OPTIMIZING HVAC CONTROL SYSTEM STRATEGY BY USING MULTI-OBJECTIVE GENETIC ALGORITHMS

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By

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DECLARATION

I hereby declare that the dissertation which is being presented in this report entitled **"OPTIMIZING HVAC CONTROL SYSTEM STRATEGY BY USING MULTI-OBJECTIVE GENETIC ALGORITHMS"** in fulfillment of the requirement of degree of Master of Technology and submitted to Department of Mechanical Engineering, Malaviya National Institute of Technology, Jaipur is an authentic record of my own work carried out during a period from July 2014 to June 2015 under the supervision of **Dr. Nirupam Rohatgi**, Associate Professor, Department of Mechanical Engineering, Malaviya National Institute of Technology Jaipur.

The results contained in this thesis have not been submitted, in part or full, to any other university or institute for the award of any degree or diploma.

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CERTIFICATE

This is to certify that the dissertation entitled, **"OPTIMIZING HVAC CONTROL SYSTEM STRATEGY BY USING MULTI-OBJECTIVE GENETIC ALGORITHMS"** being submitted by **Jermy Varghese Thomas** to the Department of Mechanical Engineering, Malaviya National Institute of Technology Jaipur for the award of the degree of **Master of Technology** is a bona fide record of work carried out by him under my supervision and guidance.

The results contained in this thesis have not been submitted, in part or full, to

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ABSTRACT

In developed countries, energy consumption of HVAC systems account for approximately twenty percent of the total energy consumption. Set-points of HVAC systems are usually controlled manually and may result in poor thermal comfort and increased energy demand. Optimizing HVAC control system strategy using genetic algorithms is attempted in this work.

An HVAC model developed from elementary equations is studied. The model has four set-points (Zone Temperature, Supply Air Temperature, Supply Duct Static Pressure and Chilled Water Temperature) as the variables which determine the total energy demand and thermal comfort (in the form of PPD) of the system. As energy demand and PPD are contradicting functions, ordered combinations of these set-points which will result in least value of energy demand and PPD (pareto-optimal solutions) are found using a multi-objective genetic algorithm called the NSGA-II. The findings are analyzed and the effect of variations of different set-points in the pareto-optimal solutions on energy demand and PPD are understood. A new model which also incorporated reheat was designed, optimized and analyzed in a similar fashion. Further, another genetic algorithm, Omni-optimizer, was also used to optimize the initial model and the changes which were observed are stated.

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Nomenclature

Tz_i	Zone Air Temperature
P_s	Supply Duct Static Pressure
T_s	Supply Air Temperature
T_W	Chiller Water Temperature
$\dot{W}_t$	Total Energy Demand
$\dot{W}_f$	Fan Energy Demand
$\dot{W}_C$	Chiller Energy Demand
H_s	Saturation Enthalpy
H_T	Enthalpy of Supply Air
M	Metabolic Rate
W	External Work
p_a	Partial Water Vapor Pressure
f_{cl}	Ratio of man's surface area while clothed to surface area while nude
h_c	Convective Heat Transfer Coefficient
t_{cl}	Surface Temperature of Clothing
t_r	Mean Radiant Temperature
p_c	Crossover Probability
p_m	Mutation Probability
$\dot{W}_{Rh}$	Reheat Energy Demand
ϕ_Z	Relative Humidity

Chapter 1

INTRODUCTION

1.1 Background

We live in a day and age where air conditioning systems have changed from a non-essential appliance to a crucial necessity for humans around the globe. These systems have made human habitation and development possible in the most adverse of places. From the dry deserts of Sudan to the marshes of the Sunderbans to the icy deserts of Antarctica, air conditioning systems have helped bring conditions prevalent at home to almost anywhere on the globe. Air conditioning is defined by the Merriam-Webster Dictionary as equipping a building with an apparatus for washing air and controlling the temperature and humidity of the air.

Heating, Ventilation and Air Conditioning (HVAC) systems are used for heating and/or cooling of homes, offices and industrial buildings. HVAC systems are also responsible for allowing adequate supply of fresh outdoor air to manage the increasing carbon dioxide concentration inside buildings as well as to dilute airborne contaminants inside the buildings such as odors from occupants, furnishings, volatile organic compounds (VOC's), vapors of chemicals used for cleaning, etc. As long as the design is proper, an HVAC system can provide indoor comfort conditions throughout the year when it is maintained properly.

An air conditioner works by passing the air over a cold coil surface, which cools and dehumidifies the air. The coil inside the air conditioner is an air to liquid heat exchanger, in which there are rows of tubes through which the cooling liquid or refrigerant flows. The overall surface area of the coil is also increased by the use of fins, thus helping to improve the heat transfer between the air and refrigerant inside the coil. The type of system determines which refrigerant is to be used. In Direct-expansion (DX) cooling coils, the refrigerant is in the liquid state. Chilled-water (CW) is also sometimes used as a liquid medium refrigerant. If the operating temperature of a chilled water system is close to the freezing point of water, salts and glycols are added to the water to protect it from freezing. The cooling coil would be cooled by a liquid delivered to it at cold temperature, whatever the refrigerant used.

As air passes over the cooling coils in a direct expansion (DX) coil system, the heat from the air is transferred to the cold liquid refrigerant. As the refrigerant heats up, it boils and vaporizes into a warm gas. This gaseous refrigerant is pumped to a compressor, where it is compressed and the pressure of the refrigerant increases. An accumulator between the cooling coils and the compressor can capture the unused liquid refrigerant, thus allowing only the vapor to enter the compressor. As the pressure of the refrigerant increases in the compressor, the temperature of the refrigerant also increases significantly. This hot refrigerant gas is then pumped through another heat exchanger (outdoor condenser) where the heat is rejected to the outside environment, condensing the gas into a liquid at high pressure. The liquid refrigerant is then pumped through a filter into an expansion device which reduced the pressure and the temperature of the liquid refrigerant. This cold, low pressure liquid enters the cooling coil, repeating the above process.

As the cold liquid refrigerant moves inside the cooling coil, the air passing over the coil loses both sensible heat as well as latent heat. This means that the temperature of the air is lowered and also, the moisture in the air is decreased if the dew point of the air is lower than the surface temperature of the coils. The total cooling capacity of an Air conditioning system is expressed as the sum of the sensible and latent cooling capacities. The cooling capacity of a DX air conditioner depends on many factors. As the outdoor temperature increases, the cooling load on the air conditioning system increases, thus decreasing the cooling. The total air flowing over the cooling coils also affects the capacity of the coil and as the flow increases, the capacity of the system increases. But, when flow rate of is higher, the latent heat removing capacity of the cooling coil is reduced. The capacity of the AC system is also affected by the Indoor temperature and humidity. The sensible capacity increases as the indoor temperature increases. Similarly, the latent capacity of the AC system increases as the indoor relative humidity increases. The Air conditioners available commercially usually come with performance charts which show how the total, sensible and latent load handling capacity of the Air conditioner vary with changes in outdoor, indoor temperatures and humidity. They also show how these variations affect the power consumption and efficiency of the air conditioner.

HVAC has the largest energy end use, in the residential as well as non-residential sectors [1]. In USA, HVAC systems consume more than half of the total energy usage total buildings. Approximately one fifth of the total national energy use of all developing nations is consumed by HVAC systems. The efficiency of HVAC systems are specified in terms of

Energy Efficiency Ratio (EER) which is the ratio of the cooling output for a particular season to the energy input during the same period.

According to the ASHRAE Standard 55, "Thermal comfort is the condition of mind that expresses satisfaction with the thermal environment and is assessed by subjective evaluation." Thermal comfort is important for the productivity and health of the occupants in a building. It has been stated that by occupying an environment with sub-par thermal comfort conditions, the productivity can drop by up to 20%. Thermal equilibrium is maintained when the heat generated inside a room is removed or allowed to dissipate into the surroundings. The Predicted Mean Vote (PMV) model is one of the most recognized thermal comfort models. In the model, the main factors that determine thermal comfort are identified as air temperature, metabolic rate, mean radiant temperature, clothing insulation, relative humidity and air speed.

To achieve the objective of sizably reducing heating, ventilating and air conditioning (HVAC) related energy costs, while not compromising indoor air quality requires implementation of better control over the HVAC system [2]. This statement forms the crux of this dissertation work. The solutions presented in the project provide options to a HVAC system controller that lets the controller choose how much of thermal comfort he is willing to sacrifice in order to obtain decreased energy consumption.

1.2 Objectives of this work

The main objectives of this work were

1. To optimize a simple HVAC model for multi-zone using multi-objective genetic algorithms. The objective functions adopted are
    a. To minimize Energy Demand and
    b. To minimize PPD

   The control parameters adopted are
    a. Zone temperature
    b. Supply duct static pressure
    c. Supply air temperature
    d. Chiller water temperature
2. To compare the performance of two different genetic algorithms, for optimization of a HVAC model described above.

3. To include relative humidity as an additional control parameter and optimize the simple HVAC model, described above.

1.3 Organization of Thesis

The thesis is organized in the following order

- **Chapter 1** gives an introduction on the background of HVAC systems and the reasons for the thesis work, the objectives of the work, and the organization of the thesis.
- **Chapter 2** reviews the literature available on the optimization of HVAC systems, Multi objective optimization using genetic algorithms, and Multi-objective optimization of HVAC systems.
- **Chapter 3** briefs on the classical methods of solving multi-objective optimization problems, the history and terminologies involved in Genetic algorithms, Genetic algorithms which can solve multi-objective optimization problems, and all the assumptions and parameters used for the optimization process.
- **Chapter 4** details about an existing HVAC Model which was optimized using multi-objective genetic algorithms. Then a new HVAC model is discussed which uses reheat.
- **Chapter 5** presents, discusses, and compares the results obtained.
- **Chapter 6** presents the conclusions obtained during the work.
- **Chapter 7** gives details about future work plans**.**

Chapter 2

LITERATURE REVIEW

2.1 Optimization of HVAC systems

The following list of publications shed light into the research going on in the field of HVAC optimization

Mathews et al. (2001) [2] used new control strategies for comfort enhancement and to increase the energy saving potential. They used a software tool, QUICKcontrol, to run building, HVAC and control simulations. The comfort audit was done with pin-pointing the problem areas like out of order HVAC components and neglected maintenance. Opinions from occupants about the comfort conditions indoors were also collected. These were used to measure the indoor air conditions. An energy audit was conducted to identify the major consumers of energy. It was found that HVAC system accounted for 54% of the energy usage, thus being the largest energy consumer. Air bypass, setback control, economizer control, reset control, CO2 control and improved start-stop times were the control strategies that were investigated. Power consumption savings of 60% were predicted. The simple payback period for using this method is calculated to be 9 months.

Fong et al. (2006) [3] described a new approach of simulation-optimization that was applied to create a reset scheme of supply air temperature and chilled water temperature set points for a local subway station HVAC system. They used a model of the entire HVAC system instead of subsystems for the simulation study. The model was a component-based model and it was built up using TRNSYS. The energy usage of the existing system was calculated by using the TRNSYS model for fixed supply air temperature and chilled water temperature set points, and was presented. The problem formulation is explained and the optimized set-points for three conditions are obtained for yearly as well as monthly reset. They find that the yearly reset yields energy savings of up to 2.68% and a monthly reset results in 6.74% of energy savings. This study proves that energy efficiency can be obtained even without sacrificing thermal comfort.

2.2 Genetic Algorithm / Multi-Objective Genetic Algorithms

The different genetic algorithms used for solving multi-objective problems are explained by the following publications and books.

In his book, “Multi-Objective Optimization using Evolutionary Algorithms” [4], Prof. Kalyanmoy Deb discusses about the advantages Genetic Algorithms have over Classical Optimization techniques for solving Multi-Objective Optimization Problems. Classical Optimization techniques find, at best, only one optimum solution in a simulation run while the Evolutionary Algorithms can find multiple optimal solutions in a single simulation run. As multi-objective problems usually have multiple optimum trade off solutions, Evolutionary Algorithms, of which Genetic Algorithms are a part of, are much more effective than the classical techniques.

