For developing network related data, inter-regional connections are taken similar to the trade-line assumptions of NIMRT model. Their capacity is also taken from the result of the planning model. For developing the transmission line related data (*e.g.* node connection, line capacity, line reactance) for intra-regional nodes, several assumptions are made. Current 400 KV transmission line connection, grid-cell level RE potential, future transmission plans, standard conductor parameters, and other assumptions are taken to develop this data set (Figure 6.4).

Apart from the data discussed above, NIPSO requires additional techno-economic information related to thermal power plants, such as start up cost, ramp rates, minimum generation limits. Due to the lack of availability of unit specific data related to operational costs and technical constraints, these values for each technology group are collected from the literature and given in Appendix D [235, 236].

6.1.2 North-Indian Power System Operational Model (NIPSO)

A crucial part of power system operation is scheduling the generators for each time blocks (*e.g.* 15 minutes, hour) and deciding their optimum dispatch (power output) levels within a short-term planning horizon (generally a day or week). Generator scheduling involves deciding the commitment status (*i.e* on-off) of the generators, or in other word the optimum time a generator should be on/ off over the planning horizon. This is essentially an optimization problem, which aims to obtain the commitment decisions by minimizing the cost of operation and simultaneously satisfying several technical constraints and maintain system reliability [33]. The total cost of operation primarily involves fuel cost, generator start-up and shutdown costs, in addition to some penalty related to load and RE curtailment *etc.* Primary operating constraints on the other hand include technical limits of generators, transmission lines, and storage.

As scheduling involves deciding on-off status of units, the corresponding optimization problem has binary variables (*i.e.* variables restricted to values 0 or 1). The problem is generally formulated as a mixed integer programming (MIP) problem to capture the discrete nature of the scheduling decisions. The problem can further be formulated as MILP or MINLP according to the treatment of non-linearity in generator cost curve or power flow equation *etc.* For utility-scale power system, corresponding UC problem can be of significant size and it takes advanced algorithms to obtain realistic results within a certain threshold time. Several new optimization approaches and algorithms are being developed to tackle these issues [237] [238] (Chapter 2)

NIPSO model performs day ahead unit commitment operation in steps for the whole year. The optimization problem is a deterministic one *i.e.* it assumes perfect foresight of RE generation as well as demand within each scheduling interval. RE generation and hourly demand are exogenous to the model. Focus of NIPSO model is to generate operational insights from the NIMRT model results for a single targeted year. Therefore, the model is developed in such a way that it can complement the planning model considering computational complexity, data availability, *etc.* It minimizes the daily total cost of operation (generation, start-up, shut-down, penalty for load-shedding and RE curtailment). Along with meeting overall generation-demand balance, it satisfies various technical constraints which are described as following. Standard mathematical formulations available in literature related to objective function and constraints, are used in developing the model [33, 239, 240].

Objective function and constraints

Objective function: It is the daily total cost of operation, which is the sum of operating cost, start-up cost, shut-down cost, penalty for RE curtailment and load-shedding.

Demand-supply balance: For each hour, supply and demand should be balanced for each node. It implies that, for every hour for each node, the sum of total power generation (from all sources), storage discharge and power flow into the node must be equal to the sum of nodal demand and energy stored, minus load shedding and power flow out of the node.

Power generation limit: The thermal generators cannot lower their generation beyond a certain limit. Therefore, at any point of time, it should operate between its minimum stable generation limit and maximum capacity. However, hydro generators can be in idle condition with zero output.

Generator ramp Rate: Each thermal generator's power output change per hour must be less than or equal to its ramp rate limit.

Minimum On/ Off Time: Thermal generators once started, cannot be stopped before its 'minimum-up time'. Also when a generator is stopped, it cannot be started before its 'minimum shut-down time'.

Power transmission related constraints: Power flow between the nodes is approximated by 'DC load flow', constrained under line capacity and power angle limits [1].

Storage technologies: Storage units work as flexible resource and store excess generation to discharge during high demand periods. It should satisfy its minimum and maximum storage level and charge-discharge within its charging discharging power limits.

NIPSO Model Setup

The NIPSO model takes a rolling horizon approach where hourly generator scheduling is done one day at a time. The unit status of the final hour of a particular day is carried forward to calculate the commitment schedules of the next day. The loop runs throughout the year until the final day is reached. The formulated optimization problem is Mixed Integer Linear Program (MILP) due to the presence of integer variables in the constraints and objective function. The model code is written the GAMS language. A commercial solver *i.e.* CPLEX is used to solve the program. The model code is separated from input data; all data transfers from excel data workbook to NIPSO and vice-versa are achieved using gdxxrw program. For better productivity, model is developed in several parts (*e.g.* declaration of sets and parameters, data read, variables and core model equations, running loops, result reporting) and executed sequentially by a master program (Appendix D).

6.2 NIPSO and NIMRT Model Linking

Utility of NIPSO is to illustrate the variation in system operation on a much granular scale compared to NIMRT model. It establishes the importance of considering operational information at planning stage, by comparing technology activity levels of both the models. Power dispatch profile of thermal generators, RE penetration level & curtailment are extracted from the annual generator dispatch profiles from NIPSO model and compared with the planning model results. From the comparison, inferences are drawn on the consequences of not having the operational insight at the planning stage. In this section first, description of the uni-directional soft-linking process is discussed along with results from the NIMRT and NIPSO models. Afterward a methodology is outlined by which information from NIPSO can be incorporated into the NIMRT model for recalculating the system capacity portfolio.

[1] Assumptions for 'DC load flow are: Line resistances are negligible compared to line reactances, voltage magnitude in each node is equal to 1.0 per unit, voltage angle differences between nodes are small.

6.2.1 Uni-directional Soft-Linking Method

Uni-directional model linking between a energy system planning model and power sector operational model have following steps, as discussed in Chapter 2. Present exercise broadly follows those steps, apart from the data preparation aspect which needs to address the difference of spatial and temporal definitions between planning and operational models. As the current study considers intra-regional RE potential in NIMRT model and intra-regional nodes compared in NIPSO model, various additional assumptions are therefore needed. Due to substantial energy demand compared to similar exercises, the operational model (*i.e.* NIPSO) has around 730 generating units, 31 nodes and 60 transmission line elements in its database. This increases the model size, which takes a significant time to solve [2]. The approach broadly follows the steps outlined in Figure 2.8, as follows.

- Prepare the data and assumptions to develop the particular scenario of interest. Incorporate the scenario definitions in the NIMRT model.
- Run NIMRT model for that specific scenario.
- From the outputs of NIMRT model extract technology capacity related information and prepare the data set for NIPSO, as explained in Subsection 6.1.1.
- Run NIPSO model for the developed data set.
- From the output of NIPSO model, analyze generator dispatch patterns, annual RE penetrations, and curtailment and compare them with NIMRT results.

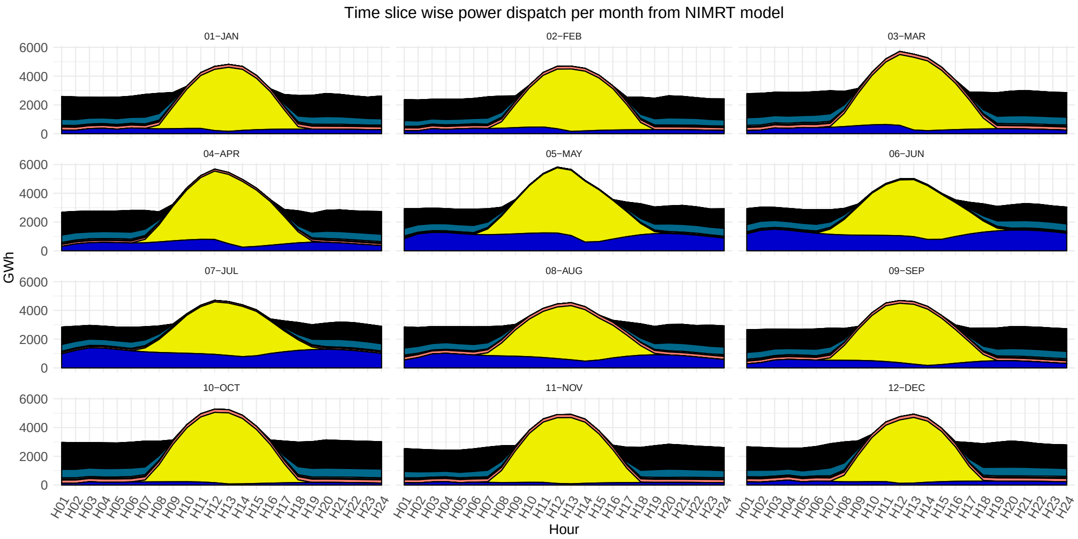
Based on the NIMRT and NIPSO model result, following results are discussed. Comparison of results focus on annual, hourly/ time slice wise and regional interpretations of activity/ dispatch profiles of thermal generators, and RE penetration and curtailment.

RE Penetration

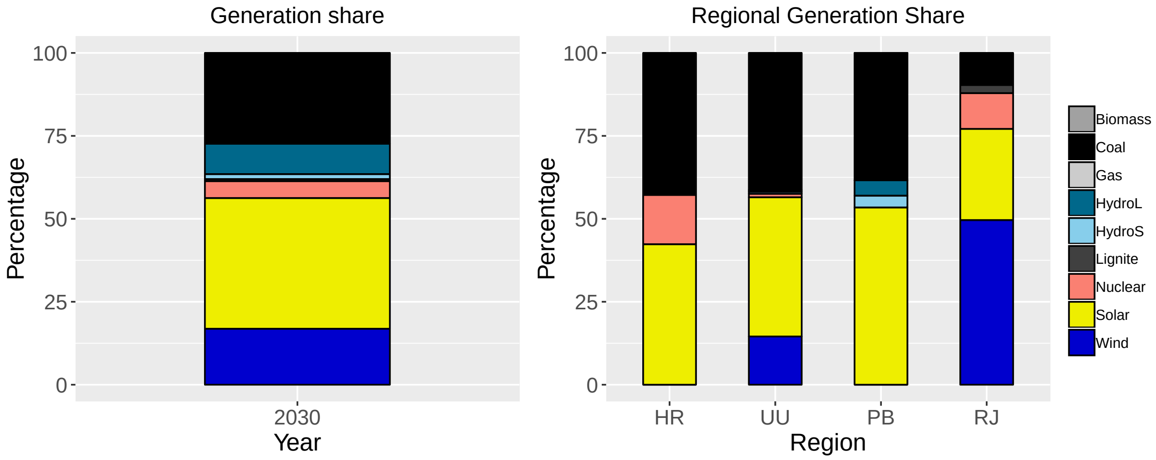
Due to the presence of various technical constraints, activity levels and patterns of power dispatch of technologies calculated by NIPSO model differ substantially from that of NIMRT. The technical constraints of NIPSO model act as bounds on hourly dispatch limits of the power plants. Difference of hourly/ time slice wise dispatch pattern leads to further variation of annual net RE penetration calculated by the two models. In the following paragraphs, generation mix from NIMRT model is outlined, followed by that of NIPSO model. For

[2]A single run of NIPSO model takes around 72 hours in a server machine having a processor with 15 threads and 32 GB RAM

NIMRT model, dispatch pattern of the whole year with respect to each time slice is illustrated, categorized by months. Due to large data volume, a single day of each month is chosen to illustrate the hourly dispatch pattern of technologies from NIPSO, for comparison.



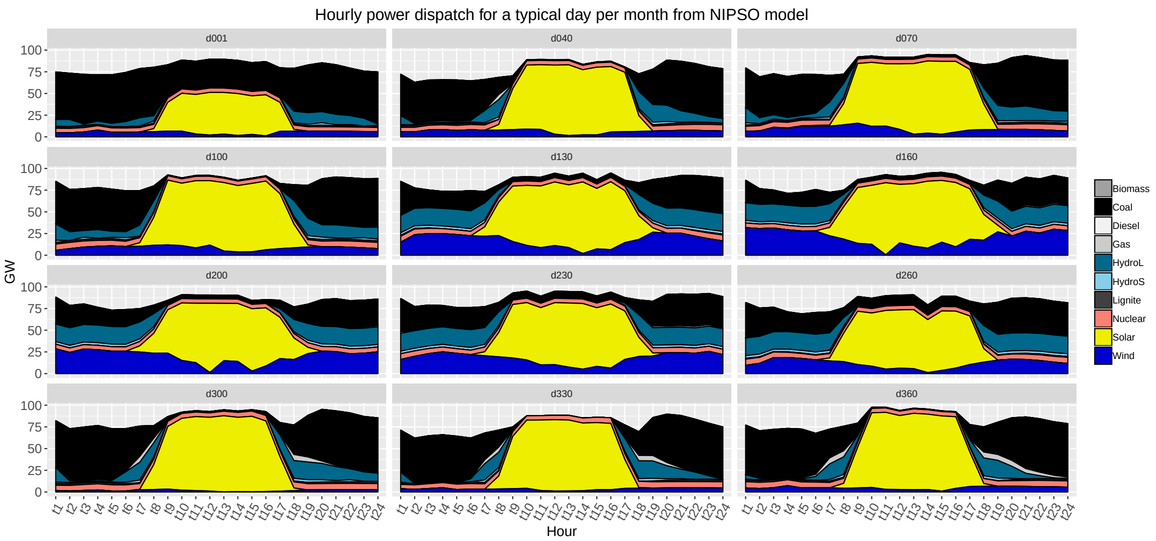
(a) Month and time slice wise variation of generation mix from NIMRT model



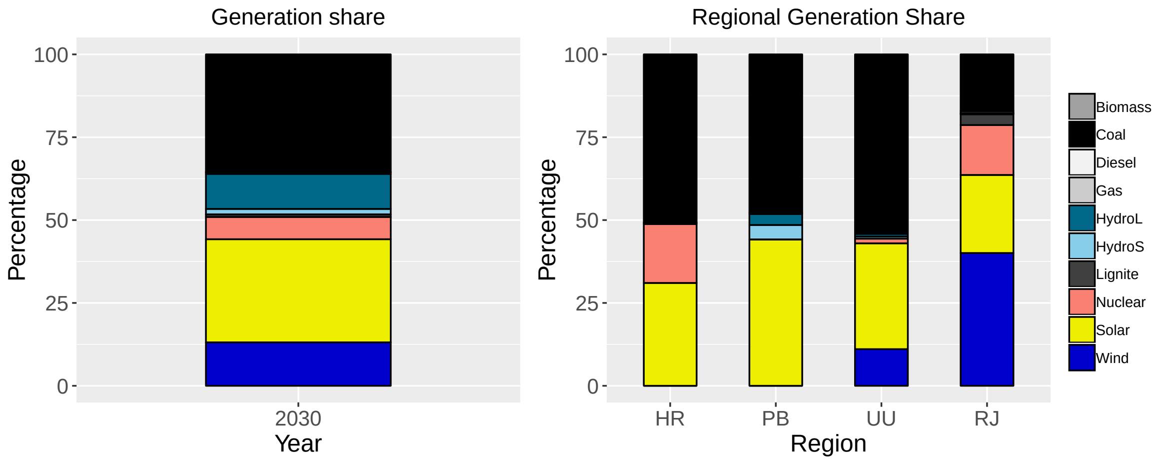
(b) Overall Annual generation mix and regional generation share from NIMRT model

Figure 6.5 Time slice wise, annual and regional generation mix from NIMRT model

RE Penetration from NIMRT Model: Figures 6.5a illustrates technology wise activity levels from NIMRT model for the year 2030, corresponding to each time slice. From the time slice wise dispatch pattern, it is evident that solar PV plays crucial role in the overall generation mix for all seasons. In the rainy seasons *i.e.*, for months May-August wind also has substantial contribution. Other than RE, coal is a major player in generation portfolio. As expected, coal based generation gets reduced at the times slices when cheaper solar based generation is available. For all time slices, system absorbs total available RE generation. Maximum solar and wind energy penetration is observed at 94% and 50% respectively in ‘10-OCT-H13’ and ‘06-JUN-H03’ time slices respectively. Maximum RE penetration reaches to approximately 99% in the time slice ‘05-MAY-H12’.



(a) Hourly aggregated dispatch profiles of generators from NIPSO model



(b) Overall Annual generation mix and regional generation share from NIPSO mode

Figure 6.6 Hourly, annual and regional generation mix from NIPSO model

From the time slice wise activity of technologies, annual RE penetration as well as generation share of other technologies is calculated. First plot of Figure 6.5b illustrates the overall technology wise generation share and in year 2030. Due to imposed constraints regarding annual total RE penetration in 2030, NIMRT ensures at least 50% RE based (solar and wind) generation. Actual RE penetration reaches 56% where generation share of solar and wind based generation are 39% and 17% respectively. Other than RE, coal and large hydro are the major generating options. Total coal based generation is around 260 TWh (27%), followed by large hydro (9%) and nuclear (5%). Capacity of solar, wind are 235 GW, and 77 GW respectively followed by coal (65 GW) and large hydro (21 GW).

Regionally, RE penetration levels vary according to RE generation availability and system configuration. Second plot of Figure 6.5b outlines technological generation share of four regions. RJ has the highest RE penetration (77%) which is constituted of 50% wind and 27% solar. Highest solar and coal based generation is seen in region UU (56%) and HR (41%) respectively.

RE Penetration from NIPSO Model: Generator dispatch patterns calculated by NIPSO are different from the results of NIMRT model. As it can be seen in Figure 6.6a, coal still plays a major role in generation mix, particularly in the months October-January when hydro power availability is low due to water shortage. As expected, large-hydro and coal based generators are backing-down when cheaper solar generation is available; working as system balancing resource. In some months, significant coal based generation is seen even in the day time when cheaper solar generation generation available (subsection 6.2.1 discuss this issue in more detail). It is mainly because of applied technical constraints like minimum up-time, minimum generation limits and ramping limits imposed on the coal based power plants. As these constraints do not apply on hydro generators, they completely back-down to accommodate cheaper RE power as when needed. Actually, significant RE curtailment is also seen during these hours, as is discussed in the next subsection.

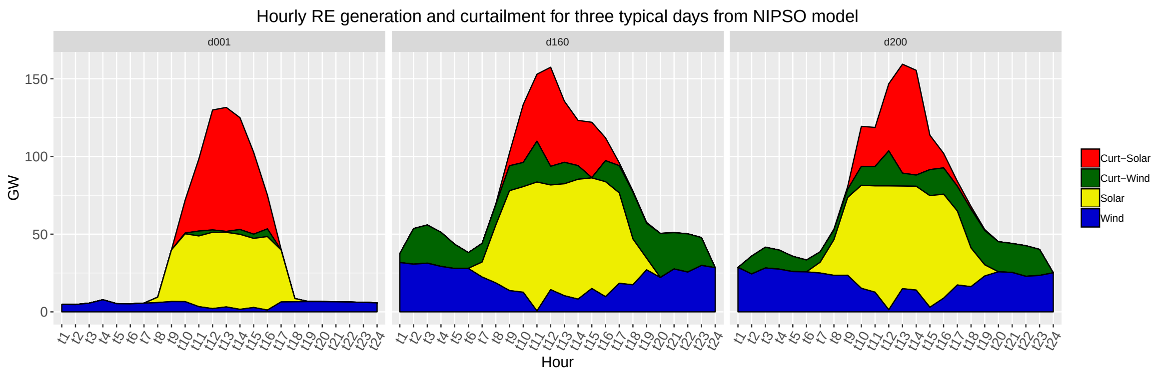


Figure 6.7 Total RE generation and curtailments for three selected days from NIPSO model

Annual generation mix calculated from the NIPSO model results has reflection of hourly dispatch profiles (Figure 6.6b). Therefore, compared to NIMRT, annual RE penetration is different in NIPSO model. Compared to NIMRT, RE penetration is 44% of total annual power generation with the same capacity of NIMRT model. Solar and wind have a generation share of approximately 31% and 13% respectively. This indicates that, even if the planning model calculates 56% RE penetration, system cannot absorb that much of RE from operational point of view. Coal enjoys 36% share in the generation mix calculated by the NIPSO model as compared to 27% in NIMRT. Regional RE share also varies from the NIMRT results. RJ has 64% RE share now in which wind plays a major role (40%). Highest solar and coal based generations are in PB (44%) and UU (54%) respectively.

RE Curtailment

One of the major difference of annual generation mix calculated by the both model is RE curtailment. In NIMRT model, all the available RE is absorbed without any curtailment (for around 56% RE penetration). But, prominent RE curtailment is observed both for solar and wind in NIPSO results. Curtailment occurs at times of significant RE penetration when there is excess RE power and lack of adequate storage capacity, and technical constraints on thermal generators restricts absorption of all the RE. Figure 6.7 illustrates hourly solar and wind energy generation and curtailment profiles from NIPSO model for three selected days. Annual curtailment percentage calculated by NIPSO model are 39%, and 26% for solar, and wind respectively.

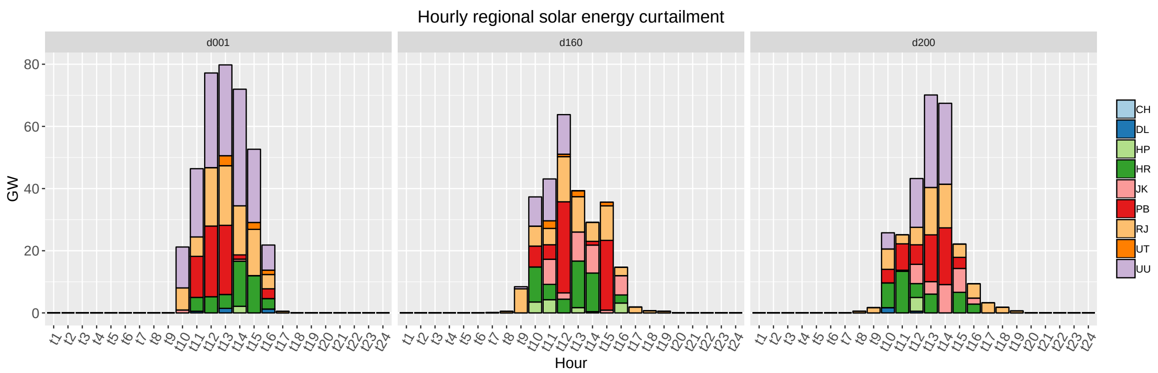


Figure 6.8 Regional solar energy curtailment for three selected days from NIPSO model

As expected, RE curtailment mostly occurs in high RE penetrated regions. Figure 6.8 and 6.9 outlines regional shares of solar and wind energy curtailment for three indicative days respectively. It can be observed that solar energy curtailment mostly occurs in UU, RJ, HR, and PB regions. Wind energy curtailment mostly occurs in RJ, due to higher penetration with some instances in UU also.

Comparison of curtailment levels from NIMRT and NIPSO indicates two aspects. First, there is excess RE capacity in the system calculated by NIMRT model. Second, all the generation from the RE capacity calculated by the NIMRT cannot be accommodated due to lack of sufficient storage capacity and technical constraints of thermal generators. Calculation of the extra RE capacity in the NIMRT is mainly due to the lack of technical constraints on thermal generators, as discussed earlier.

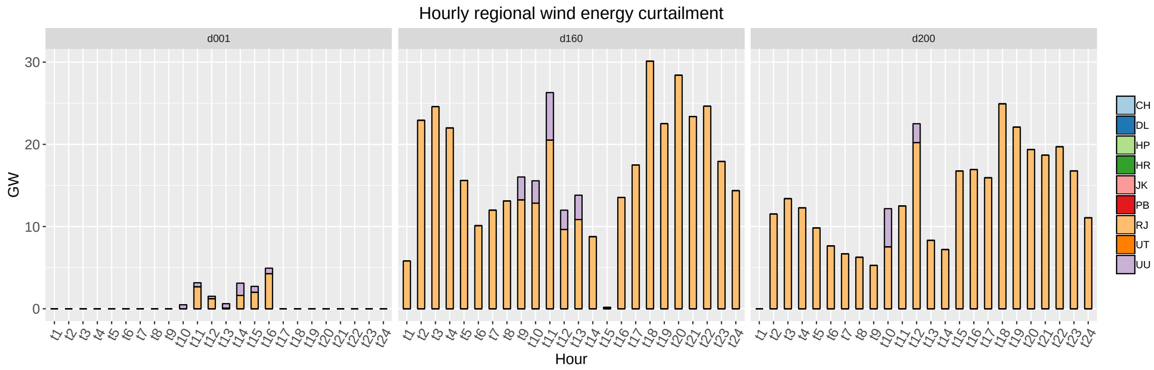


Figure 6.9 Regional wind energy curtailment for three selected days from NIPSO model

Activity Profile of Thermal Power Plants

One of the major utility of the NIPSO model is to enforce operational constraints on thermal generators, which ensures their realistic hourly dispatch compared to NIMRT model. Figures 6.10 and 6.11 respectively outlines time slice wise and hourly dispatch profiles (from NIMRT and NIPSO respectively) of three typical generators in three different regions. For NIMRT model, time slice wise monthly dispatch patterns are presented; while for NIPSO, hourly dispatch patterns for a single typical day per month is outlined. The generating units from NIMRT model results have the total new capacity of that respective technology pertaining to corresponding region. Generating units for NIPSO result are synthetic units, derived from the NIMRT results.

As intra-day hourly resolution is considered in NIMRT time slices, dispatch pattern variation of NIMRT and NIPSO are comparable. NIMRT dispatch levels represents total monthly dispatch by a single day, whereas NIPSO outlines actual daily dispatch at hourly interval. It can be observed in the result from the two models that, generators back down when solar generation becomes available to the system starting from the morning. In NIMRT model, as there is no technical constraints on intra time slice dispatch variation, ramp-down and ramp up events of the thermal generators is happening faster than their actual technical limits. Operational constraints of NIPSO on the other hand ensure that, when a generator backs down, its generation can only be reduced upto its minimum generation limit. If it is shut down to accommodate available RE, it cannot be turned on again before a minimum down-time. During back-down and backing-up of the generators, their intra-hour generation variation is within the ramp down/ up limit.

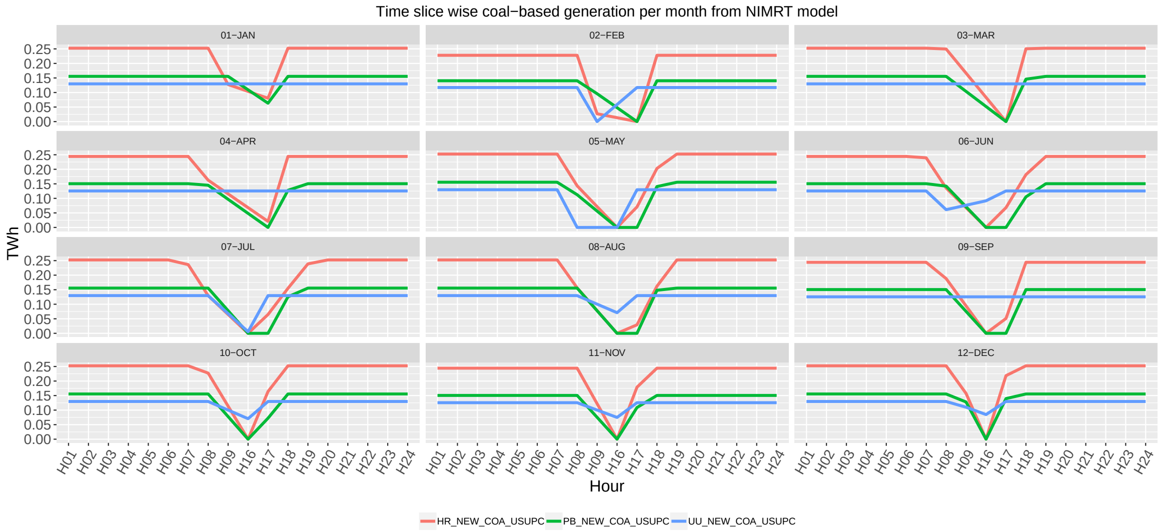


Figure 6.10 Time slice wise dispatch profiles of coal based power plants by NIMRT model

Comparison of the coal fired power plants' dispatch patterns indicates that NIMRT model underestimate the technical characteristic of these generators. In system operation, the technical constraint of the generators should be satisfied. It implies that, even if cheaper solar generation is available, a thermal generating unit must be in 'on' mode (can be ramped down to its minimum generation level) if its running time is less than its 'minimum on time'. So, at that particular hour, RE has to be curtailed to maintain system balance. If these constraints were present in NIMRT model, it would have invested in less RE capacity and in more storage/ balancing capacity. Therefore, from the NIPSO results it is evident that NIMRT model overestimates the system ability to assimilate RE, and underestimate the operational limitations of thermal power plants.

6.2.2 Bi-directional Soft-Linking

From the uni-directional soft-link approach, it is evident that the planning model overestimates the RE capacity whose generation cannot be absorbed fully by the system at the operational stage. This overestimation is mainly due to lack of technical constraints on the activity profiles of the various technologies in the planning model. Therefore, a suitable method is needed by which technology capacity related results from planning model can be improved. This section outlines a methodology to feedback the information from a power system operational model like NIPSO to a planning model like NIMRT, for re-calculation of results.

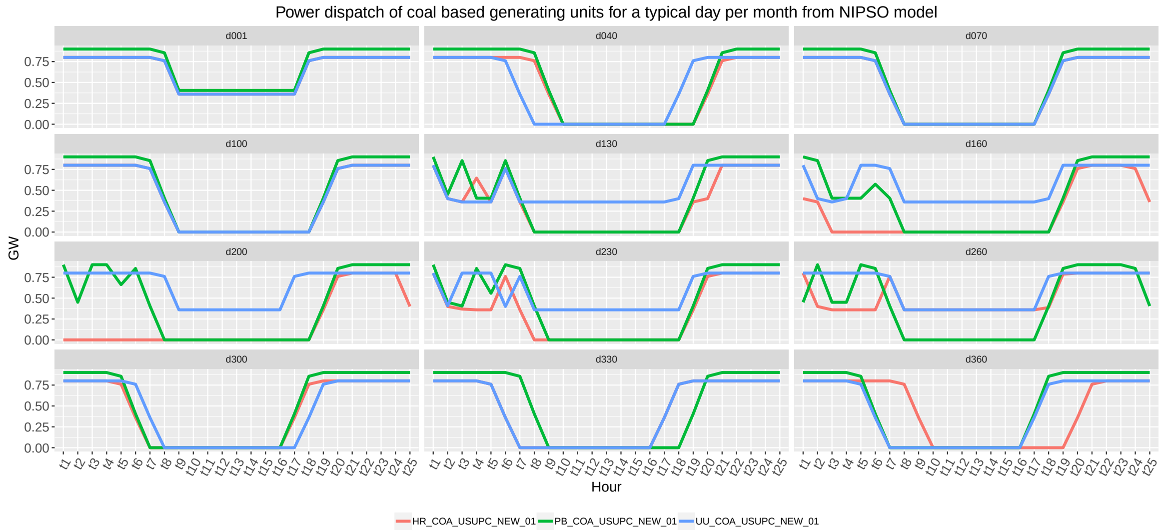


Figure 6.11 Hourly dispatch profiles of coal based power plants by NIPSO model

The planning model quantifies new capacity requirement of a technology type, based on its annual activity level, which it calculates by ensuring demand and supply balance for each time slice. Therefore, more realistic the activity profiles, more accurate the capacity calculation by the planning model. Approaches of bi-directional linking, where operational model results are fed back to the planning model, has been reported in the literature (Chapter 2). Here, a simplified approach is outlined by which realistic activity related bounds can be calculated from the operational model results and subsequently incorporated into the planning model. The overall approach involves following steps, which has further been outlined in Figure 6.12. The approach considers the planning model is a multi region one and the operational model works at sub-regional scale. It also assumes that unidirectional link between the two has already been established.

- For each milestone year of the planning model, extract the technology capacity related results, prepare data sets, and run the operational model, similar to uni-directional linking method outlined in the previous Subsection .
- For each milestone year, aggregate dispatch profiles of generators, inter-regional trade into planning model's spatial and temporal definitions (*i.e.* nodes to regions, hours to time slices).
- Calculate time slice wise capacity utilization factors (CUF) of each technology in each model region from the operational model outputs aggregated to planning model definitions.

- For existing generators consider all individual units. For new technologies, combine technology wise (New super critical coal *etc.*) power dispatch values of each individual 'synthetic' units and calculate aggregated CUF values pertaining to each region.

- For each technology, deactivate annual capacity factor values already specified in the planning model, as it may conflict with new values.

- Construct various user constraints and incorporate newly calculated time slice specific CUF values as suitable bounds in the planning model for all milestone years for all region.

- Run the planning model. Analyze the difference of technology wise new capacity values calculated by the planning model for all milestone years.

- If the difference is within acceptable range; stop. Else, repeat the above steps until the difference of capacity related results from planning model between two successive iteration is within acceptable range.

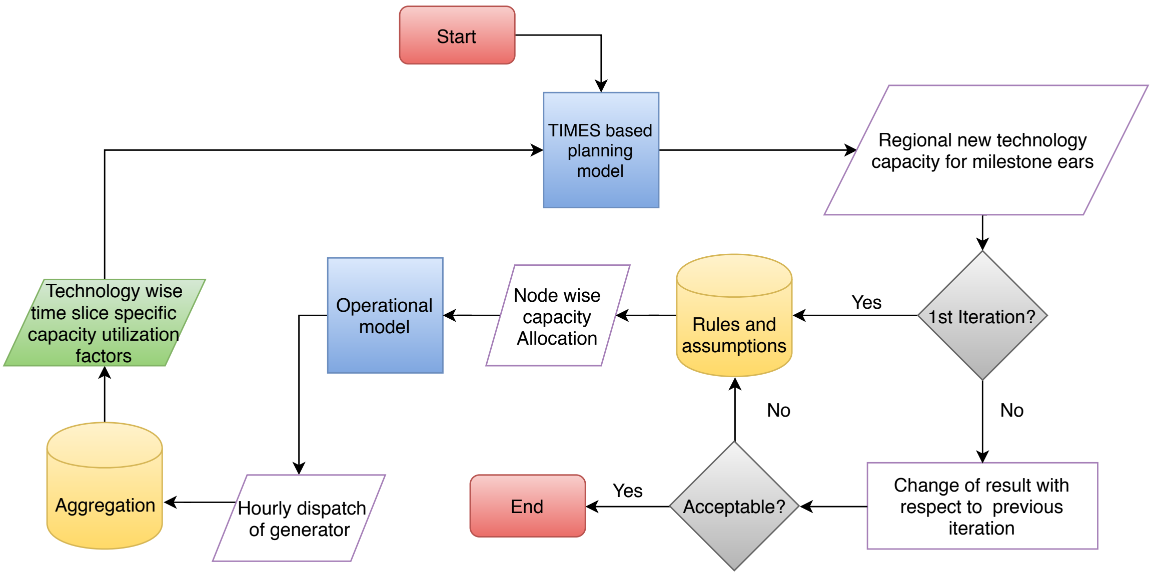


Figure 6.12 Overall bidirectional linking method between an energy system planning and a power system operational model

Overall, the bidirectional linking approach is focused to update/ incorporate new CUF values of various technologies from the operational model results to planning model in each iteration. The process is iterative, and this updation is done for each planning model milestone years for each iteration. Using the new updated CUF factor bounds pertaining to each time slices, the planning model calculates different annual activity profiles and thereby calculates different 'new capacity' of technologies. The iterative process terminates when two subsequent iterations do not result in significant change of technology capacity calculated by the planning model. The method can be applied to analyze any policy/ techno-economic scenarios. For specific RE generation share/ penetration scenarios, additional constraints needs to be incorporated in the operational model itself to ensure RE penetration similar to the planning model.