Deb et al. (2002) [5] made some serious contributions to the field of multi objective genetic algorithms through this paper. They propose a new multi-objective genetic algorithm, the NSGA-II. It improved over the existing algorithms by bringing down the computational complexity, adding in the concept and advantages of elitism and removed the need of specifying the sharing parameter for diversity preservation. They also conclude that Multi-objective Genetic Algorithms might have difficulty in dealing with highly epistatic problems.

Deb et al. (2006) [6] proposed a new algorithm, Omni-optimizer, which could solve a variety of optimization problems. It automatically degenerates so that it is also able to solve simpler problems such as single objective single optima problems also, something which the previous algorithms were incapable of. The paper also introduces new concepts like restricted selection and crowding measure. The Algorithm is also more resilient to local optima because of a better mutation scheme.

2.3 Optimization of HVAC systems using Evolutionary Algorithms

A brief summary of the research being done in the field of Optimization of HVAC systems using Evolutionary Algorithms is explained here.

Huang et al. (1997) [7] compared the use of classical optimization methods like Zeigler-Nichols method along with Simple genetic Algorithms for HVAC controller tuning optimization and found that the GA method yields a much better performance compared to the traditional algorithms. They used a proportional plus integral (PI) controller to supervise the HVAC system and the simulation was done by using a modular dynamic simulation software HVACSIM+. The GA method optimized the system in 14.5s compared to 358s used for the optimization using Zeigler-Nicholas method. Even then, the author mentioned that the higher processing time required for optimization limited the application of Genetic Algorithms for HVAC system optimization during those years.

Wright et al. (2002) [8] used Multi-objective Genetic Algorithms for finding the optimal pay-off characteristic between thermal discomfort and the energy cost of a building. The study was done for a period of three design days and three different building weights. 63 control variables including the set-points of supply air temperature and flow rate for each hour of the day are there for each day. The size of the HVAC components were also taken into account. Two sample problems have been solved to show how the method works. The author mentions the advantages of using pareto-optimization for optimization comparing it to using priori preference articulation and progressive preference articulation. The paper lauds the use of multi-objective genetic algorithms for the said problem, appreciating how quickly the algorithm could converge to optimal solutions.

Nassif et al. (2004) [9] tried to optimize two objective optimization problem using different evolutionary algorithms. The two objective problem is a simple HVAC system model, the two objective functions to be minimized being the energy demand and PPD. A few assumptions regarding terms like outdoor conditions were also used. After analyzing different evolutionary algorithms, they determined that the controlled elitist non-dominated sorting genetic algorithm offered the best potential for finding the pareto-optimal solutions. They also inferred that the two-objective optimization would offer much better energy savings as compared to single objective optimization.

Nassif et al. (2005) [10] conducted experiments by applying different control system strategies on AHUs. They created models for the different components in the HVAC system and validated them against the existing systems. The control system strategy was also designed and implemented for the experiment. They tried out different strategies and found out that by varying all the set-points as per the results obtained in the genetic algorithm, they could achieve the maximum energy savings.

Lu et al. (2005) [11] created an ANFIS model for an extended HVAC system and optimized the model for minimum energy usage using a modified genetic algorithm. They ran several simulation tests, and by varying the chilled water supply temperature set-point, they found that the fixed set-point condition may use up to 10% more energy than the optimal solution. They also conducted simulations with the fan and pump pressure set-points optimization and pump and chiller sequencing optimization. They presented the comparison of energy usages for different systems, showing that the optimized mode showed minimum energy usage. This paper also shows the lack of complete models of HVAC systems and the difficulty of optimizing complete models with techniques other than evolutionary algorithms.

Fong et al. (2009) [12] conducted studies on system optimization of HVAC energy management using the robust evolutionary algorithm (REA). Robust evolutionary algorithm was developed by the authors as an effective evolutionary algorithm for HVAC systems. It has the synergetic combination of three EA operators – arithmetic recombination, Cauchy deterministic mutation and tournament selection. They mention that both exploitation and exploration continually happen throughout the process of REA. A typical centralized HVAC system was modelled using mathematical expressions as well as by using TRNSYS simulation tool and TESS libraries. The constraint equations were also developed. They developed a monthly reset scheme for the chilled water supply temperature and supply air temperature of the AHU. The monthly energy consumption using evolutionary programming and REA were obtained by using TRNSYS, and a decrease in energy usage is noted by using REA. They also compared the decrease in energy usage when REA was used instead of Genetic Algorithms. A significant improvement was found in the results as well the efficiency and effectiveness of REA.

2.4 Conclusions of the Literature Review

It is concluded that there is a lot of work going on about the optimization of HVAC systems. The use of different techniques for optimizing HVAC systems are seen in the literature survey. We also see that the field of Genetic Algorithms is also rapidly developing and different and better algorithms are being made. The different types of optimization and simulation methods of HVAC systems are observed, especially with the use of different kinds of software like QUICKcontrol, HVACSIM+ and TRNSYS. It is understood that HVAC optimization is a trending topic of research and successful research work can help to aid in the decrease of energy consumption by large amounts.

Chapter 3

MULTI OBJECTIVE GENETIC ALGORITHMS FOR HVAC SYSTEMS

3.1 Classical Methods of solving Multi-Objective problems

This section elaborates on the classical methods used for solving multi-objective problems, i.e., methods other than the use of evolutionary or genetic algorithms for multi-objective problems. According to Deb [4], these methods have been around for the last four decades. Even though there are a number of methods available for this purpose, each has its own advantages and dis-advantages, making each one more suitable for solving specific types of multi-objective problems. This report does not delve too deeply into the details of each of these methods specifically as they are outside the scope of this project work. The different methods that are used frequently are:

- The Weighted Sum Method
- ε - Constraint Method
- Weighted Metric Method
- Benson's Method
- Value Function Method
- Goal Programming Method

These methods all involve the conversion of the multi-objective problem into a single objective problem, and then using an optimization method for solving the single-objective problem to find the optimal solution. In the weighted sum method, a weighted sum of the multiple objectives is to be minimized. The ε - Constraint Method works by optimizing one of the objective functions while the other objective functions are set as constraints. The weighted metric method involves calculating an "l_p" metric from the objective functions and minimizing it while the Value Function method works by maximizing an overall utility function or value function relating the objectives. The Goal programming method involves minimizing a weighted sum of deviations of objectives from user specific targets.

The main strength of each of these methods are their proofs of convergence. The weighted sum method and weighted metric method guarantees that the pareto-optimal curve for a convex multi-objective problem will always be evaluated. The other methods also offer similar guarantees for specific problems. The main disadvantage of these methods is that they only give one optimal solution in one simulation run, even though the multi-objective problem usually has more than one pareto-optimal solution. Also, by using some of these methods, finding all the pareto-optimal solutions of a non-convex multi-objective optimization problem is impossible. The final disadvantage is that all these methods require some problem knowledge to find the pareto-optimal solutions, such as suitable weights or target values or ε.

3.2 Genetic Algorithms

Genetic Algorithms are optimization techniques developed from the idea of natural selection. Survival of the fittest is the main inspiration and biological analogy of the GA process. Genetic algorithms are based on natural selection, the process that drives biological evolution [13]. Being analogous to genetics, Genetic algorithm is also composed of a long complex thread of DNAs and RNAs containing genetic data, as chromosomes, by which the traits of each individual is determined. Every trait of a living organism is coded with a combination of "bases" like A (Adenine), C (Cytosine), T (Thymine) and G (Guanine).

During meiotic or sexual reproduction, there is exchange of genetic material between the gametes from the parents, which is because of a process called chromosomal crossover. Thus, the children produced due to meiotic reproduction will exhibit the traits of both the parents. In some very rare cases, all the chromosomes can get mutated, and this might result in a child who has no resemblance to one of its parents. Mutation is a process by which one or more gene values are altered, resulting in new alleles, where, an allele is a variant form of a gene. For understanding this, we may take the example of a typist copying a book. He makes mistakes by copying wrongly spelled words which has no meaning and needs to be corrected or stricken off. But, there is a rare possibility that this mistake may lead to another meaningful word. So, by mutation, a species having entirely different traits from parent will be produced, which, in rare cases, may be better than its parents.

Genetic algorithms (GAs) were invented in 1960s by John Holland. He along with his students and colleagues at the University of Michigan further developed this nature based evolutionary technique by 1970s. This invention did not have any specific intention, but to study the phenomena of adaptation occurring in nature and to adopt these natural adaptation mechanisms into computer systems. Holland's book titled, "Adaptation in Natural and Artificial Systems (1975)" introduces genetic algorithm as a concept of biological evolution and explains a theoretical outline for adaptation. In those days, GA was said to be a process by which the chromosomes in the form of bit string gets transformed to a new form in the next generation by using operators like crossover, inversion and mutation. The chromosomes contains genes represented by bit and each gene has alleles in it represented by 0 or 1. Healthier individuals will be allowed to reproduce offspring than compared with unhealthier one. Crossover exchanges subparts of two chromosomes, approximately mimicking biological recombination between two single−chromosome ("haploid") organisms; mutation randomly changes the allele values of some locations in the chromosome; and inversion reverses the order of a contiguous section of the chromosome, thereby rearranging the order in which genes are arrayed.

The basic model of "genetic algorithm" by Holland has travelled a long way to reach its present state, which is absolutely nowhere its original concepts. Nevertheless, these evolutionary computational methods have been applied in almost all fields of science and engineering in the recent years.

The invention and development of computers has made revolutionary changes in the development and use of genetic algorithms. They could be used to replicate natural processes in many ways. Because of the growth of computer science, stronger and more computationally complex genetic algorithms could be developed and put into use. Real world problems present lots of challenges to engineers, like requirement of high computational strength, ability to converge on optimal solutions with less iterations and time, etc. Genetic algorithms (GAs) are good choices for solving these problems as they can easily find the global optimum solution. Genetic algorithms are used to solve problems that cannot be solved using the standard or classical methods, like when the objective function is discontinuous, non-differentiable, stochastic, or highly nonlinear.

Basic terminology in genetic algorithm are familiarized here as follows:

- *Fitness Functions:* it is the function (often called the objective function in standard optimization algorithms) meant to undergo optimization. The genetic algorithm tries to minimize this fitness function.
- *Individuals:* An individual is any point to which the fitness function can be applied. The value of the fitness function for an individual is its score. For example, if the fitness function is
    - $f(x_1, x_2, x_3) = (2x_1 + 1)^2 + (3x_2 + 4)^2 + (x_3 - 2)^2$

- Here, a vector (2, 3, 1) is an individual, whose length is the number of variables and the score of the individual is f (2, 3, 1) = 51.
- An individual is sometimes referred to as a *genome* and the vector entries of an individual is referred to as its *genes*.

- *Populations:* A population is an array of individuals. For example, for a population size of 100 and the number of variables in the fitness function is 3, a 100 X 3 matrix represents the population. The same individual can appear more than once in the population. i.e., the individual (2, 3, 1) can appear in more than one row of the array.
- *Generations:* On each iteration, genetic algorithm performs a series of computations on the current population to produce a new population. Each successive population is called a new generation.
- *Diversity:* it refers to the average distance between individuals in a population. A population with high diversity is indicated by larger average distance. In Figure 3.1, the population on the left has higher diversity than that right. Diversity is essential in genetic algorithm as it provides a larger search space.

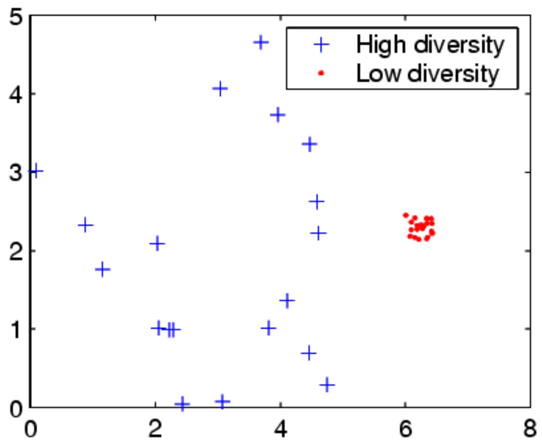

Figure 3.1: Diversity in Genetic Algorithm Population

- *Fitness Values and Best Fitness Values:* The fitness value of an individual is the value of the fitness function for that particular individual. As the toolbox works for minimizing the fitness function, the best fitness value for a population is the smallest possible fitness value for any individual in the prevailing population.
- *Parents and Children:* To create the succeeding generation, genetic algorithm searches and selects certain individuals with better fitness values in the current population, called parents, and uses them to create individuals in the next generation, called children.