6.3 Summary

After illustrating the model linking methodologies and analyzing the numerical results pertaining to both NIMRT and NIPSO model, following is the summary:

- Uni-directional model linking method highlights the importance of considering the impact of operational constraint to calculate realistic technology activity and capacity, by the planning model.
- In the absence of operational constraints on power generating units, system model neglects the impact of RE variability on system operation at certain scale.
- Therefore, it tends to overestimate RE capacity due to their low operational costs. It also underestimates the requirement of system balancing capacity and energy storage.
- Excess RE capacity calculated by the planning model can lead to significant RE curtailment at the operational stage, which can have various economic consequences.
- The operational model portrays a realistic picture of the activity profile of various technologies corresponding to system operation.
- These operational insights can, be therefore, learned from the operational model and fed back to the planning model using suitable methods and recalculation of results can be attempted.
- Compared to existing approaches in this regard, present study undertakes the model linking exercise of a long-term system model having intra-regional RE variability, and a operational model with intra-regional nodes.
- In Indian context, though there are attempts to link dedicated economic models (*e.g.* computational general equilibrium model) to long-term energy system models, this

is the first attempt to link a power sector model with the system panning model at regional scale.

- In addition to consider intra-regional RE potential variation in planing model, consideration of power system operational aspects is also important to quantify realistic future system portfolio.
- As the operational model operates at intra-regional level with hourly resolution, developed methods of constructing its data sets from the planning model results shall help similar planning exercises.

Chapter 7

Conclusion and Outlook

Aim of the present thesis is to develop and analyze various methodologies to address the impact of RE variability in long-term energy system planning. For this purpose, a system planning model is developed using a widely used modeling framework (TIMES) with higher temporal and spatial resolution, and linked with GIS and power system operational models respectively. The developed GIS and operation models provide additional insights related to intra-regional RE potential variation and power sector operational aspects respectively to the energy system model. The study also targets to develop insights of future large-scale RE integration scenarios in North-Indian power sector by the application of these methodologies. This chapter presents key summary and conclusions from the research work, including its future outlook. Discussion on conclusions and outlooks are both categorized into two parts; one is related to methodologies and other to their applications.

7.1 Conclusions Related to Methodologies

In this research work various approaches related to methodological improvement for long-term energy system planning are outlined focusing on large-scale RE integration issues. Methodological improvements are undertaken in terms of a) adopting finer temporal as well as satial resolution in the long-term planning model b) quantifying intra-regional RE potential using GIS tools and incorporating them in planning model in required temporal and spatial resolution c) develop and utilize a separate operational model to analyze the operational impact of system portfolio calculated by the planning model d) outlining a bi-directional linking method to incorporate the results calculated by the operational model into the planning model to recalculate new capacity values. Following three subsections presents overall summary and conclusion related to each method.

7.1.1 Endogenous Improvement of Energy System Planning Model

Compared to usual practice of long-term energy system modeling and planning studies, present exercise considers substantially higher number of annual time slices and model regions for a regional-scale planning study. In India, for the first time such high-resolution model settings are adopted in long-term energy system planning focusing on power sector.

There are several benefits of the endogenous modeling improvements. Higher number of annual time slices helps to capture the seasonality of demand and RE generation, and provide robust output compared to models with limited time slices. Intra-day time slices defined at hourly level helps to capture realistic variations of demand as well as RE generation at intra-day level. Regional definitions considered at state level helps to track inter-regional energy flow, regional annual generation mix, and technology activity profiles. These higher modeling settings help the planning model to ensure demand and supply balance for each region for every time slice, which improves calculation of technology capacity.

The finer modeling settings also help to perform other methodological improvements, such as incorporation of intra-regional RE variability and linking with an operational model. Higher temporal and spatial definitions help to incorporate intra-regional RE generation as well as capacity potentials calculated at grid-cell level. It also helps to track activity profiles (*i.e.* dispatch) of technologies at higher temporal and spatial detail and compare them with operational model results. Following subsections details these aspects.

7.1.2 Linking Energy System Planning Model with GIS Based Tools

Consideration of intra-regional RE variability further enhances planning model's capability to quantify RE penetration level and overall system portfolio. GIS methodologies adopted for this purpose do not precisely mimic the assumptions in official estimate calculations due to the difference in granularity and unavailability of data; but it outlines an effective way to incorporate intra-regional class wise RE potential limit in a planning model. The methodology can be scaled up or down according to requirement and data availability. Here, the intra-regional potential of RE classes is quantified at 1-degree by 1-degree geographical grid cells. Terrain suitability and exclusion criteria are also considered according to the available data resolution. It is possible to adopt a much higher resolution and employ several other exclusion/ suitability criteria to make the calculation process robust.

The planning model employs a substantially higher number of annual time slices compared to what is usually adopted in a large-scale, long-term planning study. To make use of this high temporal definition, time slice specific capacity factors are developed for each geographical grid-cells. The calculation utilizes sufficiently large quantum of historical hourly time series data of wind to develop the corresponding CF values. The data utilized in this case is openly available and satellite-derived *via* remote sensing methods; hence resolution and reliability are lower than ground measured data. Though National Institute of Wind Energy (NIWE) provides historical ground measured data for some selected Indian locations; it is not useful in the present study as its spatial resolution is not uniform. In case of PV, ready-made long-term historical hourly time series (either satellite-derived or ground measured) was unavailable in open domain. Hence a widely used tool *i.e.*, PVWatts has been utilized. This uses a representative years' data derived from historical data sets to calculate annual generation. The accuracy of solar and wind CF calculation can be improved further if long-term historical ground measured data of solar radiation and wind speed is utilized.

These detailed RE related information has been incorporated into the planning model by creating various technologies to represent different RE classes. Additional user constraints are used to define region wise capacity potential. Time slice specific capacity factors are also provided per region per RE class.To the author's knowledge, it is the first attempt to capture intra-regional spatial and temporal variability using GIS approach for a large-scale, long-term planning model for India. It outlines that open domain spatial data can be utilized by GIS methods to develop RE related information, which is not generally available at desired spatial or temporal resolution. Future studies in this regard should target to develop better assumptions, consider additional GIS data layers, and ground measured historical RE generations to develop more realistic RE resource potentials. These issues are highlighted in Section 7.3.

7.1.3 Linking between Planning and Operational Model

Linking of the system and operational models involve rigorous data preparation process, other than development of the operational model itself. Compared to existing studies in this regard, the operational model has several intra-regional nodes and it operates at hourly resolution. As the operational model operates with higher spatial and temporal resolutions compared to the planning model, availability of data at desired spatial and temporal level, development of robust assumptions and rules for data preparation *etc.*, are crucial.

In the model linking process, technological capacity related data for the operational model are extracted from the planning model results. This information along with additional data, assumptions and rules, is used to generate intra-regional nodes, their location, and their spread. Rules are applied to convert aggregated capacity values into realistic unit sizes and allocate them at suitable nodes. In operational model also, grid-cell specific RE generation potential is considered to capture realistic RE variability.

The operational model portrays system operational insights at higher spatial and temporal resolution. Due to applied constraints, it ensures that the dispatch profiles of the generators are within their technical limits and more realistic power flow between the nodes. This leads to calculation of different activity profiles of the technologies compared to the planning model. Due to a considerable number of nodes, generators, and transmission lines, volume of the operational model is large. It is computationally challenging to solve the model for multiple milestone years of the planning model and perform multiple scenario analysis within reasonable time frame. Reformulation of model and refinement of model solving methods needs to be targeted. Incorporation of specific operational constraints in the planning model itself can lead may lead to more accurate dispatch decisions of generators, regional power exchange and help streamlining data exchange between the two types of models. There is a need to identify specific constraints to incorporate in the planning model based on trade-off between additional computational complexity and result accuracy. These are further elaborated in Section 7.3.

Bi-directional method illustrates how output of an operational model working at finer spatial and temporal level can be utilized in a planning model with coarse modeling definitions. It also outlines how additional user constraints can be constructed from operational model results to update technology wise, time slice wise and region wise capacity factor in the planning model for each model iteration for attempting new solution.

7.2 Conclusion Related to Methodological Application

The methodologies are applied to analyze various study scenarios in two ways. Endogenously improved NIMRT model integrated with intra-regional RE potential information is used to analyze a large number futuristic scenarios to evaluate system development for large-scale RE integration. On the other hand, a specific RE penetration scenario is analyzed using energy system and power system model linking approach. Overall summary and conclusion regarding the model applications are described in the following two subsections.

7.2.1 Long-Term Scenario Analysis Using the Energy System Model

Results of this methodological application are based on a long-term planning model, which optimizes future North-Indian power system portfolio to satisfy projected energy demand up to 2050. Though several earlier works exists on long-term system development in India using different methods, most of them are applied on a national scale and hardly report regional details of system evolution. These works are different from the present study with respect to geographical coverage, spatial and temporal definitions, time horizon, system definition, level of details of RE granularity and other several assumptions. Specifically, there is no earlier work on long-term system development of North-Indian power sector. Therefore, direct comparison of results is a challenging task.

Overall, the results presented in this thesis are an important contribution to national energy system planning, as they indicate optimistic transition towards a high renewable penetrated system. As the present study has not modeled any specific policy inputs, results impart light on future system development for various policy formulations. Due to the primary focus of India on solar and wind for clean power generation, their variability modeling is the main focus of this modeling application.

India aims to meet sustainable development goals, such as 100% electricity access to people and to move towards low carbon economy. It is a challenging task considering India's current fast track approach towards economic progress. Drastic policy change regarding electricity supply can jeopardize existing political consensus. Managing affordable electricity supply price is therefore crucial. As solar and coal are main generating options affecting future supply price, following paragraphs provide a short discussion on their inter-dependencies, along with total CO_2 emission.

Result shows that in spite of increasing RE penetration, coal will continue to be a major player unless extreme exogenous carbon tax *etc.* related policies are imposed. Government initiatives towards implementing these taxes in power sector, and their rate are uncertain and volatile. Therefore, future domestic coal production rates should be improved. Present rates are clearly not going to be sufficient to meet future coal demand. This requires new explorations, modernizing existing mines, and streamlining environmental clearances. Though steps towards implementing these has been started, setting up realistic targets, political will as well regulatory clearances are the key challenges

Figure 7.1 outlines solar and coal-based generation in different electricity supply prices for CO_2 price and solar cost scenario groups respectively in 2050; coal price and wind cost are set to ref scenario. In Figure 7.1 A, evident diversification of three groups is seen according to CO_2 price scenario. The lowest group indicates no CO_2 price cases with low solar-based generation. The highest solar power production in this group is around 950 TWh when solar cost is at SL and storage cost is at TL scenario. On the other hand, solar generation is lowest (469 TWh) when storage and solar cost are high. In this CO_2 price scenario group, electricity price ranges from 2.5-3.37 INR/ kWh. In the middle group or CL scenario group, electricity price ranges from 2.9-4.05 INR/ kWh whereas, total solar generation ranges from 1343-791 TWh. In high CO_2 price cases (red dots), 1093 TWh solar generation is seen at an electricity price of 4.48 INR/ kWh, when storage and solar costs are at high level. On the other hand, in low solar and storage cost cases, maximum solar generation of 1561 TWh is seen at a much lower electricity price of 2.88 INR/ kWh.

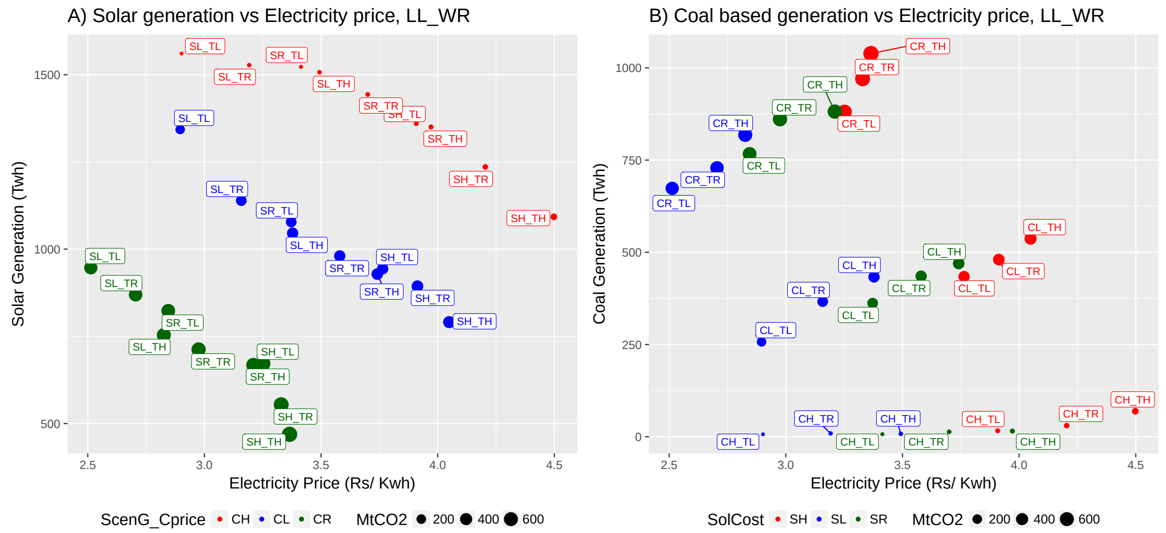


Figure 7.1 Solar and coal based power generation vs electricity price in CO_2 price and solar cost scenarios in 2050

Similar observations can be made in Figure 7.1 B, where coal-based generation is plotted with respect to electricity price for three solar cost scenario groups. Three clear clusters of model cases, due to three CO_2 price scenarios, can be seen. In each CO_2 price group, it can be observed that higher solar and storage cost leads to higher coal-based generation at higher electricity price. In the upper group of points (ref CO_2 price), low solar cost leads to coal generation as low as 673 TWh at a rate less than 2.51 INR/ kWh; while at high solar cost coal-based generation as high as 1039 TWh is seen at electricity supply price of 3.37 INR/ kWh. Within each scenario group in three point cluster, coal-based generation moves up according to the inverse variation of storage cost (as low storage favors higher solar energy generation). Coal-based generation is very low for high CO_2 price cases.

Investigation of such cases is important as various cases can be found to generate lower CO_2 emission at lower electricity price. Large number of model cases in this study constructed from three sensitivities of five parameters gives ample opportunity to analyze the system development under diverse conditions. Future studies in this direction in India will benefit from the scenario selection, model case construction and result analysis.

Energy storage technologies appear to be a key enabler of variable RE sources, especially solar PV. Though there are several policy-related instruments in India to attract investment into RE capacity, there is no clear policy towards integrating storage systems actively for RE integration. Current RE expansion plans in India are primarily involved with a substantial increase in transmission capacity. Though, this serves as a flexible resource to balance system fluctuation, it may be non-optimum in many cases where storage could perform a better job. The main issue with very high transmission capacity is that the lines are often under-utilized due to seasonal variation of RE generation, when they are exclusively built to evacuate RE power. Old pumped hydro systems mainly serve daily peak demand during evening time. New storage capacity should have faster response to cope up with operational variability from RE sources to enable large-scale RE integration and reduce curtailment. Setting up new storage capacity will require immediate formulation of policies and designing market instruments to attract investment into commercially viable new storage technologies.

7.2.2 Specific Scenario Analysis using a Model Linking Approach

Modeling application in this regard utilize an additional power system model. It is linked to the planning model having intra-regional RE variability information. As described in Chapter 6, uni-directional linking between two models brings new insights related to system operation which otherwise cannot be generated by the planning model alone. Results shows that, total generation from RE capacity calculated by the planning model may not be absorbed in operational point of view. As a consequence, operational model reports lower annual RE penetration percentage compared to that of planning model. It is also been understood that due to the lack of technical constraints on the thermal power plants, their role in system balancing and RE curtailment has been under estimated by the planning model.

India currently has diverse RE integration plans. Unless national scale system planning approaches consider the operational impact of RE variability at the planning stage, events like RE curtailment may jeopardize national RE integration and CO_2 emission reduction goals. Improved modeling and planning approaches are therefore necessary to design new energy policies, and identify optimal flexible system portfolio. Traditional approaches/ models used earlier for this purpose need to consider the importance of different sector specific models and their interlinking which include a simplified bi-directional approach, as outlined in Chapter 6. The present work reports a primary approach in this regard at regional scale for energy system planning in India, and can be further extended as discussed in Section 7.3.

7.3 Limitations and Outlook of Future Work

There are some limitation of the present study, which leads to various possibilities for future research. Planning studies in this regard can focus on further methodological improvements as well as their applications. These aspects are further elaborated in the following subsections.

7.3.1 Limitations

- There has been some recent development in TIMES modeling platform to enable modelers to incorporate operational constraints of generators, DC power flow etc. Present study does not consider these constraints but used a separate operational model to get the operational insight of the results from planning model.

- The present study focuses only on the North-Indian power sector. Being a regional model, it has limitations regarding addressing the impact of technological investment and policies in other region/ states. It has also limitation of addressing actual power exchange between North Indian region and rest of India. Accurate modeling of transmission links with other regions or extending the model to whole India would unfurl better picture of the role of transmission network for RE integration. It would also lead to quantification of more accurate transmission capacity related investment. Future studies in this regard can extend the model to whole India to get a broader picture.

- Though the model is multi-regional, it still considers large states such as UU, RJ as a single copper plate. Only the inter-regional transmission network is considered without modeling of distribution grids. Improvement in these regards *i.e* modeling of intra-regional power flow, realistic representation of state DISCOMS and DC load flow will lead to better result accuracy in terms of role of transmission network as a flexible resource. Attempt could be made to model at-least intra-regional networks of large states with large-scale RE integration plans *e.g.* RJ.