3.3 Multi- Objective Genetic Algorithms

The main problem of the classical methods discussed above is the fact that they mainly work by converting multi-objective problems into single objective problems, thus concentrating on a single pareto-optimal solution at a time. By applying them many times and by changing the parameters, these methods are sometimes able to find out different pareto-optimal solutions. But evolutionary algorithms are able to find out multiple pareto-optimal solutions in one simulation run, which make them superior to the classical methods. During the course of this dissertation work, two genetic algorithms which can solve Multi-objective problems, the NSGA-II and the Omni-Optimizer, were studied and used. The following sub-sections present details about these algorithms.

3.3.1 NSGA-II:

In 1994, Srinivas and Deb implemented the Non-Dominated Sorting Algorithm (NSGA) based on the idea of non-dominated solutions. The assignment of solutions according to non-dominated sets and trying to maintain phenotypic diversity was the main advantages of this algorithm. Although it was famous world-wide, it received criticism regarding the high computational complexity, lack of elitism and the need for specifying the sharing parameter (for maintaining the diversity among solutions). In 2002, Deb et al. published the improved NSGA-II algorithm which addressed all the issues of the original NSGA. Figure 3.2 shows how the NSGA-II algorithm solves the HVAC problem.

The algorithm is structured and works in the following way. Initially, a random parent population P_0 is generated. This population is sorted, the sorting done on the basis of non-domination. The solutions are assigned fitness ranks equal to their non-domination levels or fitness scores. Then, the binary tournament selection, recombination and mutation operators are used to create the first offspring generation. A combined population consisting of both the initial parent population and the new offspring generation population is created. This combined population is sorted based on non-domination. The best non-dominated solutions form the individuals in the best front, and subsequently each front is created based on the non-domination rank. To select the next population which would have a population size equal to that of the initial population, the best fronts are selected and added to the new parent population set till the addition of one more set would exceed the size of the new parent population than the initial population. The next remaining front is then sorted using the crowded-comparison operator, and the best solutions from among these are selected and added to the new parent population so that the population size of the new parent population is equal to the initial population.

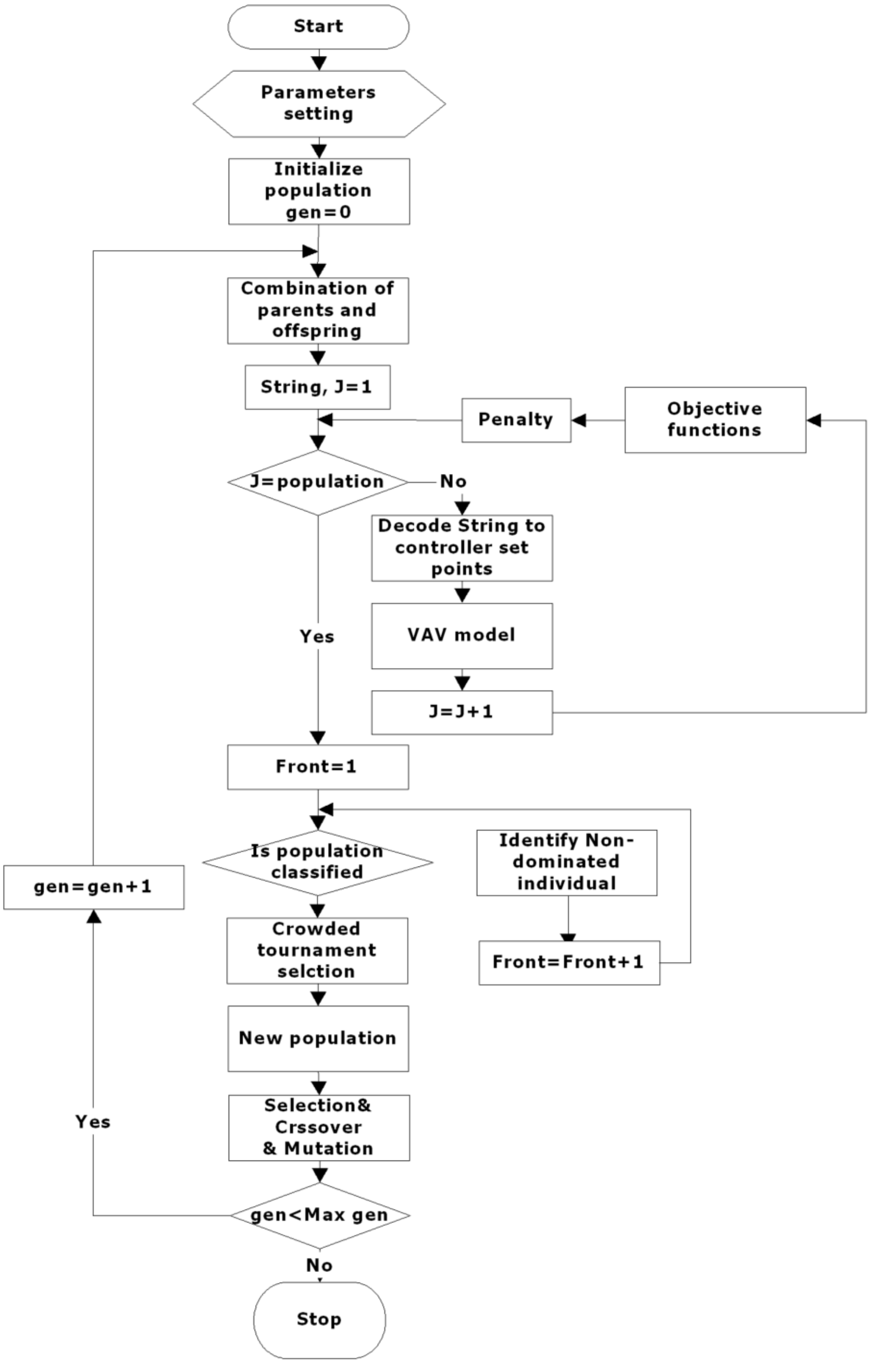

Figure 3.2: NSGA-II used for HVAC systems [10]

The non-domination sorting is done as follows. For each individual (p), the number of solutions in the whole population that dominate it (n_p) are calculated and the set of individuals that it dominates (S_p) are created. All the individuals with n_p equal to zero are added to the best front, and the S_p of each of these solutions are examined. The n_p of each individual in these sets are decreased by one, and if any individual reaches n_p equal to zero, they are added to the next front. This process continues till all the individuals are sorted.

Diversity preservation is done as follows in NSGA-II. First, a metric is calculated for estimating the density of individuals in a specific part of the objective or decision variable space. For each individual, this is done by calculating the average distance of two neighbours on either side of an individual along each objective. This metric $i_{distance}$ is then used in comparing the crowding distance between the individuals.

3.3.2 Omni-Optimizer:

In 2008, Deb, along with his students published a paper on a new genetic algorithm which could solve both multi-objective optimization problems as well as single-objective problems. Thus, this GA, Omni-optimizer [6], could handle real world problems much better than the GAs before it, as there was no need to select a specific GA that could handle the specific problem. Therefore, this GA was also used to optimize the problem in this dissertation work.

When made to handle multi-objective problems where every solution obtained is a pareto-optimal solution in the decision space, the Omni-optimizer works exactly like the NSGA-II with the following modifications.

1. Restricted selection, based on distance between the players, is used to choose the two players that will take part in the binary tournament. In NSGA-II, this was a random selection method. This tends to speed up the convergence to the optimal solution.

2. ε-Dominance is used for classifying solutions into different fronts when ranking the solutions. By making this modification, Omni-optimizer tries to increase the size of the non-dominated set by allowing some of the inferior individuals to remain in the population.

3. In Omni-optimizer, minimising objective space and variable space crowding is attempted, for ensuring diversity among the solutions in a front. In NSGA-II, only objective space crowding is applied.

   Restricted Selection and minimising variable space crowding were the main reasons for using Omni-Optimizer.

3.4 Optimization Process: Use of a Control strategy for optimizing HVAC System

This section explains the control strategy with which the genetic algorithm is used to optimize the HVAC system. The output of the optimized system supervisor are the system set-points, which will optimize the HVAC system for the specific indoor loads and output conditions. Figure 3.3 shows the optimization process as explained by Nassif et al [10]. Of the many components in this optimization process, The HVAC model and the Two-Objective genetic Algorithm are explored in this dissertation.

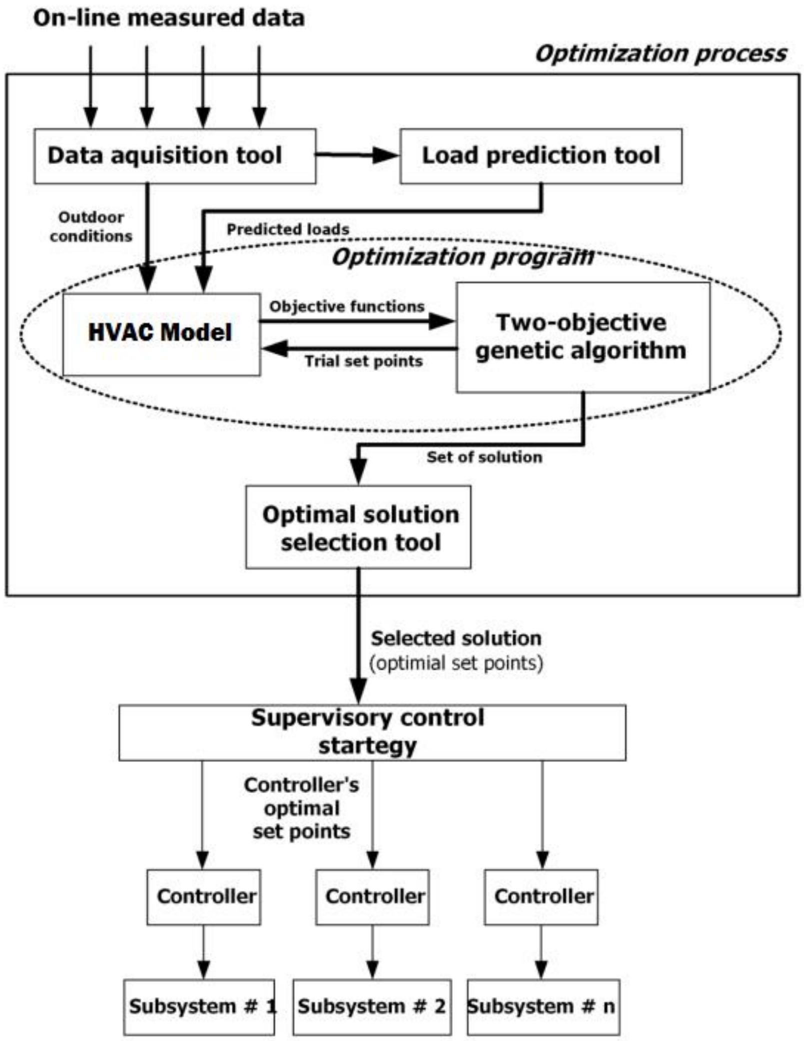

Figure 3.3: Optimization Process

The other components of the supervisory control system are the data acquisition tool, the indoor load prediction tool and the selection tool. The data acquisition tool receives and processes the online measured data. The sensible and the latent loads for the HVAC system are predicted by the load prediction tool using information from the data acquisition tool. For the last step in the optimization process, in the optimal solution selection tool, a particular solution is to be selected and the combination of set-points in this solution is used as the set-points of the HVAC system. This process of selecting one particular solution from the numerous solutions requires more information. When this information is available, it can be used by an optimal solution selection tool to find the best solution. These components were not used in this dissertation work as the data acquisition tool and the optimal solution selection tool would require a real system implementation to properly function. The load prediction tool was not used because the design conditions were assumed, the assumptions detailed in the next chapter. But incorporating the load prediction tool could be implemented as future work.