- Analysis of the role of flexible resources like DSR etc. for RE integration was not attempted as demand sector in this study is aggregated. With sector specific details (e.g. residential, industry) alternate load-curves/ incentives can be modeled to simulate DSR in the model. DSR initiatives like TOU tariff is still in early state in India and only available for a few DISCOMS. It is usually offered to industrial customers and plans are there to introduce for commercial sectors. With sector level detailing and technology details of demand side, scenario analysis could be undertaken to analyze the role of DSR.

- Present planning model does not track electricity demand by sector (industry, transport etc.). Therefore, effect of future electrification of a particular sector e.g. transport on demand is not traceable. Demand projection in the present study uses multiple regression which cannot track the impact of sector wide economic growth and activity.

Demand side interventions in terms of energy efficiency and demand side response etc. are also not modeled in this study to limit the scope of research.

7.3.2 Future Work

Methodological Improvement

- Focus of a planning study, nature of systems, and planning range play key roles in deciding different modeling assumptions, which in turn dictates the effectiveness of various modeling improvement approaches. Unnecessary adoption of high temporal or spatial resolution in a planning model may not suit a system with low intermittency, but it may be justifiable for a system with large-scale RE penetration to analyze the role of flexible systems such as energy storage.

- For existing large-scale energy system models, which are widely used for global and national scale policy analysis, it may be difficult to drastically alter their model settings endogenously. Hybrid approaches are clearly a reliable way to consider short-term system operational aspects in these models. However new model development may trade-off between various methods, considering various technical or non-technical aspects such as data, man-power, computational resources, *etc.*

- Future works in this regard can look into identifying suitable operational parameters from wider range of sensitivity analysis involving planning and operational models. Attempts can be made to realistically represent these parameters endogenously within the planning model itself. This may include defining additional constraints regarding generator technical limits, and the physics of power flow in transmission lines, *etc.* in the planning model. As technology capacity calculation is done by planning models, any endogenous modeling improvement will improve capacity related inputs for the operational model. It can ensure fast convergence, fewer iterations and quick data updation between models.

- The operational model developed for the model linking study, takes deterministic outlook of the RE generation as well as demand variability. Uncertainty of system operation is not addressed at proper scale, which can be addressed by a two stage stochastic model considering uncertainty of demand and RE generation using a suitable number of scenarios. Modeling improvement in this area should be attempted considering availability of historical demand as well as RE resource data.

- Present exercise of model linking between the planning and operational model indicate the necessity of adequate computational infrastructure. Consideration for a stochastic operational model can further increase the requirement of adequate computational power, not only for model solving but also for generating and reducing a large number of scenarios for either demand or RE resource variation. Therefore, methodological improvement in this area should take into account and manage associated additional computational costs.

Methodology Application

- Extending the existing multi-regional model to national level keeping the same spatial and temporal resolution will enable the analysis of inter-regional power transmission capacity requirement, which in turn unfurls new insight of regional system development.

- Long-term scenario analysis in the present study does not focus on modeling specific national or state level RE policy targets. Development of national scale model will enable the analysis of various existing or innovative policy related scenarios and their impact on power system evolution.

- Future RE potential assessment studies for national level RE integration planning may consider better spatial data sets as well as assumptions. Higher resolution land use and land cover maps for India can bring better insights of land suitability for RE installation. Detailed assessment of rooftop potential of solar PV capacity development can also be quantified using GIS method considering present and future urbanization.

- Along with grid-cell wise classification of RE potential assessment, future studies should also consider existing and future transmission system plans to develop national/ regional RE supply curves, considering additional cost of transmission expansion in each grid cell. This will bring further insight of technical RE potential at intra-regional scale.

- In addition to application of improved methodologies for analyzing the long-term evolution of Indian power system, availability of system and component specific data is critical for Indian context. National level planners, power system operators, regulatory authority, and academicians should coordinate more to develop advanced data maintenance and management practices in this regard to enable insightful researches in this area.

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Appendix A

Programs and data for Chapter 3

A.1 Demand Projection

A.1.1 R Program for State Wise Demand Projection

```
# --------------A program for state wise demand projection upto 2050----------------

library(forecast)
library(dplyr)
library(openxlsx)
library(ggplot2)
library(DAAG)
library(reshape2)
library(ggthemes)
library(car)
library(ggfortify)
library(broom)
library(ggpubr)
library(tidyr)

ind_forecast<-read.xlsx("ind_data.xlsx", sheet=8)
ind_forecast<-mutate(ind_forecast, POP_B=POP/10^9, GDP_T=GDP/10^6)
ind_forecast<-select(ind_forecast, Year, POP_B, GDP_T, ELC_tot)
fit<-lm(ELC_tot~POP_B+GDP_T, data=ind_forecast)
ind_forecast_test<-read.xlsx("ind_data.xlsx", sheet=9)
ind_forecast_test<-mutate(ind_forecast_test, POP_B=POP/10^9, GDP_T=GDP/10^6)
ind_forecast_test<-select(ind_forecast_test, Year, POP_B, GDP_T)
demand_NI_TWh<-predict(fit, newdata=ind_forecast_test)
x<-c(ind_forecast$ELC_tot, demand_NI_TWh)
CH<-x*.002*3.6
DL<-x*.029*3.6
HR<-x*.038*3.6
HP<-x*.008*3.6
JK<-x*.014*3.6
PB<-x*.050*3.6
RJ<-x*.052*3.6
UU<-x*.086*3.6
```

```
UT<-x*.010*3.6
demand_NI_state_PJ<-cbind.data.frame(CH, DL, HR, HP, JK, PB, RJ, UU, UT)
#demand_NI_state_PJ<-demand_NI_state_PJ%>%mutate(Year=ind_forecast_test$Year)%>%select(-'ind_forecast_test$Year')
demand_NI_state_PJ<-demand_NI_state_PJ%>%mutate(Year=c(1990:2050))
melt_test<-melt(demand_NI_state_PJ, id.vars="Year", variable.name="Region")

#11/12/19
# converting to TWh

melt_test <- melt_test %>% mutate(value = value / 3.6)

p<-ggplot(melt_test, aes(Year, value, group=Region, colour=Region))+geom_point(size=2)+stat_smooth(size=1.1)
p1<-p+xlab("Year")+ylab("TWh")
p2<-p1+theme(axis.text=element_text(size=10))
p3<-p2+scale_color_brewer(palette = "Set1")+scale_x_continuous(breaks = c(1990, 2000, 2010, 2020, 2030, 2040, 2050))
p3<-p3+theme(plot.title = element_text(hjust = 0.5, size=13), axis.text.x = element_text(hjust = .5))+
theme(axis.text=element_text(size=10), axis.title=element_text(size=10))
#p3<-p3+geom_vline(xintercept=2017, linetype="dotted", color = "black", size=1.5)+annotate("text", x=2000, y=1500, size=5,

p3<-p3+geom_vline(xintercept=2017, linetype="dotted", color = "black", size=1.5)+annotate("text", x=2000, y=450, size=5, la

melt_test %>% pivot_wider(names_from = Region, values_from = value) %>%
write.xlsx("NI_twh.xlsx")

#write.xlsx(demand_NI_state_twh, "NI_twh_11.xlsx")

#ggsave("load_proj_n.pdf", p3, width=10, height=7)

pdf("./load_proj_twh.pdf", width=10, height=7, onefile=FALSE)
plot(ggarrange(p3, ncol=1, nrow =1, legend="right", common.legend = FALSE))
dev.off()


#Model summary
layout(matrix(c(1,2,3,4),2,2))
plot(fit, cex.caption=1.5, add.smooth = getOption("add.smooth"))

# Cross Validation
cv.lm(data=ind_forecast, fit, m=3, plotit="Observed")
cvResults<-suppressWarnings(CVlm(data=ind_forecast, fit, m=10, dots=FALSE, seed=29, legend.pos="topleft",  printit=FALSE, m
attr(cvResults, 'ms')  # => 251.2783 mean squared error

#------------End of program--------------
```

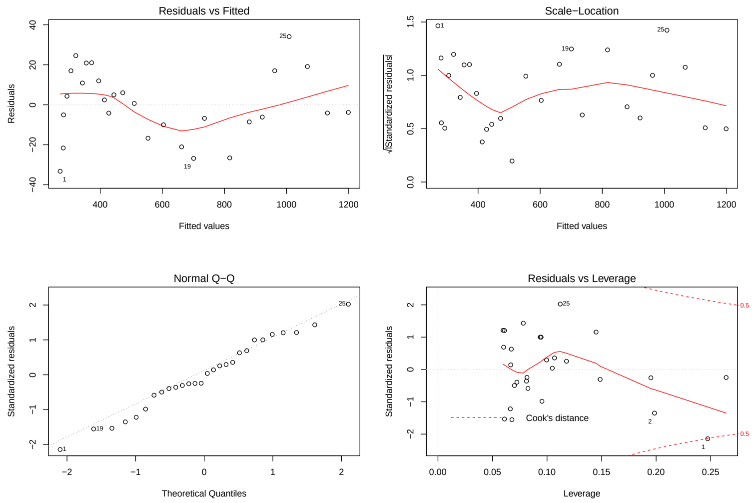
```
Call:
lm(formula = ELC_tot ~ POP_B + GDP_T, data = ind_forecast)

Residuals:
Min      1Q  Median      3Q     Max
-33.245  -8.935  -1.580  13.212  34.094

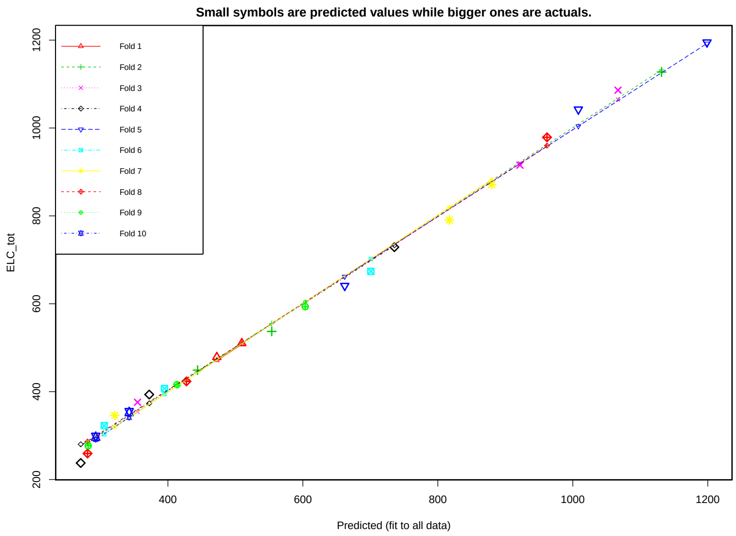
Coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept)  157.549     75.271   2.093   0.0466 *
POP_B       -145.179     88.686  -1.637   0.1142
GDP_T        231.401      9.488  24.389   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 17.88 on 25 degrees of freedom
Multiple R-squared:  0.9966,Adjusted R-squared:  0.9963
F-statistic:  3635 on 2 and 25 DF,  p-value: < 2.2e-16
```

A.1.2 Summary and Cross-Validation Report of the Demand Forecasting Model



(a) Summary of the multiple regression model for demand projection



(b) Ten fold cross validation of the multiple regression model for demand projection

Figure A.1 Summary and cross-validation report of the demand forecasting model

A.1.3 State Wise Forecasted Demand

Table A.1 State wise demand forecast (TWh)

Year	CH	DL	HR	HP	JK	PB	RJ	UU	UT
2017	2.4	34.7	45.4	9.6	16.7	59.8	62.1	102.8	12.0
2018	2.5	36.8	48.2	10.2	17.8	63.5	66.0	109.2	12.7
2019	2.7	39.0	51.1	10.8	18.8	67.2	69.9	115.6	13.4
2020	2.8	41.3	54.1	11.4	19.9	71.2	74.0	122.4	14.2
2021	3.0	43.7	57.3	12.1	21.1	75.4	78.4	129.6	15.1
2022	3.2	46.3	60.7	12.8	22.4	79.9	83.0	137.3	16.0
2023	3.4	49.1	64.3	13.5	23.7	84.6	88.0	145.5	16.9
2024	3.6	52.0	68.1	14.3	25.1	89.6	93.2	154.2	17.9
2025	3.8	55.1	72.2	15.2	26.6	95.0	98.8	163.3	19.0
2026	4.0	58.3	76.4	16.1	28.2	100.6	104.6	173.0	20.1
2027	4.3	61.8	80.9	17.0	29.8	106.5	110.8	183.2	21.3
2028	4.5	65.4	85.7	18.0	31.6	112.7	117.2	193.9	22.5
2029	4.8	69.2	90.6	19.1	33.4	119.2	124.0	205.1	23.8
2030	5.0	73.1	95.8	20.2	35.3	126.0	131.1	216.8	25.2
2031	5.3	77.2	101.2	21.3	37.3	133.1	138.5	229.0	26.6
2032	5.6	81.5	106.8	22.5	39.3	140.5	146.2	241.7	28.1
2033	5.9	86.0	112.6	23.7	41.5	148.2	154.1	254.9	29.6
2034	6.2	90.6	118.7	25.0	43.7	156.1	162.4	268.6	31.2
2035	6.6	95.3	124.9	26.3	46.0	164.3	170.9	282.7	32.9
2036	6.9	100.2	131.3	27.6	48.4	172.8	179.7	297.2	34.6
2037	7.3	105.3	137.9	29.0	50.8	181.5	188.8	312.2	36.3
2038	7.6	110.5	144.8	30.5	53.3	190.5	198.1	327.6	38.1
2039	8.0	115.8	151.8	31.9	55.9	199.7	207.7	343.4	39.9
2040	8.4	121.3	158.9	33.5	58.6	209.1	217.5	359.7	41.8
2041	8.8	126.9	166.3	35.0	61.3	218.8	227.6	376.4	43.8
2042	9.2	132.7	173.9	36.6	64.1	228.8	237.9	393.5	45.8
2043	9.6	138.6	181.6	38.2	66.9	239.0	248.6	411.1	47.8
2044	10.0	144.7	189.6	39.9	69.8	249.5	259.4	429.1	49.9
2045	10.4	150.9	197.7	41.6	72.8	260.2	270.6	447.5	52.0
2046	10.8	157.3	206.1	43.4	75.9	271.2	282.0	466.4	54.2
2047	11.3	163.8	214.6	45.2	79.1	282.4	293.7	485.7	56.5
2048	11.8	170.5	223.4	47.0	82.3	293.9	305.7	505.5	58.8
2049	12.2	177.3	232.3	48.9	85.6	305.7	317.9	525.8	61.1
2050	12.7	184.3	241.4	50.8	89.0	317.7	330.4	546.4	63.5

A.2 Some Data for NIMRT Model Development

A.2.1 State Wise Technology Potential

Table A.2 State wise technology Potential (GW)

	CH	DL	HP	HR	JK	PB	RJ	UT	UU
Small Hydro	0	0	2.39791	0.11005	1.43067	0.90	0.05717	1.70787	0.46075
Large Hydro	0	0	18.54	0.064	13.543	1.169	0.483	17.998	0.994
Biomass	0	0.016	0.4148	1.4932	1.0962	3.209	2.0083	0.5088	2.2624
Pumped Hydro	0	0	3.6	0	1.65	0	3.78	1	4.035

A.2.2 Projection of Technology Wise Investment cost

Table A.3 Projection of Technology wise Investment Cost (MINR/ GW)

	2017	2022	2027	2032	2037	2042	2047
COA_SUBC	49700	52000	54500	57000	59700	62400	65400
COA_SUPC	54900	57500	60200	63000	65900	69000	72200
COA_USUPC	63500	66400	69500	72800	76100	79700	83400
COA_IGCC	95500	99900	104600	109400	114600	119900	125500
GAS_CC	37800	39700	41600	43600	45500	47400	49300
HydroL	135214	128429	121643	114857	108071	101286	94500
HydroS	95000	95000	95000	95000	94269	93538	92808

Table A.4 Investment cost for Storage Technologies (MINR/ GW)

	2015	2030	2035	2040	2045	2050
PHS	82500	82500	82500	82500	82500	82500
Li-ION	168750	75000	67500	64125	64125	64125
NAS	255000	63750	54188	48769	46330	46330
Flow	168750	82500	70125	63113	59957	59957

A.2.3 Projection of state-wise coal production rate in three coal price scenarios

Low coal price

Table A.5 Mine wise coal yearly coal production estimate in low coal price scenario (PJ)

	Chattishgarh	Jharkhand	Madhya Pradesh	Odisha	Uttarakhand	West Bengal
2012	493.86	337.53	329.57	244.93	301.21	35.92
2013	510.81	345.78	358.17	255.74	274.81	39.28
2014	551.16	334.90	350.69	262.21	274.09	39.94
2015	584.45	390.97	406.35	287.08	278.48	43.65
2016	566.36	360.98	500.40	321.52	236.25	35.29
2017	623.96	385.88	488.19	323.61	298.94	38.40
2020	765.44	425.90	569.07	393.49	320.43	44.54
2025	956.27	476.97	714.12	493.04	358.48	49.90
2030	1257.95	573.98	942.50	650.00	430.97	60.07
2035	1600.91	678.20	1202.47	828.58	508.79	71.00
2040	1985.13	789.65	1494.03	1028.79	591.92	82.69
2045	2410.61	908.31	1817.18	1250.63	680.38	95.15
2050	2877.37	1034.18	2171.92	1494.10	774.16	108.36

High coal price

Table A.6 Mine wise coal yearly coal production estimate in high coal price scenario (PJ)

	Chattishgarh	Jharkhand	Madhya Pradesh	Odisha	Uttarakhand	West Bengal
2012	493.86	337.53	329.57	244.93	301.21	35.92
2013	510.81	345.78	358.17	255.74	274.81	39.28
2014	551.16	334.90	350.69	262.21	274.09	39.94
2015	584.45	390.97	406.35	287.08	278.48	43.65
2016	566.36	360.98	500.40	321.52	236.25	35.29
2017	623.96	385.88	488.19	323.61	298.94	38.40
2020	695.85	387.18	517.34	357.72	291.30	40.49
2025	819.66	408.83	612.11	422.61	307.27	42.77
2030	943.47	430.48	706.88	487.50	323.23	45.05
2035	1067.27	452.14	801.65	552.39	339.19	47.33
2040	1191.08	473.79	896.42	617.27	355.15	49.62
2045	1314.88	495.44	991.19	682.16	371.12	51.90
2050	1438.69	517.09	1085.96	747.05	387.08	54.18

Very low coal price

Table A.7 Mine wise coal yearly coal production estimate in very low coal price scenario (PJ)

	Chattishgarh	Jharkhand	Madhya Pradesh	Odisha	Uttarakhand	West Bengal
2012	493.86	337.53	329.57	244.93	301.21	35.92
2013	510.81	345.78	358.17	255.74	274.81	39.28
2014	551.16	334.90	350.69	262.21	274.09	39.94
2015	584.45	390.97	406.35	287.08	278.48	43.65
2016	566.36	360.98	500.40	321.52	236.25	35.29
2017	623.96	385.88	488.19	323.61	298.94	38.40
2020	835.03	464.62	620.80	429.26	349.57	48.58
2025	1092.88	545.11	816.14	563.48	409.69	57.03
2030	1572.44	717.47	1178.13	812.49	538.71	75.09
2035	2134.54	904.27	1603.29	1104.77	678.38	94.67
2040	2779.18	1105.51	2091.64	1440.31	828.69	115.77
2045	3506.35	1321.17	2643.17	1819.10	989.64	138.40
2050	4316.06	1551.28	3257.87	2241.16	1161.24	162.54

A.2.4 Fuel prices

Coal price for domestic import

Table A.8 Region and mine wise domestic coal price projection (MINR/ PJ)

	2013	2017	2040	2050
IMP-D-COA_CHH_DL	107	113	160	180
IMP-D-COA_JHA_DL	122	129	184	206
IMP-D-COA_MAD_DL	105	111	157	177
IMP-D-COA_ODI_DL	146	152	218	246
IMP-D-COA_UTT_DL	107	113	160	180
IMP-D-COA_WES_DL	154	161	230	259
IMP-D-COA_CHH_HP	127	133	191	215
IMP-D-COA_JHA_HP	136	142	204	229
IMP-D-COA_MAD_HP	125	131	187	210
IMP-D-COA_ODI_HP	169	176	253	285
IMP-D-COA_UTT_HP	125	131	187	210
IMP-D-COA_WES_HP	171	178	256	288
IMP-D-COA_CHH_HR	113	119	169	190
IMP-D-COA_JHA_HR	128	134	192	215
IMP-D-COA_MAD_HR	111	118	167	187
IMP-D-COA_ODI_HR	154	161	231	260
IMP-D-COA_UTT_HR	115	122	173	194
IMP-D-COA_WES_HR	162	170	243	274
IMP-D-COA_CHH_JK	141	147	212	238
IMP-D-COA_JHA_JK	149	156	224	252
IMP-D-COA_MAD_JK	139	145	208	234
IMP-D-COA_ODI_JK	178	185	267	300
IMP-D-COA_UTT_JK	139	145	208	234
IMP-D-COA_WES_JK	182	189	273	307
IMP-D-COA_CHH_PB	127	133	191	215
IMP-D-COA_JHA_PB	140	146	210	236
IMP-D-COA_MAD_PB	124	130	185	208
IMP-D-COA_ODI_PB	169	176	253	285
IMP-D-COA_UTT_PB	126	133	189	213
IMP-D-COA_WES_PB	176	183	264	297
IMP-D-COA_CHH_RJ	116	122	174	196
IMP-D-COA_JHA_RJ	137	143	205	231
IMP-D-COA_MAD_RJ	115	122	173	194
IMP-D-COA_ODI_RJ	156	162	233	263
IMP-D-COA_UTT_RJ	121	128	182	205
IMP-D-COA_WES_RJ	173	180	259	291
IMP-D-COA_CHH_UT	109	115	163	183
IMP-D-COA_JHA_UT	118	125	178	200
IMP-D-COA_MAD_UT	107	113	160	180
IMP-D-COA_ODI_UT	146	152	218	246
IMP-D-COA_UTT_UT	107	113	160	180
IMP-D-COA_WES_UT	147	154	220	248
IMP-D-COA_CHH_UU	88	94	132	148
IMP-D-COA_JHA_UU	96	103	144	162
IMP-D-COA_MAD_UU	84	91	126	142
IMP-D-COA_ODI_UU	117	123	175	197
IMP-D-COA_UTT_UU	84	91	126	142
IMP-D-COA_WES_UU	120	127	180	202

Coal price for foreign import

Table A.9 Region, country and port wise foreign coal import price projection (MINR/ PJ)

	2017	2040	2050
IMP-F-COA_SA_KN_DL	244	366	420
IMP-F-COA_IN_VJ_DL	332	498	570
IMP-F-COA_SA_KN_HP	258	387	443
IMP-F-COA_IN_VJ_HP	346	518	593
IMP-F-COA_SA_KN_HR	244	366	420
IMP-F-COA_IN_VJ_HR	338	507	581
IMP-F-COA_SA_KN_JK	265	397	455
IMP-F-COA_IN_VJ_JK	352	528	605
IMP-F-COA_SA_KN_PB	248	372	426
IMP-F-COA_IN_VJ_PB	344	516	591
IMP-F-COA_SA_KN_RJ	228	342	391
IMP-F-COA_IN_VJ_RJ	333	500	572
IMP-F-COA_SA_KN_UT	257	386	442
IMP-F-COA_IN_VJ_UT	337	506	580
IMP-F-COA_SA_KN_UU	254	381	436
IMP-F-COA_IN_VJ_UU	310	465	533

Gas and oil price

Table A.10 gas and oil price projection (MINR/ PJ)

	2012	2017	2022	2027	2032	2037	2042	2047
Gas import	768	688	656	660	669	685	701	718
Gas domestic	194	253	656	661	669	686	703	719
Oil	891	894	933	978	1020	1057	1094	1134

Biomass price

Table A.11 Biomass price projection (MINR/ PJ)

Region	Price
CH	236.9279
DL	236.9279
HP	236.9279
HR	252.1426
JK	236.9279
PB	263.7205
RJ	220.0857
UT	236.9279
UU	225.3485

Appendix B

Programs and data for Chapter 4

B.1 Programs for Annual and Time Slice Wise RE CF Calculation

B.1.1 R Program for Time Slice Wise Solar PV CF Calculation

```
#----------------------------------------------
#solar_pvwatts.r
# --------------A program for annual and time slice wise solar capacity factor calculation for each grid-cell ----
library(dplyr)
library(openxlsx)
library(ggplot2)
library(ggthemes)
library(reshape2)

#this code relies on NREL PVWatts tool for hourly generation calculation
#This code is only used for data aggregation ad summarization purpose
#technical details

#DC System Size (kW): 4
#Module Type: Standard polycristalline
#Array Type: fixed Open rack
#Array Tilt (deg): latitude
#Array Azimuth (deg):180
#System Losses:14
#Invert Efficiency:96%
#DC to AC Size Ratio:1.1


gid_state_index<-read.xlsx("F:/PhD/RE Supply curve/merra_soda/new_index.xlsx", sheet=1);
wb<-createWorkbook("nrel_sol")
Month<-c(1:12)
#Month<-c("01","02","03","04","05","06","07","08","09","10","11","12")
Season<-c("01-JAN", "02-FEB", "03-MAR", "04-APR", "05-MAY", "06-JUN", "07-JUL",
"08-AUG", "09-SEP", "10-OCT", "11-NOV", "12-DEC")
#Season<-c("JAN", "FEB", "MAR", "APR", "MAY", "JUN", "JUL", "AUG", "SEP", "OCT", "NOV", "DEC")
```

```
index_match1<-cbind.data.frame(Month, Season)
Hour_n<-c(1:24)
d<-c("H01","H02","H03","H04","H05","H06", "H07", "H08", "H09", "H10","H11", "H12",
"H13", "H14", "H15", "H16", "H17", "H18", "H19", "H20", "H21", "H22", "H23", "H24")
index_match2<-cbind.data.frame(Hour_n, d)
Month_day<-c(31,28,31,30,31,30, 31, 31, 30,31,30,31)
day_month<-cbind.data.frame(Season, Month_day)

#read data
files_solar=list.files(path="F:/PhD/RE Supply curve/merra_soda/pvwatts_new",
pattern=".csv", full.names=T, recursive=FALSE)

#create empty vectors for saving results
grid_cells=NULL
ANN_CF=NULL
ts_gcells<-NULL

#read data

for(i in 1:length(files_solar)){
filename_sol<-files_solar[i];
sol_pvwatts<-read.table(filename_sol, sep=',', skip=18, nrows = 8760);

sol_pvwatts<-select( sol_pvwatts, V1,V3,V8, V11)%>% rename(Month=V1, Hour=V3, IR_Module=V8, SG_AC=V11)
sol_pvwatts<-mutate(sol_pvwatts, Hour_n=Hour+1)

sol_pvwatts$Month<-as.numeric(sol_pvwatts$Month)

sol_pvwatts<-left_join(sol_pvwatts, index_match1, by="Month"); sol_pvwatts<-left_join(sol_pvwatts,
index_match2, by="Hour_n")
sol_pvwatts<-mutate(sol_pvwatts, ts=paste(Season,d, sep="-"))
sol_pvwatts<-select(sol_pvwatts, Season, ts, IR_Module, SG_AC)

sol_pvwatts_group<-group_by(sol_pvwatts, Season, ts)%>%summarise(SG_TS=sum(SG_AC))
sol_pvwatts_group<-left_join(sol_pvwatts_group, day_month, by="Season")
sol_pvwatts_group$CF_TS<-sol_pvwatts_group$SG_TS/(sol_pvwatts_group$Month_day)/4000
sol_pvwatts_group$AFA=sum(sol_pvwatts_group$SG_TS)/(8760*4000);
sol_pvwatts_group$COM_FR=sol_pvwatts_group$SG_TS/sum(sol_pvwatts_group$SG_TS);
sol_pvwatts_group<-mutate(sol_pvwatts_group, Gid=gid_state_index$GID[i])
sol_pvwatts_final<-select(as.data.frame(sol_pvwatts_group), Gid, ts, SG_TS, AFA, CF_TS, COM_FR)

#Write data
file1<-paste("F:/PhD/RE Supply curve/merra_soda/PVWATTS_Out_Sol_New/new", "/","PVWatts_Sol_NI.xlsx", sep="")
addWorksheet(wb, gid_state_index$GID[i])
writeData(wb, gid_state_index$GID[i], sol_pvwatts_final, rowNames = T )

#save output in matrix
# output[i,]<-sol_pvwatts_final$CF_TS

grid_cells=as.vector(append(grid_cells, gid_state_index$GID[i]))
ANN_CF=as.vector(append(ANN_CF, sol_pvwatts_final$AFA[1]))

ts_gcells<-as.matrix(cbind(ts_gcells, sol_pvwatts_final$CF_TS))
#colnames(ts_gcells, grid_cells)
}
```

```
saveWorkbook(wb, file1, overwrite = TRUE)

colnames(ts_gcells)<-grid_cells; rownames(ts_gcells)<-sol_pvwatts_final$ts
grid_CF = data.frame(grid_cells, ANN_CF)

write.xlsx(grid_CF, "F:/PhD/RE Supply curve/merra_soda/PVWATTS_Out_Sol_New/new/sol_AFA.xlsx")
write.xlsx(ts_gcells, "F:/PhD/RE Supply curve/merra_soda/PVWATTS_Out_Sol_New/new/ts_sol_gcells.xlsx", rowNames = TRUE)

#------------End of program--------------
```

B.1.2 R Program for Time Slice Wise Wind CF Calculation

```
#----------------------------------
# wind_merra.r
# --------------A program for annual and time slice wise wind capacity factor calculation for each grid-cell ----
library(dplyr)
library(openxlsx)
library(ggplot2)
library(ggthemes)
library(reshape2)

# http://www.suzlon.com/products/S111#parentHorizontalTab5

#turbine technical specs
rp<-2.1
cin<-3
cout<-21
cr<-10
sa<-9817
rho<-1.225
cp<-.35

#wind speed extrapolation to hub height
Z1<-10
Z2<-120
sh<-1/7

gid_state_index<-read.xlsx("F:/PhD/RE Supply curve/merra_soda/new_index.xlsx", sheet=1);
wb<-createWorkbook("test")
Month<-c(1:12)
#Season<-c("JAN", "FEB", "MAR", "APR", "MAY", "JUN", "JUL", "AUG",
"SEP", "OCT", "NOV", "DEC")
Season<-c("01-JAN", "02-FEB", "03-MAR", "04-APR", "05-MAY", "06-JUN",
 "07-JUL", "08-AUG", "09-SEP", "10-OCT", "11-NOV", "12-DEC")
index_match1<-cbind.data.frame(Month, Season)
Hour<-c(1:24)
d<-c("H01","H02","H03","H04","H05","H06", "H07", "H08", "H09", "H10","H11", "H12",
"H13", "H14", "H15", "H16", "H17", "H18", "H19", "H20", "H21", "H22", "H23", "H24")
index_match2<-cbind.data.frame(Hour, d)
Month_day<-c(31,28,31,30,31,30, 31, 31, 30,31,30,31)
day_month<-cbind.data.frame(Season, Month_day)

#create empty vectors for saving results
```

```
grid_cells=NULL
ANN_CF=NULL
ts_gcells<-NULL

#read data
files=list.files(path="F:/PhD/RE Supply curve/merra_soda/merra_new_data/Data_1", pattern=".csv",
full.names=T, recursive=FALSE)
for(i in 1:2){
filename<-files[i];
merra<-read.table(filename, sep=';', skip=21);
 sep=';', skip=21); head(merra)

merra<-select(merra, V1,V2,V6)%>% rename(Date=V1, Hour=V2, WS_10=V6)
merra<-mutate(merra, WS_p=WS_10*(Z2/Z1)^sh)
merra<-mutate(merra, Year=as.numeric(substr(Date,1,4)),
Month=as.numeric(substr(Date,6,7)), Day=as.numeric(substr(Date,9,10)))
merra$Hour=as.numeric(merra$Hour);
merra<-left_join(merra, index_match1, by="Month"); merra<-left_join(merra, index_match2, by="Hour")
merra<-mutate(merra, ts=paste(Season,d, sep="-"))

merra<-select(merra, Season, ts, WS_10, WS_p)

#wind generation calculation
merra<-mutate(merra, WG=ifelse((WS_p>=cin & WS_p<=cr), 0.5*rho*(WS_p^3)*sa*cp/10^6,ifelse((WS_p>=cr & WS_p<=cout),rp,0)))

#merra<-mutate(merra, WG=0.5*rho*(WS_80m^3)*sa*cp/10^6)

merra_group<-group_by(merra, Season, ts)%>%summarise(WG_TS=sum(WG)/37)
merra_group<-left_join(merra_group, day_month, by="Season")
merra_group$CF_TS<-merra_group$WG_TS/(merra_group$Month_day*rp)
merra_group$AFA=sum(merra_group$WG_TS)/(8760*rp);
merra_group$COM_FR=merra_group$WG_TS/sum(merra_group$WG_TS);
#merra_group<-mutate(merra_group, Pset_PN=paste("T_WIN_",gid_state_index$GID[i]))
merra_final<-select(as.data.frame(merra_group), ts, WG_TS, AFA, CF_TS, COM_FR)

#Write data
file1<-paste("F:/PhD/RE Supply curve/merra_soda/MERRA_Out_Win_New_test/120", "/","merra_win_NI.xlsx", sep="")
addWorksheet(wb, gid_state_index$GID[i])
writeData(wb, gid_state_index$GID[i], merra_final, rowNames = T )

#save output in matrix

grid_cells=as.vector(append(grid_cells, gid_state_index$GID[i]))
ANN_CF=as.vector(append(ANN_CF, merra_final$AFA[1]))
ts_gcells<-as.matrix(cbind(ts_gcells, merra_final$CF_TS))
}

saveWorkbook(wb, file1, overwrite = TRUE)

colnames(ts_gcells)<-grid_cells; rownames(ts_gcells)<-merra_final$ts
grid_CF = data.frame(grid_cells, ANN_CF)


write.xlsx(grid_CF, "F:/PhD/RE Supply curve/merra_soda/MERRA_Out_Win_New_test/120/win_AFA.xlsx")
write.xlsx(ts_gcells, "F:/PhD/RE Supply curve/merra_soda/MERRA_Out_Win_New_test/120/ts_win_gcells.xlsx", rowNames = TRUE)
```

```
#------------End of program--------------
```

B.2 Class Wise Solar and Wind Energy Capacity Potential

Table B.1 Class wise solar energy capacity potential (GW)

	CH	DL	HP	HR	JK	PB	RJ	UT	UU
Sol_Class_01	0.00	0.00	0.00	0.00	0.00	0.00	2719.64	56.09	0.00
Sol_Class_02	0.00	0.00	34.55	0.00	0.00	0.00	1317.64	27.77	102.70
Sol_Class_03	0.00	0.00	0.00	1.31	0.00	0.00	1436.41	118.90	74.75
Sol_Class_04	0.02	0.00	125.66	362.62	0.00	10.69	178.37	76.96	572.63
Sol_Class_05	0.00	0.00	55.36	564.30	68.33	878.29	221.22	43.19	1698.18
Sol_Class_06	0.00	3.94	0.00	50.30	0.00	219.37	0.00	0.00	2250.66
Sol_Class_07	0.00	0.00	0.00	0.00	49.45	0.00	0.00	0.00	465.22
Sol_Class_08	0.00	0.00	0.01	0.00	11.52	0.00	0.00	0.00	0.00
Sol_Class_09	0.00	0.00	0.00	0.00	54.59	0.00	0.00	0.00	0.00
Sol_Class_10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table B.2 Class wise wind energy capacity potential (GW)