Chapter 4

GA OPTIMIZATION MODEL AND PROCESS FOR HVAC SYSTEMS

4.1 Existing HVAC Model

HVAC systems are usually designed after calculating approximate system loads for the particular application and also taking the past outdoor climate data into account. This dissertation involves the investigation of an existing HVAC system installed at the Montreal campus of École de technologie supérieure (ETS). The model describes a simplified form of AHU – 6 which is part of a group of ten Air handling units at École de technologie supérieure. It caters to 70 zones in the second floor of the building. The HVAC system is modeled after this Air handling unit [10].The thermal comfort conditions were calculated from equations obtained from the ISO standard: 7730 [14]. This work was validated using the results in Nassif et al. (2004) [9]. The schematic diagram of the HVAC system is shown in Figure 4.1 below.

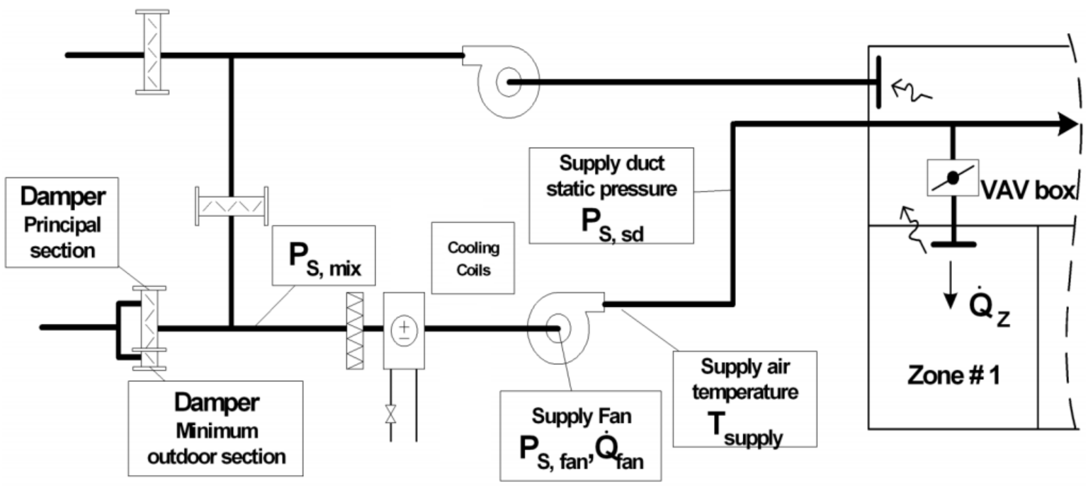

Figure 4.1: Schematic Diagram of simple HVAC system

The HVAC system is optimized for certain conditions, some of which were taken from the design conditions provided in Nassif et al. (2004) [9]. Some other conditions were assumed and ensured that these be under the ranges usually found in similar real world conditions. The outdoor condition in Nassif et al. (2004) [9] relates to a time period on a summer day. The enthalpy of the outdoor air was assumed as 71.25 kJ/kg, with the outdoor air temperature as 28 °C and relative humidity as 70%.

In Nassif et al. (2005) [10], the load for the system is obtained from predictions using previous data. But here, the total load for the HVAC system was taken as the sum of the load in each zone in the building. The zones were assumed to be perfectly similar, with each zone having a total load equal to one ton of refrigeration (1 Ton = 3.52 kW). The ratio of the sensible heat to the total load of the building (SHR) is assumed to be 0.75. Therefore, the latent load makes up 25% of the total load of the system. For the system model, four set-points were decided to be the decision variables for the genetic algorithm optimization process. These are

1. The zone temperature, $(Tz_i)_{PV}$ in °C
2. The supply duct static pressure, $(P_s)_{PV}$ in Pa
3. The supply air temperature, $(T_s)_{PV}$ in °C
4. The chilled water supply temperature, $(T_W)_{PV}$ in °C,

   where PV was used as a suffix for identifying these as the problem variables. The upper and lower limits of these set-points were taken as follows

1. The zone temperature, $(Tz_i)_{PV}$ (21 to 25 °C)
2. The supply duct static pressure, $(P_s)_{PV}$ (150 – 250 Pa)
3. The supply air temperature, $(T_s)_{PV}$ (13 to 18 °C)
4. The chilled water supply temperature, $(T_W)_{PV}$ (6 to 11 °C)

Although Nassif et al. (2004) [9] treated the optimization problem as a constrained problem, for the sake of simplicity and generalization, in this dissertation work, constraint equations were not considered.

The total energy demand of the system was taken as the first objective function for the genetic algorithm. The energy demand was calculated as the sum of the chiller energy use and the fan energy use. The following equations were used for modelling:

Total Energy Demand $\dot{W}_t$ (kW),

$$\dot{W}_t = \dot{W}_f + \dot{W}_C \tag{1}$$

Fan Energy use $\dot{W}_f$ (kW), was calculated as a function of fan air flow rate and the total static pressure drop. The total static pressure drop is obtained by the addition of the supply duct static pressure and the pressure drop because of the ducts and the fan (this is calculated as a function of the fan flow rate).

$$\dot{W}_f = \frac{\dot{Q}_f\left((P_s)_{PV} + 2 \cdot 10^{-3} \cdot \dot{Q}_f^2\right)}{0.68 \cdot 1000} \tag{2}$$

where, the fan air flow rate $\dot{Q}_f$ (m^3/s) is taken as the sum of the individual air flow rate into each zone,

$$\dot{Q}_f = \sum \dot{Q}_{Z_i} = \sum \frac{(qs_i)_{IV}}{1.2 \cdot ((Tz_i)_{PV} - (T_s)_{PV})} \tag{3}$$

For calculating the Chiller Energy use, $\dot{W}_C$ (kW), the outdoor air fraction (λ) is assumed to be 0.2 and the air leaving the cooling coil is assumed to be saturated with its enthalpy (H_s) calculated as a function of the supply air temperature (T_s),

$$\dot{W}_C = \frac{\left[\lambda \cdot \dot{Q}_f \cdot ((H_o)_{IV} - H_S) + (qt)_{IV} \cdot (1-\lambda)\right]}{COP}, \tag{4}$$

$$H_s = 1.01 \cdot (T_s) + X \cdot \left(2502 + 1.84 \cdot (T_s)\right), \tag{5}$$

where X is the specific humidity (kg of water vapour/kg of dry air)

The coefficient of performance of the chiller (COP) was calculated as,

$$\begin{aligned} COP = {} & 7.9275 \cdot PLR^3 - 21.194 \cdot PLR^2 + 16.485 \cdot PLR \\ & + 2.2139 + 0.1 \cdot ((T_W)_{PV} - 6) \end{aligned} \tag{6}$$

where PLR represents the part load ratio, which is equal to the ratio of the cooling coil load to its design load (assumed to be 722 kW)

The second objective function of the genetic algorithm was taken as the Percentage of people dissatisfied (PPD) [14], which represented the thermal comfort in the room. It was calculated as a function of the predicted mean vote (PMV). The equations and assumptions used for calculating PPD and PMV is as follows

$$PPD = 100 - 95 \cdot EXP\{-(0.03353 \cdot PMV^4 + 0.2179 \cdot PMV^2)\} \tag{7}$$

$$\begin{aligned} PMV = {} & (0.303\, e^{-0.036M} + 0.028)\{(M-W) \\ & - 3.05 \cdot 10^{-3} \cdot [5733 - 6.99(M-W) - p_a] \\ & - 0.42 \cdot [(M-W) - 58.15] \\ & - 1.7 \cdot 10^{-5} M(5867 - p_a) - 0.0014M(34 - (Tz_i)_{PV}) \\ & - 3.96 \cdot 10^{-8} f_{cl} \cdot [(t_{cl} + 273)^4 - (t_r + 273)^4] \\ & - f_{cl} h_c (t_{cl} - (Tz_i)_{PV})\} \end{aligned} \tag{8}$$

$$t_{cl} = 35.7 - 0.028(M - W) - I_{cl}\{3.96 \cdot 10^{-8} f_{cl} \cdot [(t_{cl} + 273)^4 - (t_r + 273)^4] + f_{cl} h_c (t_{cl} - (Tz_i)_{PV})\} \quad (9)$$

f_{cl} was assumed to be 1.2

h_c was assumed to be 3.8 W/(m^2 °C)

I_{cl} was assumed to be 1 clo

t_r was assumed to be 27 °C

M was assumed to be 60 W/m^2

W was assumed to be 0 W/ m^2

p_a is water vapor pressure and is calculated from relative humidity and Buck's fomula.

The following flow chart (Figure 4.2) shows how the model calculates the fitness function values from the decision variables.

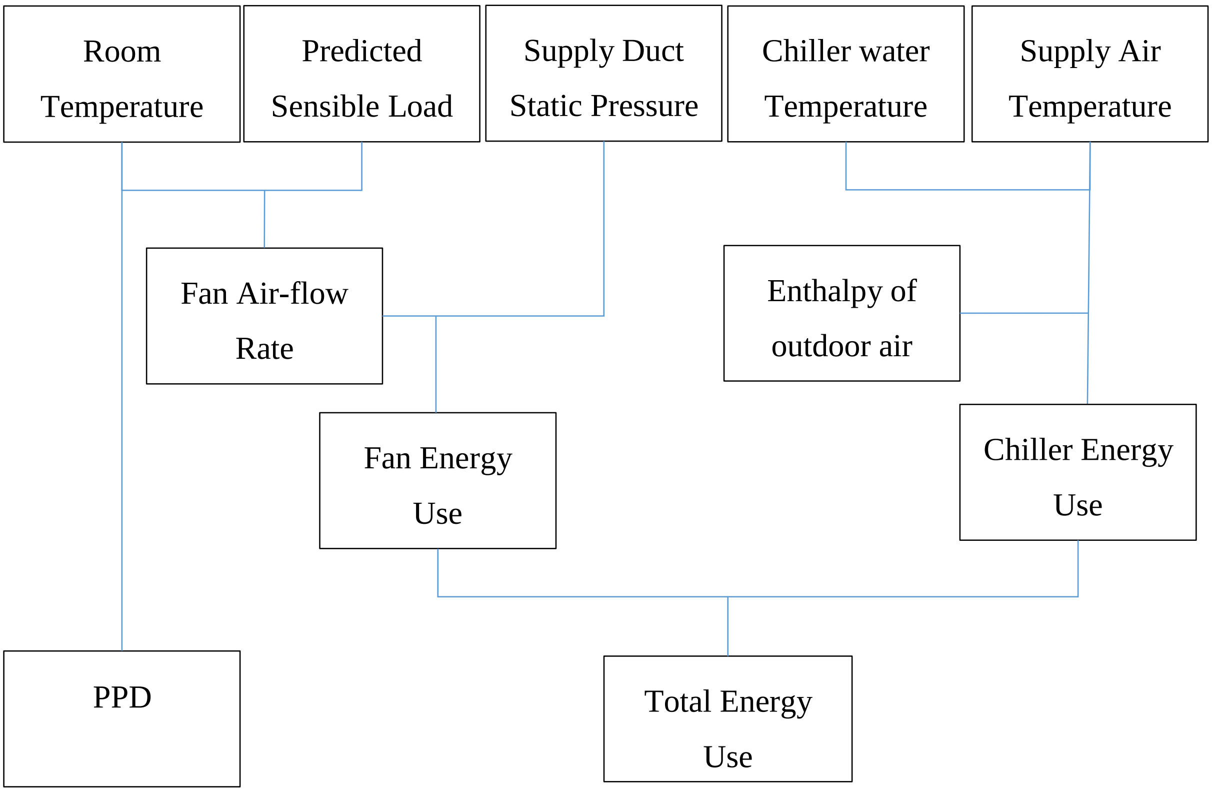

Figure 4.2: Fitness value calculation from set-points

For the genetic algorithm, the following parameters were used, as used in literature [9],

GA used – NSGA-II

Population Size = 200

Generations = 500

Crossover probability = $p_c = 0.9$

Mutation Probability = $p_m = 0.04$

For the sake of simplicity and generalization, in this problem, no constraint equations were taken into consideration, even though there are a lot of constraints which depend on the specifications of the components used in real life systems.

4.2 Modified HVAC Model with Reheat

The HVAC Model mentioned in section 4.1 did consider the latent load of the building and the humidity of the room. For remedying this, the HVAC model was modified to include reheat also. This model is shown in Figure 4.3.

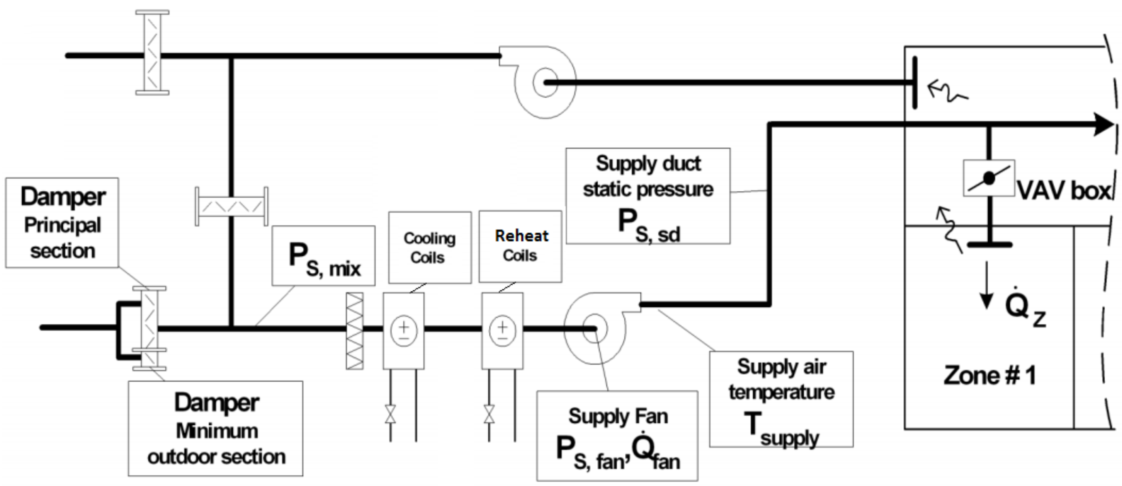

Figure 4.3: HVAC Model with Reheat

The relative humidity in the room (ϕ_Z) was identified as the fifth set-point and decision variable (problem variable) of the HVAC model. The energy used for reheating depends on the conditions of the air supplied to the zone (T_Z) and of the air leaving the cooling coil. The condition of the supply air was determined by using the latent load of the room, thus making it a function of the relative humidity of the room. Thus, the energy demand of reheat is added to the total energy demand of the HVAC system, to be minimized, with the relative humidity set-point ranging the upper and lower limits specified in the supervisory controller. The equations used for reheat energy demand is as given below:

$$\dot{W}_{Rh} = \dot{Q}_f \ (H_T - H_W), \quad (10)$$

where the enthalpy of the supply air (H_T) and the enthalpy of the air leaving the cooling coil (H_W) are functions of $T_W,\ T_Z\ and\ \phi_Z$ similar to equation (5).

ϕ_Z was made to take values between the bounds of 0.4 and 0.6.

Without the loss of generality, the relative humidity of the air leaving the cooling coil is assumed to be 95%.

Thus, in this model the first objective function changes into

Total Energy Demand $\dot{W}_t\ (kW)$,

$$\dot{W}_t = \dot{W}_f + \dot{W}_C + \dot{W}_{Rh} \quad (11)$$

The second objective function, i.e., PPD is calculated in the same way, using equations (7), (8) and (9). The assumptions made and the parameters used are also the same as the ones in the previous model. The results of optimization are presented in the next chapter.

Chapter 5

RESULTS AND DISCUSSION

The HVAC models mentioned in the previous chapter were optimized using the algorithms mentioned in Chapter 3. The main objective of this project was to produce an output which was similar to the results in Nassif et al. [9]. After successfully completing this objective, a new HVAC model was used to incorporate humidity as a new set-point. This model was modelled and optimized in a similar fashion as the first model. A newer algorithm, Omni-optimizer, was also used to optimize the original HVAC model. The results obtained by the use of this algorithm was compared with the results obtained by the original algorithm, NSGA-II.

5.1 The Existing HVAC model optimized using NSGA-II

The graphs below display the result of optimizing the existing HVAC model using NSGA-II with the parameters and assumptions mentioned in Chapter 4. The graph shows an inverse relation between energy demand and PPD. This work, Figure 5.1, was similar to the work done by Nassif et al. (2004) [9],

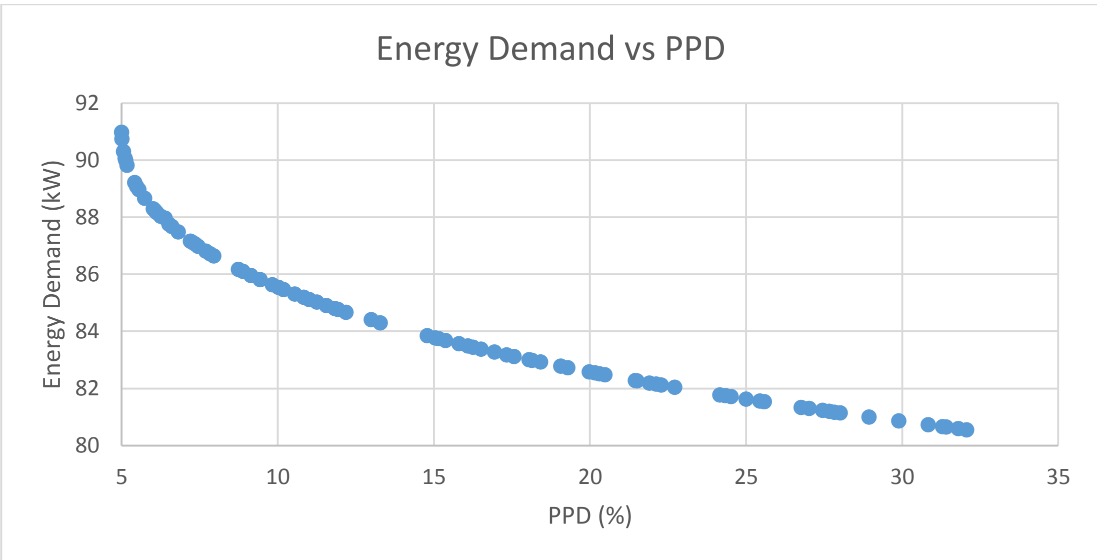

Figure 5.1: NSGA-II - Energy Demand vs. PPD

Upon examining the individual set-points of the solution, it is noted that the variations in Zone temperature or room temperature play a major role in the variation of energy demand

and of PPD (Figure 5.2 and Figure 5.3). We find that as zone temperature decreases, the energy demand of the HVAC system increases. We also see that as Zone temperature is less, the PPD is less and then it increases at a higher rate with increase in zone temperature. But from 23 °C we see that the relationship changes into a more linear one. These variations are expected because of the higher powers of the zone temperature in the PPD-PMV equation.

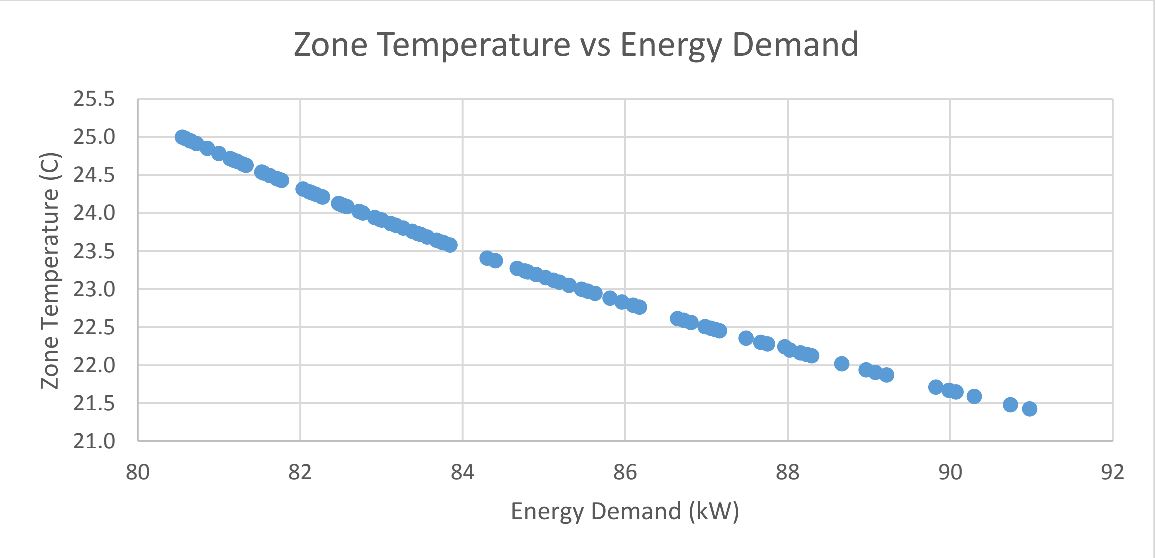

Figure 5.2: NSGA-II - Zone Temperature vs. Energy Demand

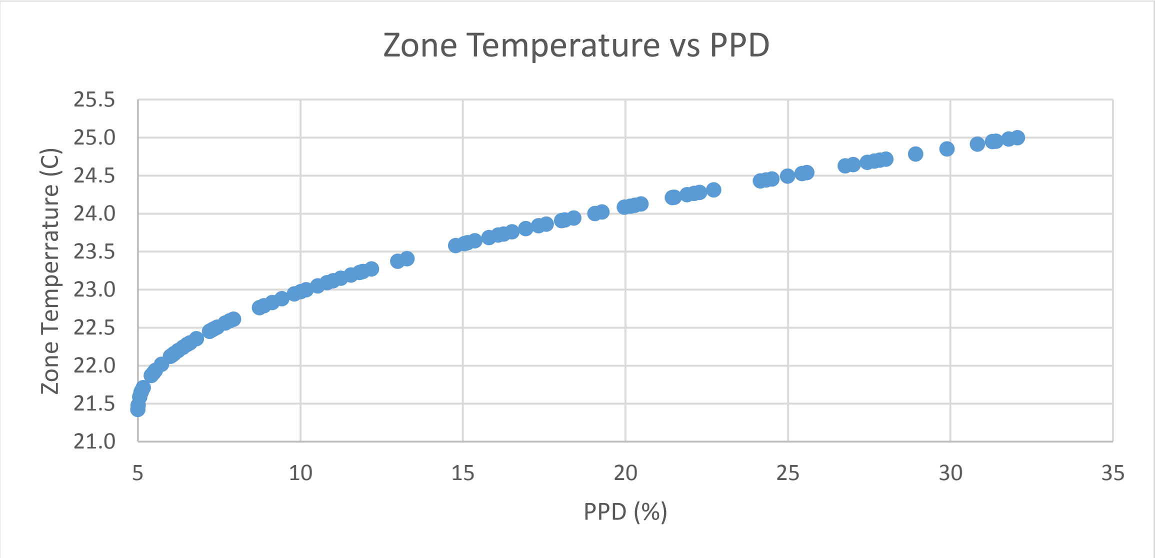

Figure 5.3: NSGA-II - Zone Temperature vs. PPD

In Figure 5.4 to Figure 5.9, we find that the set-points other than the room temperature set-point (T_Z) tend to assume an almost constant value for the pareto-optimal solutions. Any stray points in these figures may be due to mutation caused by the genetic algorithm code. It was assumed that this was due to the fact that these variables (set-points) were not in both the objective functions simultaneously. To test this theory as well as to make the model a more generalized one, one more variable which affected both thermal comfort as well as energy demand was introduced in the next model.