	CH	DL	HP	HR	JK	PB	RJ	UT	UU
Win_Class_01	0	0.00	0.00	0.00	0.00	0.00	22.13	0.00	0.00
Win_Class_02	0	0.00	0.00	0.00	0.00	0.00	19.26	0.00	0.00
Win_Class_03	0	0.00	0.00	0.00	0.00	0.00	66.41	0.00	0.00
Win_Class_04	0	0.00	0.00	0.00	0.00	0.00	91.85	0.00	0.00
Win_Class_05	0	0.00	0.00	0.00	0.00	0.00	140.78	0.00	0.00
Win_Class_06	0	0.00	0.00	0.00	0.00	0.00	136.01	0.04	36.49
Win_Class_07	0	0.42	0.00	42.67	0.00	0.00	104.01	0.00	443.47
Win_Class_08	0	0.00	0.61	60.94	0.00	25.35	40.92	0.92	48.16
Win_Class_09	0	0.00	5.86	0.00	5.78	54.85	0.50	33.23	18.68
Win_Class_10	0	0.00	16.35	0.00	13.69	37.16	0.00	0.00	0.00

Appendix C

Numerical Results for Chapter 5

C.1 Base Case Generation mix

Table C.1 Base case generation mix (TWh)

Technology	2014	2017	2020	2025	2030	2035	2040	2045	2050
Biomass	3.45	4.04	0.00	0.05	0.98	0.00			
Coal	200.70	247.26	306.92	404.70	487.06	590.86	656.89	732.67	860.68
Gas	27.26	26.22	3.47	0.05	0.06	0.25	0.33	0.28	0.22
HydroL	70.01	83.04	93.87	100.67	107.50	105.96	164.42	225.92	231.79
HydroS	2.83	3.03	23.86	29.03	31.68	31.68	31.68	31.68	31.71
Lignite	7.29	7.29	8.83	8.83	8.83	7.48	7.56	7.79	7.75
Nuclear	10.08	11.35	21.17	30.98	50.47	49.90	49.11	48.50	47.03
Solar	1.30	3.82	10.87	29.42	77.86	198.00	329.78	495.34	712.32
Wind	7.00	10.76	17.87	32.56	63.15	76.43	95.48	103.94	102.94

C.2 Base Case Capacity mix

Table C.2 Base case capacity mix (GW)

Technology	2014	2017	2020	2025	2030	2035	2040	2045	2050
Biomass	1.12	1.32	1.12	0.79	0.46	0.13			
Coal	33.50	40.19	59.97	74.56	96.42	114.77	131.58	138.79	151.61
Gas	5.06	4.88	3.76	2.96	2.86	16.04	21.13	19.85	19.72
HydroL	15.97	18.99	21.33	22.89	24.50	24.12	37.72	51.49	52.79
HydroS	0.61	0.66	5.31	6.47	7.06	7.06	7.06	7.06	7.06
Lignite	1.58	1.58	1.83	1.83	1.83	1.83	1.83	1.83	1.83
Nuclear	1.62	1.62	3.02	4.42	7.20	7.12	7.01	6.92	6.71
Oil	0.18	0.18	0.10	0.03					
Solar	0.79	2.35	7.07	19.05	49.54	126.10	208.71	312.99	450.14
Wind	2.78	4.28	6.85	12.17	23.60	29.08	37.03	41.39	41.39

C.3 Base Case Region Wise Capacity Mix in 2050

Table C.3 Base case region wise capacity mix in 2050 (GW)

Technology	DL	HP	HR	JK	PB	RJ	UT	UU
Coal	0.06	0.00	31.63	0.01	14.92	17.68		87.31
Gas			3.97		5.73	10.02		
HydroL		18.54	0.06	13.54	1.17	0.48	18.00	0.99
HydroS		2.40	0.11	1.43	0.90	0.06	1.71	0.46
Lignite						1.83		
Nuclear			2.80			3.68		0.23
Solar	3.94	24.94	83.74	20.38	96.87	85.72	24.40	110.15
Wind						41.39		

Appendix D

Programs and data for Chapter 6

D.1 RE Generation Calculation

D.1.1 R Program for Hourly Wind CF Calculation

```
library(dplyr)
library(openxlsx)
library(ggplot2)
library(ggthemes)
library(reshape2)
#library(MASS)
library(fitdistrplus)

# http://www.suzlon.com/products/S111#parentHorizontalTab5

#turbine technical specs
rp<-2.1

cin<-3
cout<-21
cr<-10
sa<-9817
rho<-1.225
cp<-.35

#wind speed extrapolation to hub height
Z1<-10
Z2<-120
sh<-1/7

gid_state_index<-read.xlsx("D:/Partha/new_index.xlsx", sheet=1);
partha<-createWorkbook("test")
Month<-c(1:12)
#Season<-c("JAN", "FEB", "MAR", "APR", "MAY", "JUN", "JUL", "AUG",
"SEP", "OCT", "NOV", "DEC")
Season<-c("01-JAN", "02-FEB", "03-MAR", "04-APR", "05-MAY", "06-JUN",
"07-JUL", "08-AUG", "09-SEP", "10-OCT", "11-NOV", "12-DEC")
index_match1<-cbind.data.frame(Month, Season)
```

```
Hour<-c(1:24)
d<-c("H01","H02","H03","H04","H05","H06", "H07", "H08", "H09", "H10",
"H11", "H12", "H13", "H14", "H15", "H16", "H17", "H18", "H19",
"H20", "H21", "H22", "H23", "H24")
index_match2<-cbind.data.frame(Hour, d)
Day<-c(1:31)
Din<-c("d01","d02","d03","d04","d05","d06","d07","d08","d09","d10",
"d11","d12","d13","d14","d15","d16","d17","d18","d19","d20","d21",
"d22","d23","d24","d25","d26","d27","d28","d29","d30","d31")
index_match3<-cbind.data.frame(Day,Din)
Month_day<-c(31,28,31,30,31,30, 31, 31, 30,31,30,31)
day_month<-cbind.data.frame(Season, Month_day)

#create empty vectors for saving results
grid_cells=NULL
ANN_CF=NULL
ts_gcells<-NULL

#read data
files=list.files(path="D:/Partha/Data/Wind/Data_1", pattern=".csv", full.names = TRUE, recursive=FALSE)
for(i in 1:143)
{
filename<-files[i];
merra<-read.table(filename, sep=';', skip=21);

merra<-dplyr::select(merra, V1,V2,V6)%>% rename(Date=V1, Hour=V2, WS_10=V6)
merra<-mutate(merra, WS_p=(WS_10*(Z2/Z1)^sh)+.000001)
merra<-mutate(merra, Year=as.numeric(substr(Date,1,4)), Month=as.numeric(substr(Date,6,7)),
Day=as.numeric(substr(Date,9,10)))
merra$Hour=as.numeric(merra$Hour);
merra<-left_join(merra, index_match1, by="Month");
merra<-left_join(merra, index_match2, by="Hour");
merra<-left_join(merra, index_match3, by="Day")
merra<-mutate(merra, ts=paste(Season,Din,d, sep="-"))

merra<-dplyr::select(merra, Year, Season,ts, d,Din, WS_10, WS_p)
a<-merra$ts
ab<-unique(a)
xyz<-list()
for(j in 1:length(ab))
{
merra1<-merra[merra$ts==ab[j],]
me<-fitdist(merra1$WS_p,"weibull", lower=c(0,0))
mei<-rweibull(10000,shape=me$estimate[[1]],scale=me$estimate[[2]])
m_ws<-mean(mei)
meia<-data.frame(m_ws)
xyz[[j]]<-meia
}
p<- dplyr::bind_rows(xyz)
ts<-ab[1:8784]
winra<-cbind.data.frame(ts,p)

winra<-mutate(winra, WG=ifelse((m_ws>=cin & m_ws<=cr), 0.5*rho*(m_ws^3)*sa*cp/10^6,ifelse((m_ws>=cr & m_ws<=cout),rp,0)))
winra<-winra[-c(1417:1440),]
winra$CF_TS<-winra$WG/rp
```

```
winra$AFA=sum(winra$WG)/(8760*rp);
winra$COM_FR=winra$WG;
winra_final<-dplyr::select(as.data.frame(winra), ts, WG, AFA, CF_TS, COM_FR)


file1<-paste("F:/Partha", "/","merra_win_NI7.xlsx", sep="")
addWorksheet(partha, gid_state_index$GID[i])
writeData(partha, gid_state_index$GID[i], winra_final, rowNames = T )
}

saveWorkbook(partha, file1, overwrite = TRUE)
```

D.1.2 R Program for Hourly Solar CF Calculation

```
library(dplyr)
library(openxlsx)
library(ggplot2)
library(ggthemes)
library(reshape2)

#this code relies on NREL PVWatts tool for hourly generation calculation
#This code is only used for data aggregation ad summarization purpose
#technical details

#DC System Size (kW): 4
#Module Type: Standard polycristalline
#Array Type: fixed Open rack
#Array Tilt (deg): latitude
#Array Azimuth (deg):180
#System Losses:14
#Invert Efficiency:96%
#DC to AC Size Ratio:1.1


gid_state_index<-read.xlsx("D:/Partha/new_index.xlsx", sheet=1);
wb<-createWorkbook("nrel_sol")
Month<-c(1:12)
#Month<-c("01","02","03","04","05","06","07","08","09","10","11","12")
Season<-c("01-JAN", "02-FEB", "03-MAR", "04-APR", "05-MAY",
"06-JUN", "07-JUL", "08-AUG", "09-SEP", "10-OCT", "11-NOV", "12-DEC")
#Season<-c("JAN", "FEB", "MAR", "APR", "MAY", "JUN", "JUL",
 "AUG", "SEP", "OCT", "NOV", "DEC")
index_match1<-cbind.data.frame(Month, Season)
Hour_n<-c(1:24)
d<-c("H01","H02","H03","H04","H05","H06", "H07", "H08",
 "H09", "H10","H11", "H12", "H13", "H14", "H15", "H16",
 "H17", "H18", "H19", "H20", "H21", "H22", "H23", "H24")
index_match2<-cbind.data.frame(Hour_n, d)
Day<-c(1:31)
Din<-c("d01","d02","d03","d04","d05","d06","d07","d08","d09",
"d10","d11","d12","d13","d14","d15","d16","d17","d18","d19",
"d20","d21","d22","d23","d24","d25","d26","d27","d28",
"d29","d30","d31")
index_match3<-cbind.data.frame(Day,Din)
```

```
Month_day<-c(31,28,31,30,31,30, 31, 31, 30,31,30,31)
day_month<-cbind.data.frame(Season, Month_day)

#read data
files_solar=list.files(path="D:/Partha/Data/Solar/pvwatts_new", pattern=".csv", full.names=T, recursive=FALSE)

#create empty vectors for saving results
grid_cells=NULL
ANN_CF=NULL
ts_gcells<-NULL

#read data

for(i in 1:10){
filename_sol<-files_solar[i];
sol_pvwatts<-read.table(filename_sol, sep=',', skip=18, nrows = 8760);


sol_pvwatts<-dplyr::select( sol_pvwatts, V1,V2,V3,V8, V11)%>% rename(Month=V1, Day=V2, Hour=V3, IR_Module=V8, SG_AC=V11)
sol_pvwatts<-mutate(sol_pvwatts, Hour_n=Hour+1)

sol_pvwatts$Month<-as.numeric(sol_pvwatts$Month)
sol_pvwatts$Day<-as.numeric(sol_pvwatts$Day)

sol_pvwatts<-left_join(sol_pvwatts, index_match1, by="Month");
sol_pvwatts<-left_join(sol_pvwatts, index_match2, by="Hour_n");
sol_pvwatts<-left_join(sol_pvwatts, index_match3, by="Day")
sol_pvwatts<-mutate(sol_pvwatts, ts=paste(Season,Din, d, sep="-"))
sol_pvwatts<-dplyr::select(sol_pvwatts, Season, ts, IR_Module, SG_AC)

sol_pvwatts$CF_TS<-sol_pvwatts$SG_AC/4000
sol_pvwatts$AFA=sum(sol_pvwatts$SG_AC)/(8760*4000);
sol_pvwatts$COM_FR=sol_pvwatts$SG_AC/sum(sol_pvwatts$SG_AC);

sol_pvwatts<-mutate(sol_pvwatts, Gid=gid_state_index$GID[i])
sol_pvwatts_final<-dplyr::select(as.data.frame(sol_pvwatts), Gid, ts, SG_AC, AFA, CF_TS, COM_FR)

#Write data
file1<-paste("F:/Partha", "/","PVWatts_Sol_NI.xlsx", sep="")
addWorksheet(wb, gid_state_index$GID[i])
writeData(wb, gid_state_index$GID[i], sol_pvwatts_final, rowNames = T )

}
saveWorkbook(wb, file1, overwrite = TRUE)
```

D.2 Technology Group Wise Data for NIPSO Model

Table D.1 Technology group wise data for NIPSO model

Attributes	Minimum stable generation	Operating cost (INR/MW)	Start-up/Shut-down cost (INR)	Minimum up-time (Hour)	Minimum dowm-time (Hour)	Ramp up/dowm Limit (%/ hour)
Coal (<210 MW)	45%	2460	739570	24	10	30%
Coal (>210 MW, <250 MW)	45%	2460	1445470	24	10	30%
Coal (>500 MW, <600 MW)	45%	2460	3450005	24	10	30%
Coal (>600 MW)	55%	2160	4290000	24	10	50%
Gas	10%	4250	51610	2	2	100%
Lignite	55%	2460	739570	24	10	30%
Nuclear	70%	2500	6500000			5%
Biomass	20%	2460	6500	24	10	30%

D.3 NIPSO Model Structure

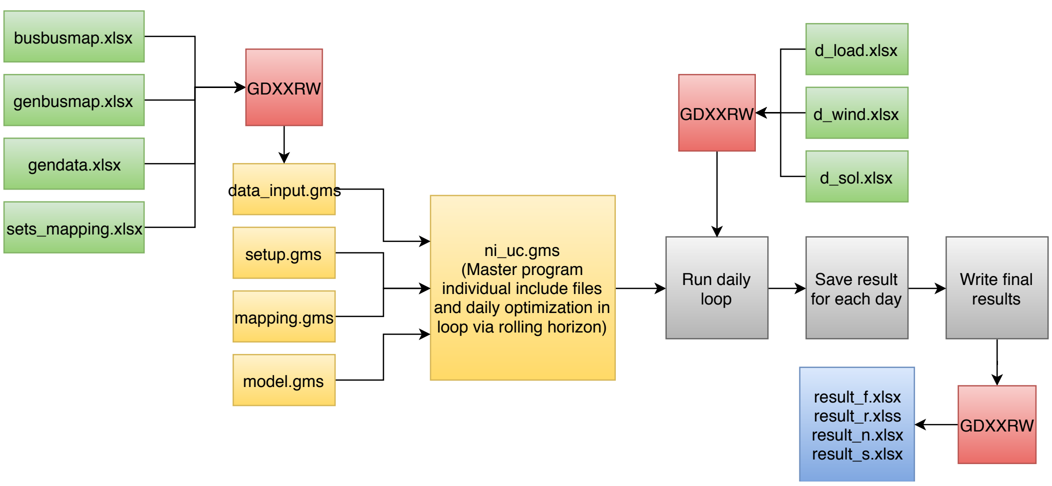


Figure D.1 Overall structure of the NIPSO model program

D.3.1 Description of Each NIPSO Model Component

D.3.2 GAMS Programs

data_input.gms Reads technical parameters of generators, inter-nodal mapping, generator and node mapping, node and state mapping.

setup_.gms Defines sets, aliases, parameters, and scalars for input data

model_.gms Defines variables and equations.

mapping_.gms Defines mapping set between nodes and regions.

ni_uc.gms Master program which defines global variables and calls other .gms files. It generates the whole model, calls solver or solving, and writes results after the optimization completes.

D.3.3 Input Data

busbusmap.xlsx Map of one node to another, *i.e.* which nodes are connected to other nodes via transmission lines.

genbusmap.xlsx Map of all generator to nodes; *i.e.* which generator is connected to a particular node.

gendata.xlsx Technical characteristics of each generators.

sets_mapping.xlsx List of nodes, regions, aggregated technology groups.

d_load.xlsx Daily load profile for each node at hourly resolution.

d_sol.xlsx Daily solar generation profile for each node at hourly resolution.

d_wind.xlsx Daily wind generation profile for each node at hourly resolution.

D.3.4 Output Results

result_f.xlsx Overall daily dispatch profiles of technology groups (thermal, hydro etc.)

result_i.xlsx Daily dispatch profiles of each generators.

result_n.xlsx Node wise daily dispatch profiles of technology groups (thermal, hydro etc.), RE generation and curtailment over the year.

result_r.xlsx Region wise daily dispatch profiles of technology groups (thermal, hydro etc.), RE generation and curtailment over the year.

result_s.xlsx Model solve status for each day.