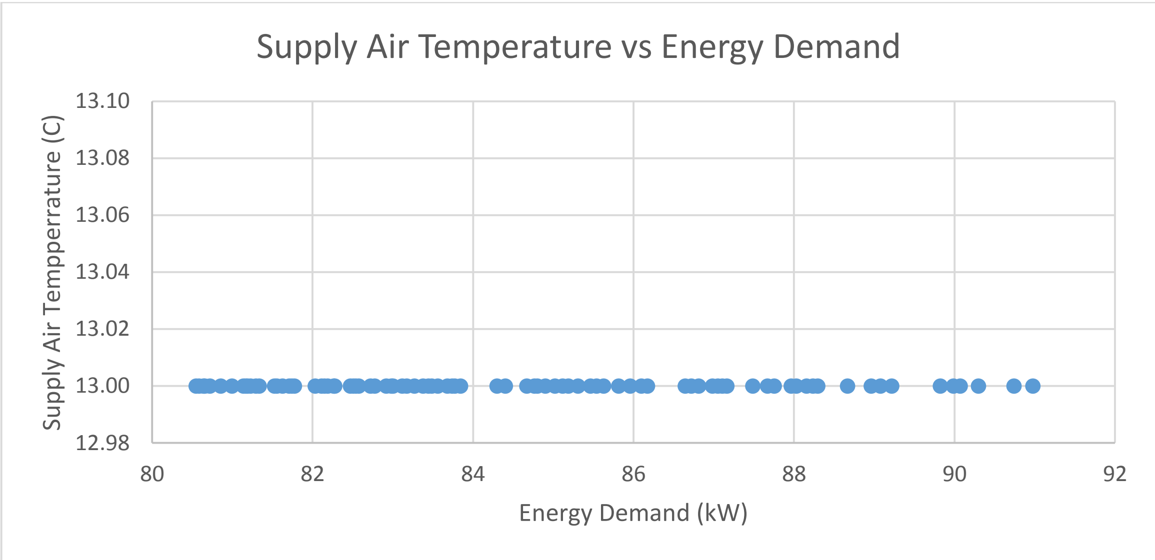

Figure 5.44: NSGA-II - Supply Air Temperature vs. Energy Demand

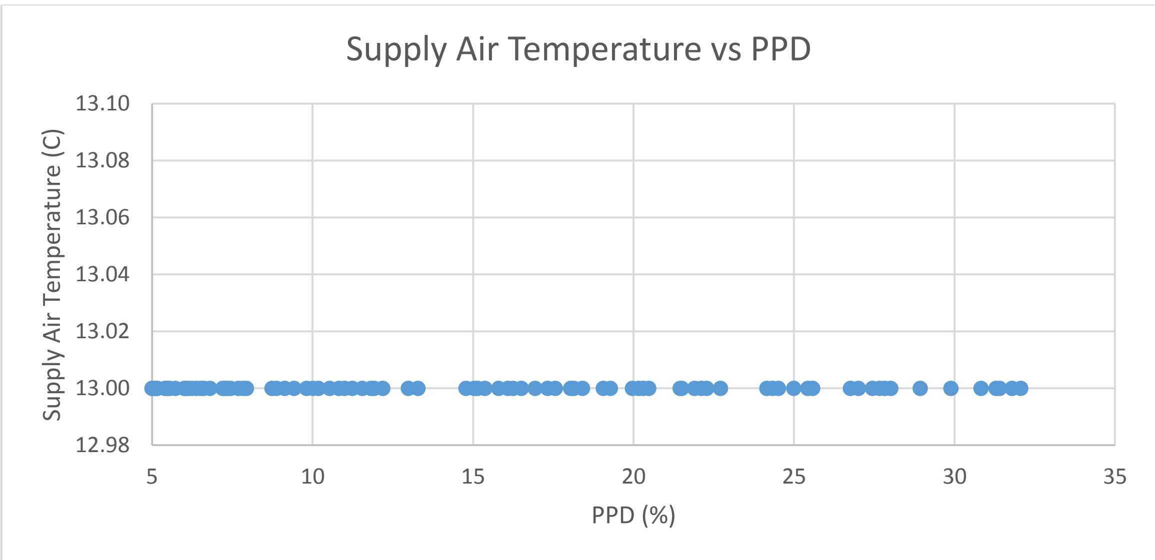

Figure 5.55: NSGA-II - Supply Air Temperature vs. PPD

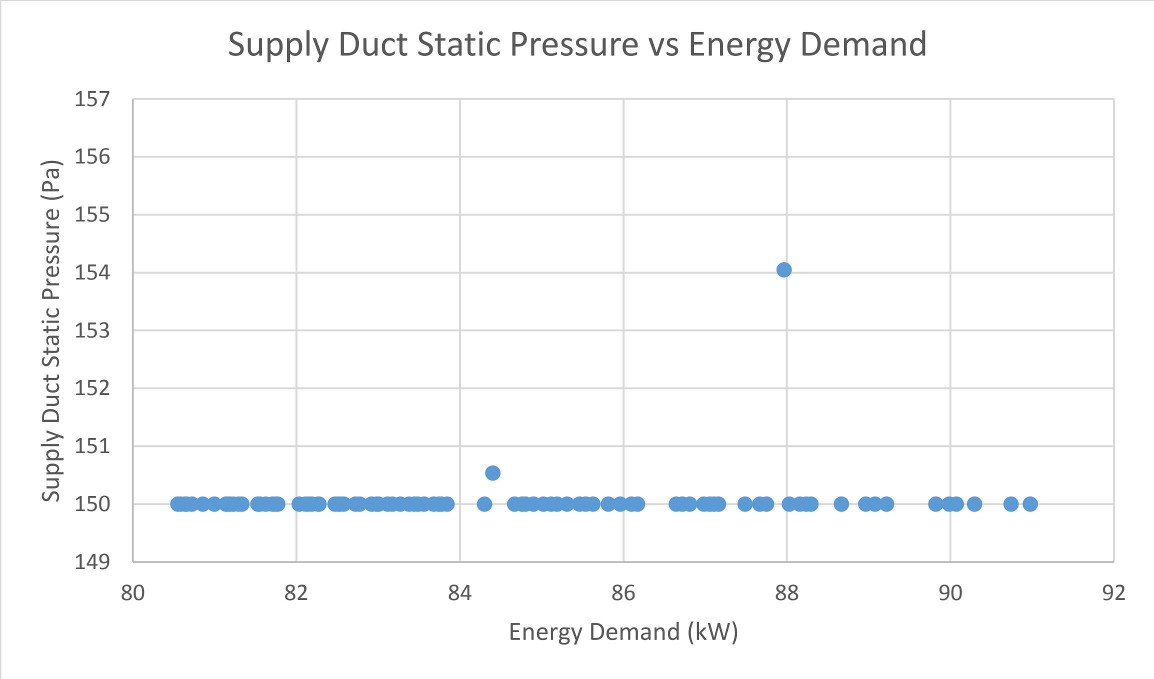

Figure 5.66: NSGA-II - Supply Duct Static Pressure vs. Energy Demand

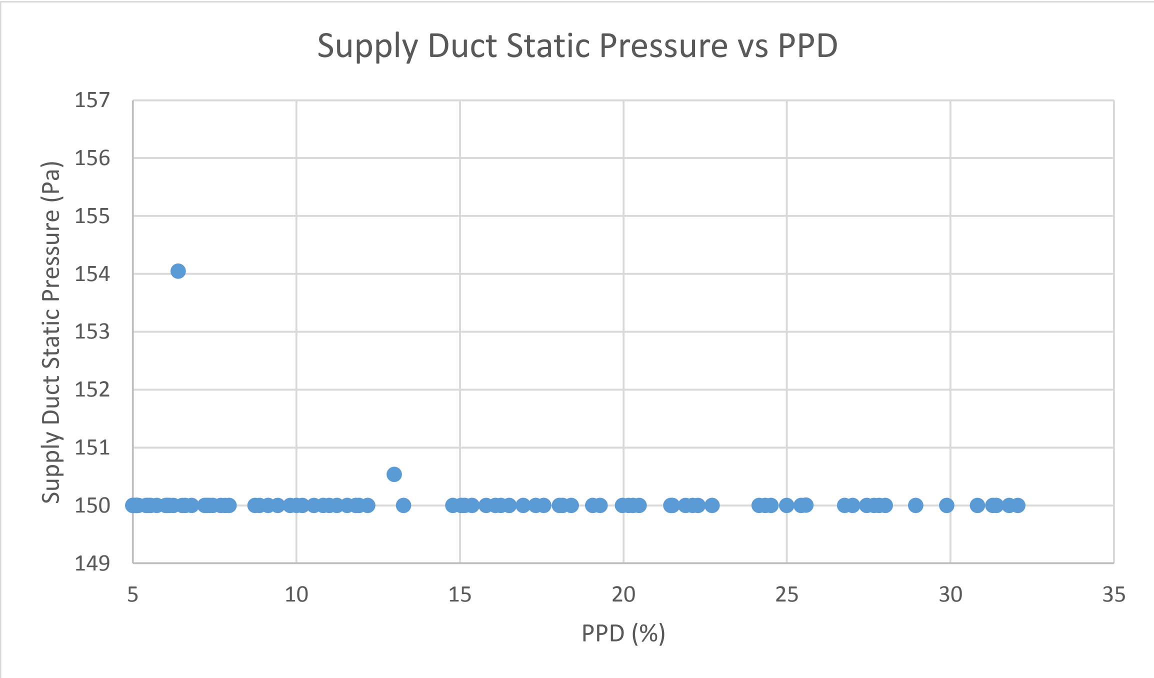

Figure 5.77: NSGA-II - Supply Duct Static Pressure vs. PPD

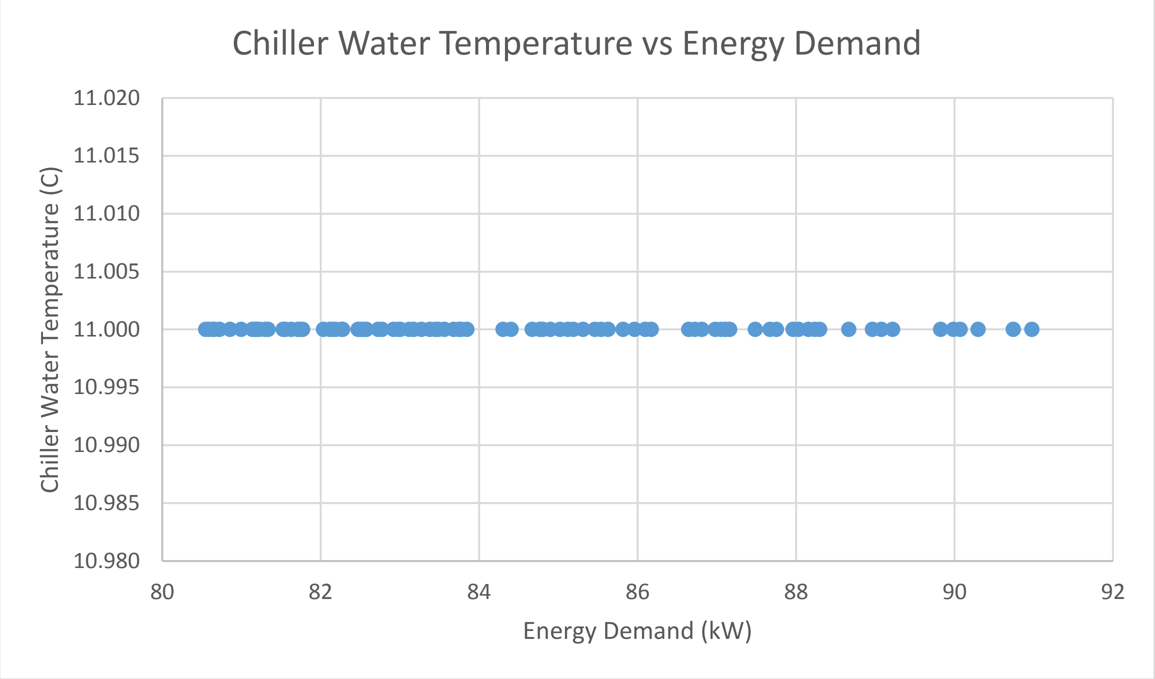

Figure 5.88: NSGA-II - Chiller Water Temperature vs. Energy Demand

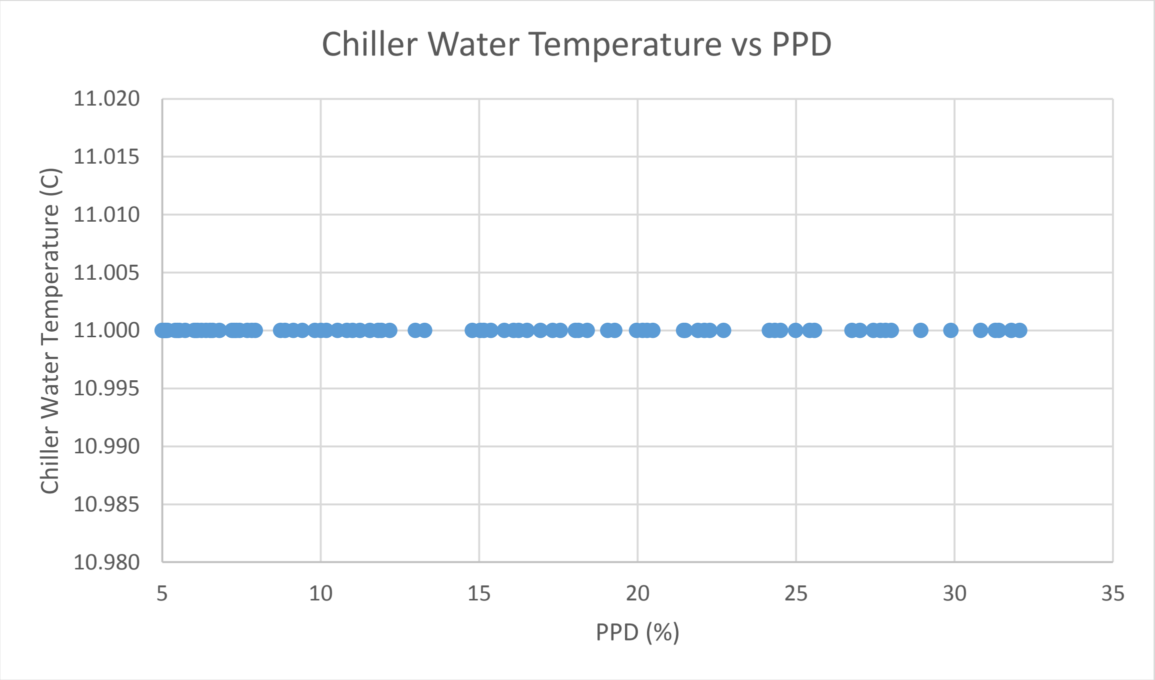

Figure 5.99: NSGA-II - Chiller Water Temperature vs. PPD

5.2 The modified HVAC model with reheat optimized using NSGA-II

In this model, reheat was added to the model, the main purpose being, the need to study the effect of a second variable which is in both of the two objective functions. The variable which was added was the relative humidity of the zone. The graphs below show how the Genetic Algorithm optimized the new HVAC model.

Comparing Figure 5.10 with Figure 5.1, the shape of the graph generated remains the same, but we see that adding reheat has increase the energy demand by almost 60 kW. We also notice a higher variation in energy demand, and also that the maximum PPD in an optimum solution has reduced to around 27%.

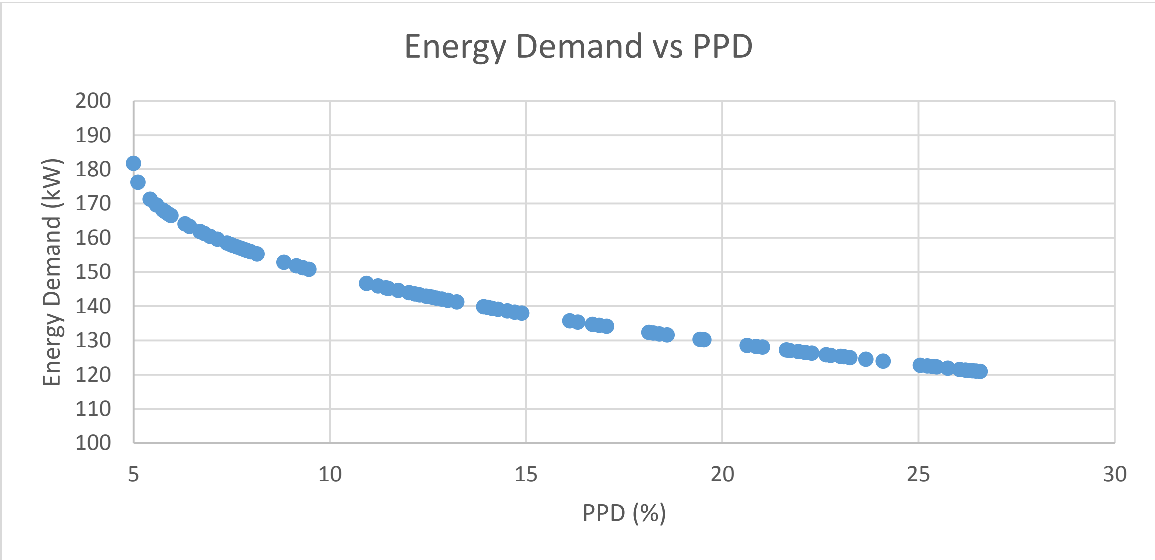

Figure 5.1010: NSGA-II with reheat - Energy Demand vs. PPD

The higher variation in Energy Demand vs PPD means that the new system can provide much better energy savings when compared to the existing model. Thus, this model has shown incremental improvement compared to the previous model.

Figure 5.11 and Figure 5.12 show the variation of zone temperature with energy demand and PPD. As was observed before, we find that the zone temperature is inversely related to energy demand and that as zone temperature decreases, the energy demand increases.

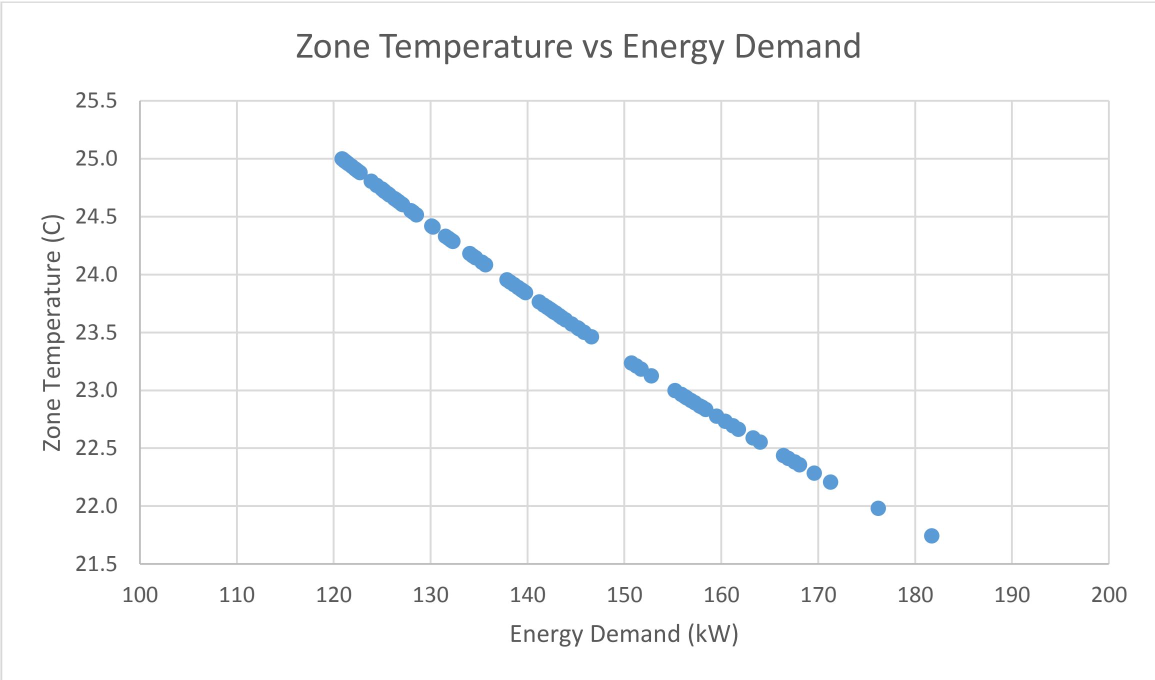

Figure 5.1111: NSGA-II with reheat - Zone Temperature vs. Energy Demand

In Figure 5.12, we notice an interesting variation from the case without reheat (Figure 9). We find that the variation in the zone temperature from 22 °C to 24 °C results in a change of PPD from 5% to 15% as contrasted to Figure 9 where the same variation in zone temperature will result in a change of PPD from 5% to 20 %. Thus, we see that under the accepted levels of thermal comfort temperature conditions (22 °C to 24 °C), we have managed to attain better levels of comfort (less PPD) than what was attained using the model without reheating. But, this is achieved at the price of increased energy demand as seen in (Figure 5.2 and Figure 5.11).

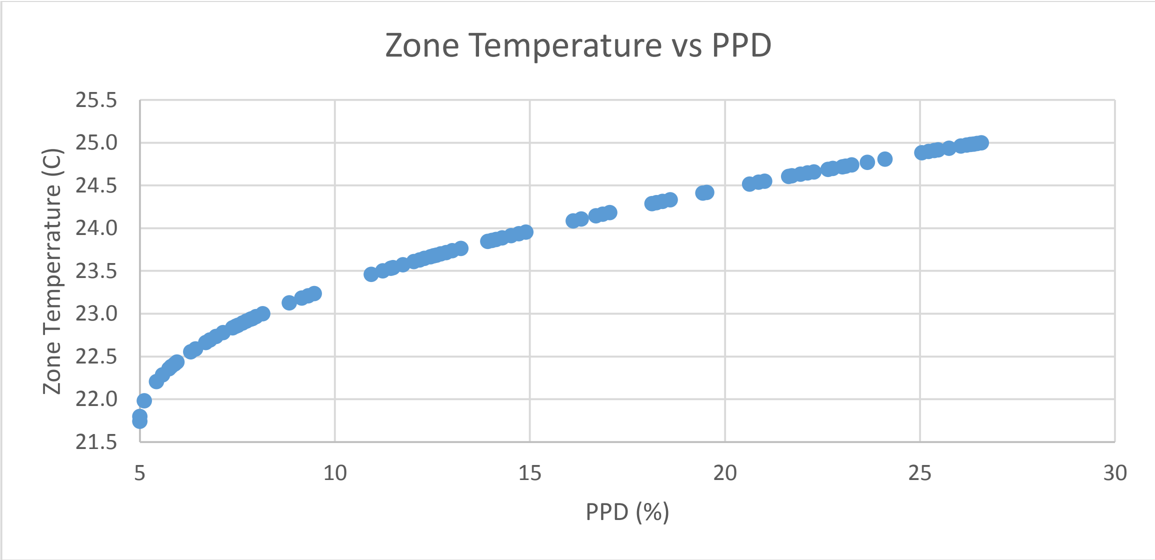

Figure 5.12: NSGA-II with reheat - Zone Temperature vs. PPD

Figure 5.13 to Figure 5.16 exhibit results similar to the results obtained when using the model without reheating. This was expected as these set-points were not used as variables in the PPD equation.