D.3.5 NIPSO Model Programs Written in GAMS

data_input.gms

```
*------------------------------------------------------------------*
data_input.gms
*------------------------------------------------------------------*
*                          Loading Data                            *
*------------------------------------------------------------------*

***From Excel Sheets

%Excel_dataload%$ontext

$call "gdxxrw %datadir%sets_mapping.xlsx Squeeze=N @%datadir%sets_mapping.txt o=%datadir%sets_mapping.gdx" ;
$gdxin %datadir%sets_mapping.gdx
$load  n, r, tech, f

$call "gdxxrw %datadir%gendata.xlsx Squeeze=N @%datadir%gendata.txt o=%datadir%gendata.gdx" ;
$gdxin %datadir%gendata.gdx
$load  h, g, ps, gendata_thermal, gendata_hydro, gendata_phs

$call "gdxxrw %datadir%busbusmap.xlsx Squeeze=N @%datadir%busbusmap.txt o=%datadir%busbusmap.gdx"
$gdxin %datadir%busbusmap.gdx
$load  busbusmap, susceptance, translim

$call "gdxxrw %datadir%genbusmaps.xlsx Squeeze=N @%datadir%genbusmaps.txt o=%datadir%genbusmaps.gdx" ;
$gdxin %datadir%genbusmaps.gdx
$load  genbusmap_phs, genbusmap_thermal, genbusmap_hydro

$call "gdxxrw %datadir%gentechmap.xlsx Squeeze=N @%datadir%gentechmap.txt o=%datadir%gentechmap.gdx" ;
$gdxin %datadir%gentechmap.gdx
$load  gentechmap_thermal, gentechmap_hydro

*$call "gdxxrw %datadir%lc.xlsx Squeeze=N @%datadir%demdata.txt o=%datadir%demdata.gdx" ;
*$gdxin %datadir%demdata.gdx
*$load  t, demdata

*$call "gdxxrw %datadir%regen.xlsx Squeeze=N @%datadir%regen.txt o=%datadir%regen.gdx" ;
*$gdxin %datadir%regen.gdx
*$load  sol_gen, wind_gen

$ontext
$offtext

***From GDX

%GDX_dataload%$ontext


$gdxin %datadir%busbusmap.gdx
$load n, busbusmap, susceptance, translim

$gdxin %datadir%gendata.gdx
```

```
$load    h, g, ps, gendata_thermal, gendata_hydro, gendata_phs

$gdxin %datadir%genbusmaps.gdx
$load  genbusmap_phs, genbusmap_thermal, genbusmap_hydro

$gdxin %datadir%gentechmap.gdx
$load  gentechmap_thermal, gentechmap_hydro

*$gdxin %datadir%demdata.gdx
*$load    t, demdata

*$gdxin %datadir%regen.gdx
*$load    sol_gen, wind_gen

$ontext
$offtext

*------------------------------------------------------------------*
*                         Data Processing                          *
*------------------------------------------------------------------*

*-------------------------thermal generator parameters-----------------------*
cost_marginal(g,t)       =       gendata_thermal(g,'Cost_Marginal');
cost_fixed(g)            =       gendata_thermal(g,'Cost_Fixed');
cost_startup(g)          =       gendata_thermal(g,'ST_Cost');
cost_shutdown(g)         =       gendata_thermal(g,'SD_Cost');
pmax_t(g)                =       gendata_thermal(g,'Pmax');
pmin_t(g)                =       gendata_thermal(g,'Pmin');
rampup_t(g)              =       gendata_thermal(g,'Ramp_Up');
rampdown_t(g)            =       gendata_thermal(g,'Ramp_Down');
minup_t(g)               =       gendata_thermal(g,'Up_Min');
mindown_t(g)             =       gendata_thermal(g,'Down_Min');
uptime_t(g)              =       gendata_thermal(g,'U0');
downtime_t(g)            =       gendata_thermal(g,'S0');
inistatus_t(g)           =       gendata_thermal(g,'Uini');




*------------------hydro generator parameters--------------------------------*
hyd_elim(h)              =       gendata_hydro(h,'Daily_Energy_Limit');
ramp_h(h)              =         gendata_hydro(h,'Ramp_Up');
hyd_pmax(h)              =       gendata_hydro(h,'Pmax');


*-------------------------Storage parameters-----------------------*
store_eff(ps)            =       gendata_phs(ps,'EFF');
store_cap(ps)            =       gendata_phs(ps,'Pmax');
store_en(ps)             =       gendata_phs(ps,'Daily_Storage');
```

setup.gms

```
*---------------------------*
*setup.gms
*-----------------------A Progrm for Day Ahead Unit Commitment of North Indian Power Grid-----------------------*
$ontext
*date: 27.03.2017
*Author: Partha Das
$offtext

*------------------------------------------------------------------------*
*                 SCALARS, SETS, ALIAS, and PARAMETERS                   *
*------------------------------------------------------------------------*

*------------------------------------------------------------------------*
*                              Sets                                      *
*------------------------------------------------------------------------*

SCALARS
vcl     value of lost load      /500000/
vcw     value of curtailed wind power   /50000/
vcs     value of curtailed pv power  /50000/
Sbase/100/ ;


*------------------------------------------------------------------------*
*                              Sets                                      *
*------------------------------------------------------------------------*
***for inputs

sets
t/t1*t25/
n
g        thermal power plants
h        hydro plants
ps       pumped hydro storage plants
tech     technology
f        fuel
r        regions
s/1*25/
char/ch1*ch2/
d/d1*d365/;

***for outputs

*------------------------------------------------------------------------*
*                              Aliases                                   *
*------------------------------------------------------------------------*

alias(t,tt);
alias(n,nn);

*------------------------------------------------------------------------*
*                        Defining Parameters                             *
*------------------------------------------------------------------------*
parameters
```

```
****for thermal generators
gendata_thermal(g,*)           thermal generators techncical characteristics
genbusmap_thermal(g,n)
gentechmap_thermal(g,f)
cost_marginal(g,t), cost_fixed(g), cost_startup(g), cost_shutdown(g), pmax_t(g), pmin_t(g)
rampup_t(g), rampdown_t(g), minup_t(g), mindown_t(g), uptime_t(g), downtime_t(g), inistatus_t(g)

***for hydro generators
gendata_hydro(h,*)               hydro generators' technical charateristics
genbusmap_hydro(h,n)
gentechmap_hydro(h,f)
hyd_pmax(h)
hyd_elim(h)
ramp_h(h)

***for pumped storage
gendata_phs(ps,*)               pumped hydro storage plants technical characteristics
genbusmap_phs(ps,n)
store_cap(ps)
store_eff(ps)
store_en(ps)

***for transmission lines

busbusmap(n,nn)        mapping a bus to another bus
susceptance(n,nn)       suceptance (B) matrix
translim(n,nn)           transmission limit on lines

***for demand

demdata(t,n)

***for RE generation

sol_gen(t,n)             solar PV hourly generation input
wind_gen(t,n)            wind hourly genration input

hydro_daywise(h,*)
hydro_dlim(h)

scalar Tload1/0/;
```

model.gms

```
*----------------------------------------------------------------------*
*     model.gms
*----------------------------------------------------------------------*
*----------------------------------------------------------------------*
*                             Variables                                *
*----------------------------------------------------------------------*

variables

cost            dispatch cost
```

```
flow(n,nn,t)     power flow between buses
delta(n,t)       bus voltage angle
pg_s
ph_s
store_g_s
sg_s
wg_s ;

positive variables

pg(g,t)                 thermal generator output at time t
generation_cost(g,t)    cost of generation
startup_cost(g,t)       start up cost
shutdown_cost(g,t)      shut down cost
ph(h,t)                 hydro generator output at time t
c_su(g,t)               thermal generator start up cost
c_sd(g,t)               thermal generator shut down cost
level(ps,t)             energy level in pump storage ps in hour t
store_g(ps,t)           power generation at time t
store_p(ps,t)           power pumped at time t
c_l(n,t)                curtailed load
sg(n,t)                 generated PV power
wg(n,t)                 generated wind power
c_w(n,t)
c_s(n,t);

Binary variables

v(g,t)           thermal unit committed status
y(g,t)           thermal unit started status
z(g,t)           thermal unit shut-down status
scs(ps,t)        storage charging status
sds(ps,t)        storage discharging status;

*--------------------------------------------------------------------*
*                            Equations                               *
*--------------------------------------------------------------------*

Equations

objective        objective function
*objective2

*equations for thermal units.....

st_cost          startup cost of thermal generators
sd_cost          shut down cost of thermal generators
gen_cost         fuel cost of thermal generators
energybalance    balance of supply and demand at each and at each hour
mingen_t         minimum generation limit of thermal generators
maxgen_t         maximum generation limit of thermal generatorss
rampu_t          ramp up limit of thermal generators
rampd_t          ramp down limit of thermal generators
uptime1
uptime2
```

```
uptime3
downtime1
downtime2
downtime3

binaryrelation   relations between binary variables
binaryrelation2   relations between binary variables


*equations for lines flows.......
lineflow         line flow on transmission lines
linecap_pos      upper limit (+) line flow
linecap_neg      lower limit (-) line flow
deltadiff_max    bus angle difference maximum limit
deltadiff_min    bus angle difference minimum limit


*equations for loasd, wind ,solar limits............
lim_c_l          load-shedding upper bound
lim_wingen       wind generation schedule upper bound
lim_solgen       solar generation schedule upper bound

*equations for hydro units...........................
hyd_lim          hydro plant daily energy limit
rampu_h         ramp up limit of hydro generators
rampd_h         ramp down limit of hydro generators
maxgen_h         maxgen generation limit of hydro generators

storage1         pumped-storage pumping limit
storage2         pumped-storage pumping limit
storage3         pumped-storage generation limit
storage4         pumped-storage generation limit
storage5         pumped-storage level (SOC)
storage6         pumped-storage stauts ;
*eq61, eq62, eq63, eq64, eq65, eq66, eq67;


scalar gen_t1 /0/;
scalar gen_h1 /0/;
scalar gen_ps1 /0/;
scalar gen_sn1 /0/;
scalar gen_wn1 /0/;

parameter bt(n,nn);

busbusmap(n,nn)$(busbusmap(nn,n))=1;
busbusmap(n,nn)$(translim(n,nn)and translim(nn,n))=1;
susceptance(n,nn)$(susceptance(n,nn)=0)=susceptance(nn,n);
translim(n,nn)$(translim(n,nn)=0)=translim(nn,n);
bt(n,nn)$translim(n,nn)=1/susceptance(n,nn);


objective..             cost    =e=     sum((g,t),generation_cost(g,t)+startup_cost(g,t)+shutdown_cost(g,t) )
+ sum((n,t),vcl*c_l(n,t))+sum((n,t),vcw*c_w(n,t))+sum((n,t),vcs*c_s(n,t));
```

```
st_cost(g,t)..          startup_cost(g,t)       =e=     cost_startup(g)*y(g,t)  ;
sd_cost(g,t)..          shutdown_cost(g,t)      =e=     cost_shutdown(g)*z(g,t)       ;
gen_cost(g,t)..         generation_cost(g,t)    =e=     cost_fixed(g)*v(g,t)+cost_marginal(g,t)*pg(g,t) ;

energybalance(n,t)..    sum(g, pg(g,t)*genbusmap_thermal(g,n)) +
sum(h, ph(h,t)*genbusmap_hydro(h,n)) + sum(ps, store_g(ps,t)*genbusmap_phs(ps,n))
+ sg(n,t) + wg(n,t)+sum(nn, busbusmap(n,nn)*flow(n,nn,t))
=e=     demdata(t,n)-c_l(n,t) + sum(ps, store_p(ps,t)*genbusmap_phs(ps,n))       ;

mingen_t(g,t)..         pg(g,t) =g=     pmin_t(g)*v(g,t)        ;
maxgen_t(g,t)..         pg(g,t) =l=     pmax_t(g)*v(g,t)        ;

rampu_t(g,t)$(ord(t)>1)..          pg(g,t)-pg(g,t-1)      =l=     rampup_t(g)*v(g,t-1) + pmin_t(g)*y(g,t)   ;
rampd_t(g,t)$(ord(t)>1)..          pg(g,t-1)-pg(g,t)      =l=     rampdown_t(g)*v(g,t) + pmin_t(g)*z(g,t)   ;



****minimum up and down timr........................................................
Parameter unit(g,char);
unit(g,'ch1')=25;
unit(g,'ch2')=(minup_t(g)-uptime_t(g))*inistatus_t(g) ;
gendata_thermal(g,'Lj')=smin(char,unit(g,char));


Parameter unit2(g,char);
unit2(g,'ch1')=25;
unit2(g,'ch2')=(mindown_t(g)-downtime_t(g))*(1-inistatus_t(g));
gendata_thermal(g,'Fj')=smin(char,unit2(g,char));

****up time equations
uptime1(g)$(gendata_thermal(g,'Lj')>0)..
sum(t$(ord(t)<(gendata_thermal(g,'Lj')+1)),1-v(g,t))=e=0;

uptime2(g)$(minup_t(g)>1)..
sum(t$(ord(t)>25-minup_t(g)+1),v(g,t)-y(g,t))=g=0;

uptime3(g,t)$(ord(t)>gendata_thermal(g,'Lj') and
ord(t)<25-minup_t(g)+2 and not(gendata_thermal(g,'Lj')>25-minup_t(g)))..
sum(tt$((ord(tt)>ord(t)-1) and (ord(tt)<ord(t)+minup_t(g))),v(g,tt))=g=minup_t(g)*y(g,t);


****down time equations
downtime1(g)$(gendata_thermal(g,'Fj')>0)..
sum(t$(ord(t)<(gendata_thermal(g,'Fj')+1)),v(g,t))=e=0;

downtime2(g)$(mindown_t(g)>1)..
sum(t$(ord(t)>25-mindown_t(g)+1),1-v(g,t)-z(g,t))=g=0;

downtime3(g,t)$(ord(t)>gendata_thermal(g,'Fj') and ord (t)<25-mindown_t(g)+2
and not(gendata_thermal(g,'Fj')>25-mindown_t(g)))..
sum(tt$((ord(tt)>ord(t)-1) and (ord(tt)<ord(t)+mindown_t(g))),1-v(g,tt))=g=
mindown_t(g)*z(g,t);

binaryrelation(g,t)$(ord(t)>0)..   v(g,t)=e=v(g,t-1)$(ord(t)>1)+
```

```
inistatus_t(g)$(ord(t)=1)+y(g,t)-z(g,t);
binaryrelation2(g,t)..            y(g,t)+z(g,t)   =l=     1;

****line flow equations.....


lineflow(n,nn,t)$(busbusmap(n,nn) eq 1)..        flow(n,nn,t)    =e=     -bt(n,nn)*(delta(n,t)-delta(nn,t))*Sbase     ;
deltadiff_max(n,nn,t)..                          delta(n,t)-delta(nn,t)  =l= pi/3        ;
deltadiff_min(n,nn,t)..                          delta(n,t)-delta(nn,t)  =g= -pi/3        ;

linecap_pos(n,nn,t)$(busbusmap(n,nn) eq 1)..     flow(n,nn,t)    =l=     translim(n,nn);
linecap_neg(n,nn,t)$(busbusmap(n,nn) eq 1)..     flow(n,nn,t)    =g=     -translim(n,nn);




****load, wind and solar limits........,
lim_c_l(t,n)..                                    c_l(n,t)        =l=     demdata(t,n)    ;
lim_wingen(t,n)..                                wg(n,t)+c_w(n,t) =e=     wind_gen(t,n)   ;
lim_solgen(t,n)..                                sg(n,t)+c_s(n,t) =e=     sol_gen(t,n)    ;

***for hydro
hyd_lim(h)..                                      sum(t,ph(h,t))        =l=     hydro_dlim(h)   ;
rampu_h(h,t)$(ord(t)>1)..                        ph(h,t)-ph(h,t-1)       =l=     ramp_h(h)       ;
rampd_h(h,t)$(ord(t)>1)..                        ph(h,t-1)-ph(h,t)       =l=     ramp_h(h)       ;
maxgen_h(h,t)..                                  ph(h,t)                 =l=     hyd_pmax(h)     ;

***for Storage

storage1(ps,t)..              store_p(ps,t)       =l=     store_cap(ps)*scs(ps,t);
storage2(ps,t)..              store_p(ps,t)       =g=     0.01*store_cap(ps)*scs(ps,t);
storage3(ps,t)..              store_g(ps,t)       =l=     store_cap(ps)*sds(ps,t);
storage4(ps,t)..              store_g(ps,t)       =g=     0.01*store_cap(ps)*sds(ps,t);
level.up(ps,t)        =      store_en(ps);
level.lo(ps,t)        =      store_en(ps)*0.2;
level.fx(ps,'t1')     =      store_en(ps)*0.2;
storage5(ps,t)$(ord(t)>1)..   level(ps,t)         =e=     level(ps,t-1) +(store_p(ps,t)*store_eff(ps)-store_g(ps,t));
storage6(ps,t)..              scs(ps,t)+sds(ps,t)  =l=     1;

display gendata_phs, gendata_thermal, gendata_hydro  ;
display genbusmap_phs, genbusmap_thermal, genbusmap_hydro        ;
display n, h, g, ps, busbusmap, susceptance                       ;
```

mapping.gms

```
*-----------------------------------------------------
* mapping.gms
*-----------------------------------------------------

set      mapping(n,r) mapping op nodes to TIMES zones
/
CH_CH_01        .       CH
DL_BA_02        .       DL
```

```
HP_CH_03        .       HP
HP_KR_04        .       HP
HP_NA_05        .       HP
HR_AB_06        .       HR
HR_BA_07        .       HR
HR_BI_08        .       HR
JK_NI_09        .       JK
JK_KI_10        .       JK
JK_WA_11        .       JK
PB_JH_12        .       PB
PB_PA_13        .       PB
RJ_BK_14        .       RJ
RJ_BM_15        .       RJ
RJ_BS_16        .       RJ
RJ_JO_17        .       RJ
RJ_KO_18        .       RJ
RJ_KR_19        .       RJ
RJ_RA_20        .       RJ
RJ_SI_21        .       RJ
UT_KA_22        .       UT
UT_RI_23        .       UT
UU_AD_24        .       UU
UU_AG_25        .       UU
UU_BL_26        .       UU
UU_BN_27        .       UU
UU_KP_28        .       UU
UU_LU_29        .       UU
UU_ME_30        .       UU
UU_RH_31        .       UU/;

alias (n,nn)   ;

display  mapping ;
```

ni_uc.gms

```
*-------------------------------------------------------------------------*
* ni_uc.gms
*-------------------------------------------------------------------------*
*                             Global options                               *
*-------------------------------------------------------------------------*
* Set star to either use excel or gdx dataload
$setglobal datadir       data\
$setglobal result       result_\
$setglobal Excel_dataload "*"
$setglobal GDX_dataload ""

*-------------------------------------------------------------------------*
*                             Solver options                               *
*-------------------------------------------------------------------------*

options
reslim = 1000000000 ;
*-------------------------------------------------------------------------*
```

```
*                              Execution                           *
*------------------------------------------------------------------*

*Include the following GAMS files
$include setup.gms
$include data_input.gms
$include mapping.gms
$include model.gms

delta.fx('UU_RH_31',t)=0;

****Solve and output*****************************************************

parameter iter, k(g,s,*), value(g,*), count(g,*), ut(g,*), statussolver(d),statusmodels(d);

count(g,'us')=0;
count(g,'ds')=0;
ut(g,'u')=0;
ut(g,'d')=0;

$set xls C:\Users\Administrator\Documents\gamsdir\new_final_model_Hydro_exp8\d_solar.xlsx
$set gdx  sol_gen.gdx

file cd /task21.txt/;

$set xls C:\Users\Administrator\Documents\gamsdir\new_final_model_Hydro_exp8\d_wind.xlsx
$set gdx  wind_gen.gdx

file ab /task11.txt/;

$set xls C:\Users\Administrator\Documents\gamsdir\new_final_model_Hydro_exp8\d_load.xlsx
$set gdx  demdata.gdx

file ef /task31.txt/;

$set xls C:\Users\Administrator\Documents\gamsdir\new_final_model_Hydro_exp8\hydro_d.xlsx
$set gdx  hydro_daywise.gdx

file gh /task41.txt/;

$set xls C:\Users\Administrator\Documents\gamsdir\new_final_model_Hydro_exp8\Tload_d.xlsx
$set gdx  Tload_d.gdx

file ij /task51.txt/;

model NI_UC /all/;

* Solver options
$onecho>cplex.opt
scaind 0
rerun yes
iis yes
lpmethod 4
baralg 1
barcrossalg 1
```

```
barorder 2
parallelmode 0
threads -1
$offecho

ni_uc.optfile=1;

parameter       gen_tn(d,n,t)    total thermal generation by node
gen_hn(d,n,t)     total hydro generation by node
gen_psn(d,n,t)    total stoarge generation by node
pump_psn(d,n,t)   total stoarge charging by node
gen_sn(d,n,t)     total solar generation by node
gen_wn(d,n,t)     total wind generation by node
cur_sn(d,n,t)     total solar curtailment by node
cur_wn(d,n,t)     total wind curtailment by node
cur_ln(d,n,t)     total load curtailment by node
load(d,n,t)       total load by node
gen_tr(d,r,t)     total thermal generation by region
gen_hr(d,r,t)     total hydro generation by region
gen_sr(d,r,t)     total solar genration by region
gen_wr(d,r,t)     total wind generation by region
re_share(r)       total RE share by region
cur_lr(d,r,t)     total load sheding by region
flow_n (d,n,t)
pump_psr(d,r,t)
gen_psr(d,r,t)
cur_sr(d,r,t)
cur_wr(d,r,t)
loadr(d,r,t)
gen_t(d,g,t)
gen_h(d,h,t)
gen_ps(d,ps,t)
pump_ps(d,ps,t)
gen_tf(d,f,t)
gen_hf(d,f,t)
gen_tf_t
gen_hf_t;

loop(d,

putclose cd, 'par=sol_gen rng='d.tl:0,'!a1 rdim=1 cdim=1'/
execute 'gdxxrw input=d_solar.xlsx output=sol_gen.gdx @task21.txt trace=2';
execute_loaddc 'sol_gen.gdx', sol_gen;
display sol_gen;

putclose ab,'par=wind_gen rng=',d.tl:0,'!b1 rdim=1 cdim=1'/
execute 'gdxxrw input=d_wind.xlsx output=wind_gen.gdx @task11.txt trace=2';
execute_loaddc 'wind_gen.gdx',wind_gen;
display wind_gen;

putclose ef,'par=demdata rng=',d.tl:0,'!a1 rdim=1 cdim=1'/
execute 'gdxxrw input=d_load.xlsx output=demdata.gdx @task31.txt trace=2';
execute_loaddc 'demdata.gdx',demdata;
display demdata;
```

```
putclose gh, 'par=hydro_daywise rng='d.tl:0,'!a1 rdim=1 cdim=1'/
execute 'gdxxrw input=hydro_d.xlsx output=hydro_daywise.gdx @task41.txt trace=2';
execute_loaddc 'hydro_daywise.gdx',hydro_daywise;
display hydro_daywise;

hydro_dlim(h)  = hydro_daywise(h,'Daily_Energy_Limit');
display hydro_dlim;

solve NI_UC using mip minimising cost;

statussolver(d)=NI_UC.solvestat;
statusmodels(d)=NI_UC.modelstat;


gen_t(d,g,t)       = pg.l(g,t);
gen_h(d,h,t)       = ph.l(h,t);
gen_ps(d,ps,t)      = store_g.l(ps,t);
pump_ps(d,ps,t)     = store_p.l(ps,t);


gen_tf(d,f,t)    =  sum(g$gentechmap_thermal(g,f),pg.l(g,t));
gen_hf(d,f,t)    =  sum(h$gentechmap_hydro(h,f),ph.l(h,t));


gen_tn(d,n,t)    =  sum(g$genbusmap_thermal(g,n),pg.l(g,t));
gen_hn(d,n,t)    =  sum(h$genbusmap_hydro(h,n),ph.l(h,t));
gen_psn(d,n,t)   =  sum(ps$genbusmap_phs(ps,n),store_g.l(ps,t));
pump_psn(d,n,t)  =  sum(ps$genbusmap_phs(ps,n),store_p.l(ps,t));
gen_sn(d,n,t)    =  sg.l(n,t);
gen_wn(d,n,t)    =  wg.l(n,t);
cur_sn(d,n,t)    =  c_s.l(n,t);
cur_wn(d,n,t)    =  c_w.l(n,t);
cur_ln(d,n,t)    =  c_l.l(n,t);
load(d,n,t)      =  demdata(t,n);
flow_n(d,n,t)    =  sum(nn$busbusmap(n,nn),flow.l(n,nn,t));

gen_tr(d,r,t)    =  sum(n$mapping(n,r),gen_tn(d,n,t));
gen_hr(d,r,t)    =  sum(n$mapping(n,r),gen_hn(d,n,t));
gen_psr(d,r,t)   =  sum(n$mapping(n,r),gen_psn(d,n,t));
pump_psr(d,r,t)  =  sum(n$mapping(n,r),pump_psn(d,n,t));
gen_sr(d,r,t)    =  sum(n$mapping(n,r),gen_sn(d,n,t));
gen_wr(d,r,t)    =  sum(n$mapping(n,r),gen_wn(d,n,t));
cur_sr(d,r,t)    =  sum(n$mapping(n,r),cur_sn(d,n,t));
cur_wr(d,r,t)    =  sum(n$mapping(n,r),cur_wn(d,n,t));
loadr(d,r,t)     =  sum(n$mapping(n,r),load(d,n,t));
cur_lr(d,r,t)    =  sum(n$mapping(n,r),cur_ln(d,n,t));

gen_t(d,g,t)$(Not gen_t(d,g,t))=EPS;
gen_h(d,h,t)$(Not gen_h(d,h,t))=EPS;
gen_ps(d,ps,t)$(Not gen_ps(d,ps,t))=EPS;
pump_ps(d,ps,t)$(Not pump_ps(d,ps,t))=EPS;

gen_tf(d,f,t)$(Not gen_tf(d,f,t))=EPS;
gen_hf(d,f,t)$(Not gen_hf(d,f,t))=EPS;
```

```
gen_tn(d,n,t)$(Not gen_tn(d,n,t))=EPS;
gen_hn(d,n,t)$(Not gen_hn(d,n,t))=EPS;
gen_psn(d,n,t)$(Not gen_psn(d,n,t))=EPS;
pump_psn(d,n,t)$(Not pump_psn(d,n,t))=EPS;
gen_sn(d,n,t)$(Not gen_sn(d,n,t))=EPS;
gen_wn(d,n,t)$(Not gen_wn(d,n,t))=EPS;
cur_sn(d,n,t)$(Not cur_sn(d,n,t))=EPS;
cur_wn(d,n,t)$(Not cur_wn(d,n,t))=EPS;
cur_ln(d,n,t)$(Not cur_ln(d,n,t))=EPS;
load(d,n,t)$(Not load(d,n,t))=EPS;

gen_tr(d,r,t)$(Not gen_tr(d,r,t))=EPS;
gen_hr(d,r,t)$(Not gen_hr(d,r,t))=EPS;
gen_sr(d,r,t)$(Not gen_sr(d,r,t))=EPS;
gen_wr(d,r,t)$(Not gen_wr(d,r,t))=EPS;
cur_lr(d,r,t)$(Not cur_lr(d,r,t))=EPS;
gen_psr(d,r,t)$(Not gen_psr(d,r,t))=EPS;
pump_psr(d,r,t)$(Not pump_psr(d,r,t))=EPS;
cur_sr(d,r,t)$(Not cur_sr(d,r,t))=EPS;
cur_wr(d,r,t)$(Not cur_wr(d,r,t))=EPS;
loadr(d,r,t)$(Not loadr(d,r,t))=EPS;

display gen_t, gen_h, gen_ps, pump_ps;
display  gen_tn, gen_hn, gen_psn, pump_psn, gen_sn, gen_wn, cur_sn, cur_wn, cur_ln, load, flow_n;
display gen_tf, gen_hf;
display  gen_tr, gen_hr, gen_sr, gen_wr, cur_lr, gendata_thermal,cur_sr, cur_wr ;


gendata_thermal(g,'Uini')=v.l(g,'t25');
inistatus_t(g)=gendata_thermal(g,'Uini');
Pg.fx(g,'t1')=Pg.l(g,'t25');
ph.fx(h,'t1')=ph.l(h,'t25');
c_l.fx(n,'t1')=c_l.l(n,'t25');
sg.fx(n,'t1')=sg.l(n,'t25');
wg.fx(n,'t1')=wg.l(n,'t25');
c_w.fx(n,'t1')=c_w.l(n,'t25');
c_s.fx(n,'t1')=c_s.l(n,'t25');
store_p.fx(ps,'t1')=store_p.l(ps,'t25');
store_g.fx(ps,'t1')=store_g.l(ps,'t25');
level.fx(ps,'t1')=level.l(ps,'t25');

*to store the unit status in parameter k in reverse order

loop(t,
loop(s,
if(ord(s)<=(26-ord(t)),
k(g,s,'us')=v.l(g,t)$(26-ord(t)eq ord(s));
);
);
);
display v.l,k;


*to count the consecutive 1's of parameter k to set as start time of previous day - U0
```

```
iter=2;
loop(g,
while((iter le card(s)),
value(g,'us')=Sum(s,k(g,s,'us')$(ord(s)=iter));
if( value(g,'us')=1,
count(g,'us')=count(g,'us')+1;
else iter=card(s);
);
iter=iter+1;
);
iter=2;
);
loop(g,
if(count(g,'us')=0,
ut(g,'u')=0;
elseif (count(g,'us')=24),
ut(g,'u')= ut(g,'u')+ count(g,'us');
else
ut(g,'u')= count(g,'us');
);
);
gendata_thermal(g,'U0')=ut(g,'u');
uptime_t(g)=gendata_thermal(g,'U0');

unit(g,'ch1')=25;
unit(g,'ch2')=(minup_t(g)-uptime_t(g))*inistatus_t(g);
gendata_thermal(g,'Lj')=smin(char,unit(g,char));


*to count the consecutive 0's of parameter k to set as stop time of previous day - S0
iter=2;
loop(g,
while((iter le card(t)),
value(g,'us')=Sum(s,k(g,s,'us')$(ord(s)=iter));
if( value(g,'us')=0,
count(g,'ds')=count(g,'ds')+1;
else iter=card(s);
);
iter=iter+1;
);
iter=2;
);
loop(g,
if(count(g,'ds')=0,
ut(g,'d')=0;
elseif (count(g,'ds')=24),
ut(g,'d')= ut(g,'d')+ count(g,'ds');
else
ut(g,'d')= count(g,'ds');
);
);
gendata_thermal(g,'S0')=ut(g,'d');
downtime_t(g)=gendata_thermal(g,'S0');

unit2(g,'ch1')=25;
```

```
unit2(g,'ch2')=(mindown_t(g)-downtime_t(g))*(1-inistatus_t(g));
gendata_thermal(g,'Fj')=smin(char,unit2(g,char));
display count, ut;

count(g,'us')=0;
count(g,'ds')=0;

);

gen_tf_t(f)=sum((d,t),gen_tf(d,f,t));
gen_hf_t(f)=sum((d,t),gen_hf(d,f,t));

display gen_tf_t, gen_hf_t

execute_unload "%result%result_f.gdx" gen_tf, gen_hf
execute_unload "%result%result_s.gdx" statussolver, statusmodels
execute_unload "%result%result_i.gdx" gen_t, gen_h, gen_ps, pump_ps
execute_unload "%result%result_n.gdx" gen_tn, gen_hn, gen_psn, pump_psn, gen_sn, gen_wn,
cur_sn, cur_wn, cur_ln, load, flow_n, gen_tr, gen_hr, gen_psr, pump_psr, gen_sr, gen_wr,
cur_sr, cur_wr, loadr, cur_lr
execute_unload "%result%result_r.gdx" gen_tr, gen_hr, gen_psr, pump_psr, gen_sr, gen_wr,
 cur_sr, cur_wr, loadr, cur_lr


*execute 'gdxxrw.exe %result%result_t.gdx O= %result%result_t.xlsx par=ren_pnt1    Squeeze=N   rng=ren!a1'
execute 'gdxxrw.exe %result%result_i.gdx O= %result%result_i.xlsx par=gen_t    Squeeze=N   rng=thermal_i!a1'
execute 'gdxxrw.exe %result%result_i.gdx O= %result%result_i.xlsx par=gen_h    Squeeze=N   rng=hydro_i!a1'
execute 'gdxxrw.exe %result%result_i.gdx O= %result%result_i.xlsx par=gen_ps   Squeeze=N   rng=stogen_i!a1'
execute 'gdxxrw.exe %result%result_i.gdx O= %result%result_i.xlsx par=pump_ps  Squeeze=N   rng=stopum_i!a1'

execute 'gdxxrw.exe %result%result_n.gdx O= %result%result_n.xlsx par=gen_tn   Squeeze=N   rng=thermal_n!a1'
execute 'gdxxrw.exe %result%result_n.gdx O= %result%result_n.xlsx par=gen_hn   Squeeze=N   rng=hydro_n!a1'
execute 'gdxxrw.exe %result%result_n.gdx O= %result%result_n.xlsx par=gen_psn  Squeeze=N   rng=stogen_n!a1'
execute 'gdxxrw.exe %result%result_n.gdx O= %result%result_n.xlsx par=pump_psn Squeeze=N   rng=stopum_n!a1'
execute 'gdxxrw.exe %result%result_n.gdx O= %result%result_n.xlsx par=gen_sn   Squeeze=N   rng=solgen_n!a1'
execute 'gdxxrw.exe %result%result_n.gdx O= %result%result_n.xlsx par=gen_wn   Squeeze=N   rng=wingen_n!a1'
execute 'gdxxrw.exe %result%result_n.gdx O= %result%result_n.xlsx par=cur_sn   Squeeze=N   rng=solcur_n!a1'
execute 'gdxxrw.exe %result%result_n.gdx O= %result%result_n.xlsx par=cur_wn   Squeeze=N   rng=wincur_n!a1'
execute 'gdxxrw.exe %result%result_n.gdx O= %result%result_n.xlsx par=cur_ln   Squeeze=N   rng=lodcur_n!a1'
execute 'gdxxrw.exe %result%result_n.gdx O= %result%result_n.xlsx par=load     Squeeze=N   rng=load_n!a1'
execute 'gdxxrw.exe %result%result_n.gdx O= %result%result_n.xlsx par=flow_n   Squeeze=N   rng=flow_n!a1'

execute 'gdxxrw.exe %result%result_r.gdx O= %result%result_r.xlsx par=gen_tr   Squeeze=N   rng=thermal_r!a1'
execute 'gdxxrw.exe %result%result_r.gdx O= %result%result_r.xlsx par=gen_hr   Squeeze=N   rng=hydro_r!a1'
execute 'gdxxrw.exe %result%result_r.gdx O= %result%result_r.xlsx par=gen_psr  Squeeze=N   rng=stogen_r!a1'
execute 'gdxxrw.exe %result%result_r.gdx O= %result%result_r.xlsx par=pump_psr Squeeze=N   rng=stopum_r!a1'
execute 'gdxxrw.exe %result%result_r.gdx O= %result%result_r.xlsx par=gen_sr   Squeeze=N   rng=solgen_r!a1'
execute 'gdxxrw.exe %result%result_r.gdx O= %result%result_r.xlsx par=gen_wr   Squeeze=N   rng=wingen_r!a1'
execute 'gdxxrw.exe %result%result_r.gdx O= %result%result_r.xlsx par=cur_sr   Squeeze=N   rng=solcur_r!a1'
execute 'gdxxrw.exe %result%result_r.gdx O= %result%result_r.xlsx par=cur_wr   Squeeze=N   rng=wincur_r!a1'
execute 'gdxxrw.exe %result%result_r.gdx O= %result%result_r.xlsx par=cur_lr   Squeeze=N   rng=lodcur_r!a1'
execute 'gdxxrw.exe %result%result_r.gdx O= %result%result_r.xlsx par=loadr    Squeeze=N   rng=load_r!a1'


execute 'gdxxrw.exe %result%result_s.gdx O= %result%result_s.xlsx par=statussolver    Squeeze=N   rng=solv_s!a1'
```

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execute 'gdxxrw.exe %result%result_s.gdx O= %result%result_s.xlsx par=statusmodels    Squeeze=N   rng=mode_s!a1'

execute 'gdxxrw.exe %result%result_f.gdx O= %result%result_f.xlsx par=gen_tf   Squeeze=N   rng=thermal_f!a1'
execute 'gdxxrw.exe %result%result_f.gdx O= %result%result_f.xlsx par=gen_hf   Squeeze=N   rng=hydro_f!a1'
```