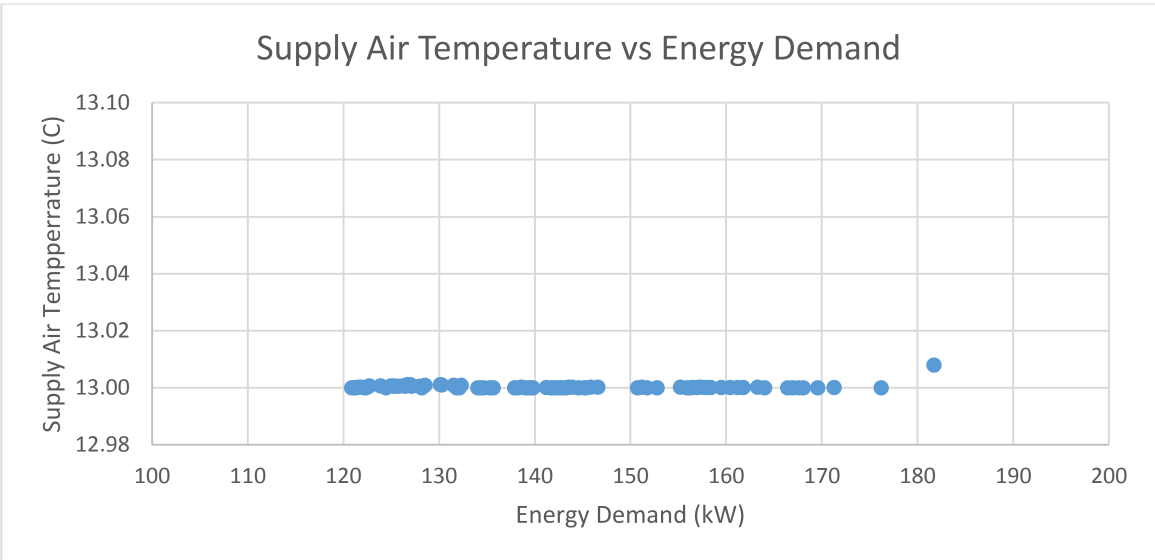

Figure 5.1312: NSGA-II with reheat - Supply Air Temperature vs. Energy Demand

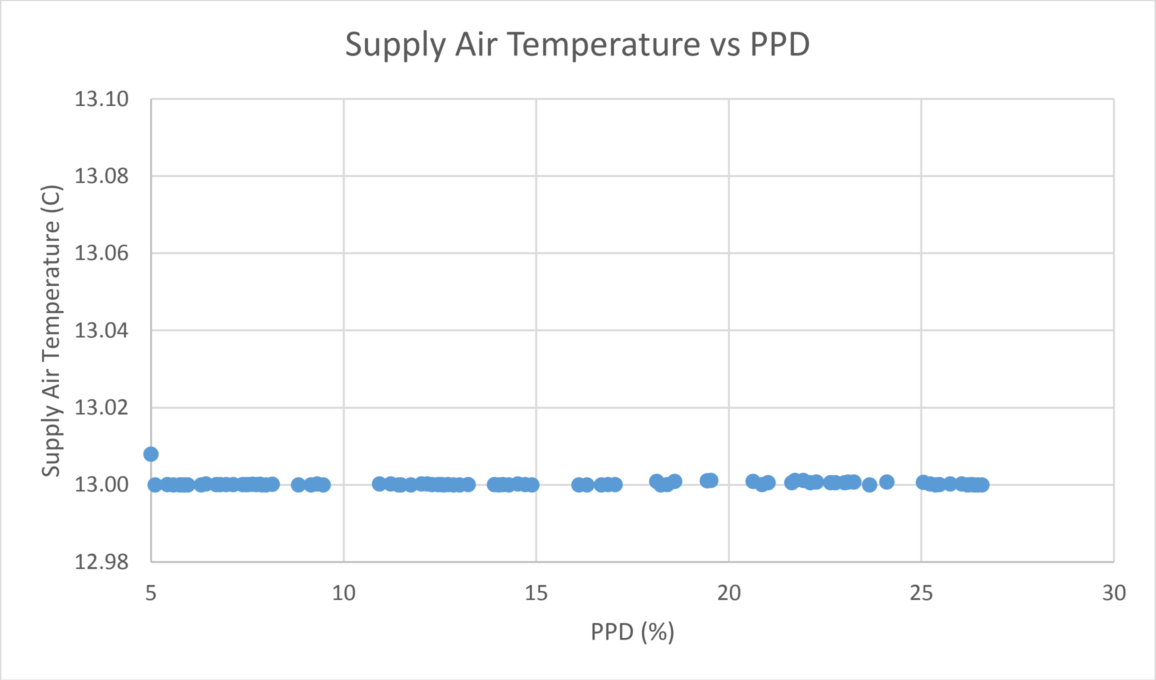

Figure 5.1413: NSGA-II with reheat - Supply Air Temperature vs. PPD

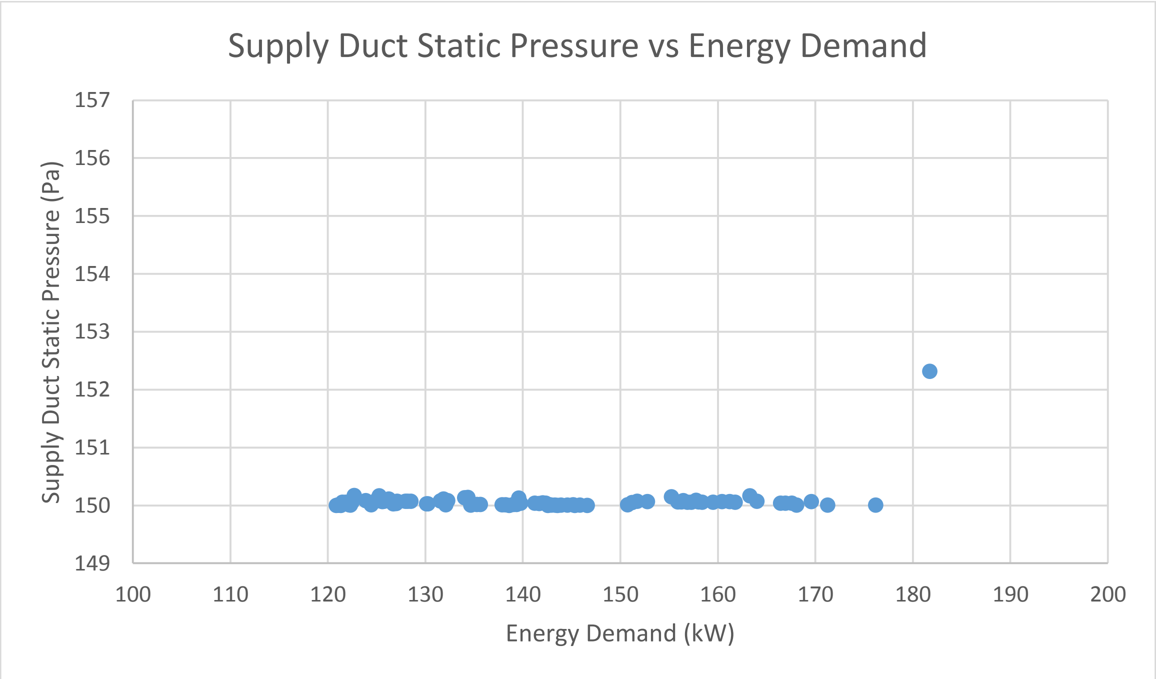

Figure 5.1514: NSGA-II with reheat - Supply Duct Static Pressure vs. Energy Demand

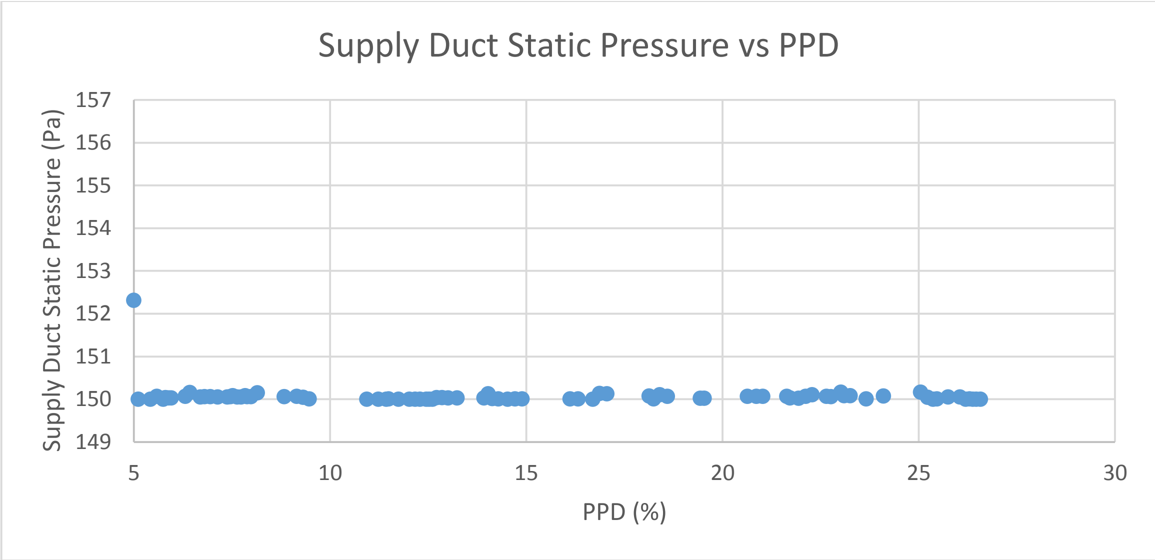

Figure 5.1615: NSGA-II with reheat - Supply Duct Static Pressure vs. PPD

In Figures 5.17 and Figure 5.18 we note a small variation in the chiller water temperature affecting energy demand as well as PPD. This set-point is a variable in the PPD equation as it affects the humidity. It is inferred that this is because the temperature off the chiller water dictates the temperature of the air leaving the cooling coils of the AHU, thus controlling the amount of water vapor that can be held by the saturated air.

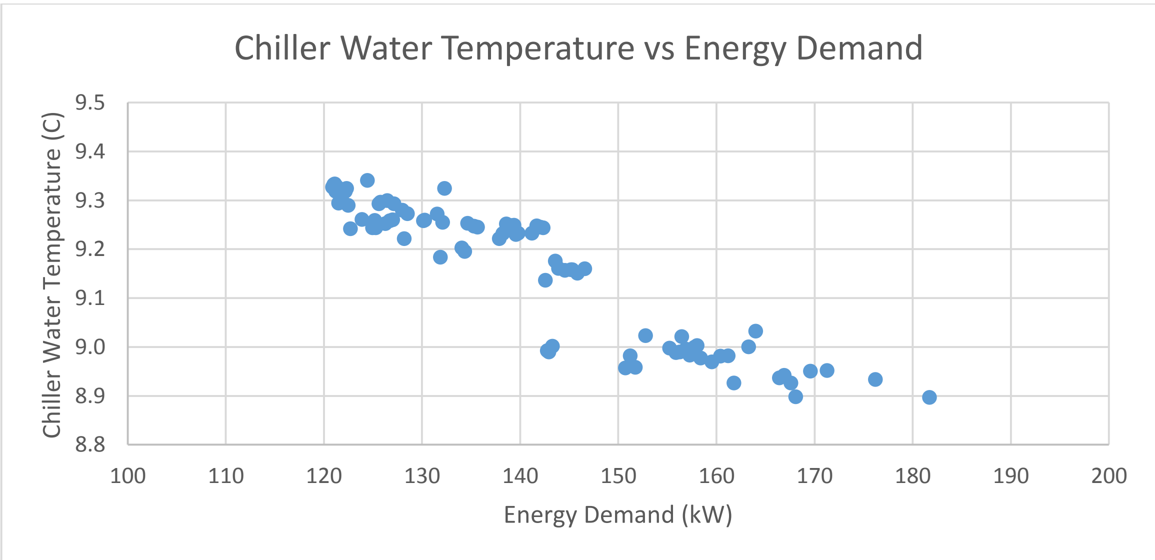

Figure 5.1716: NSGA-II with reheat - Chiller Water Temperature vs. Energy Demand

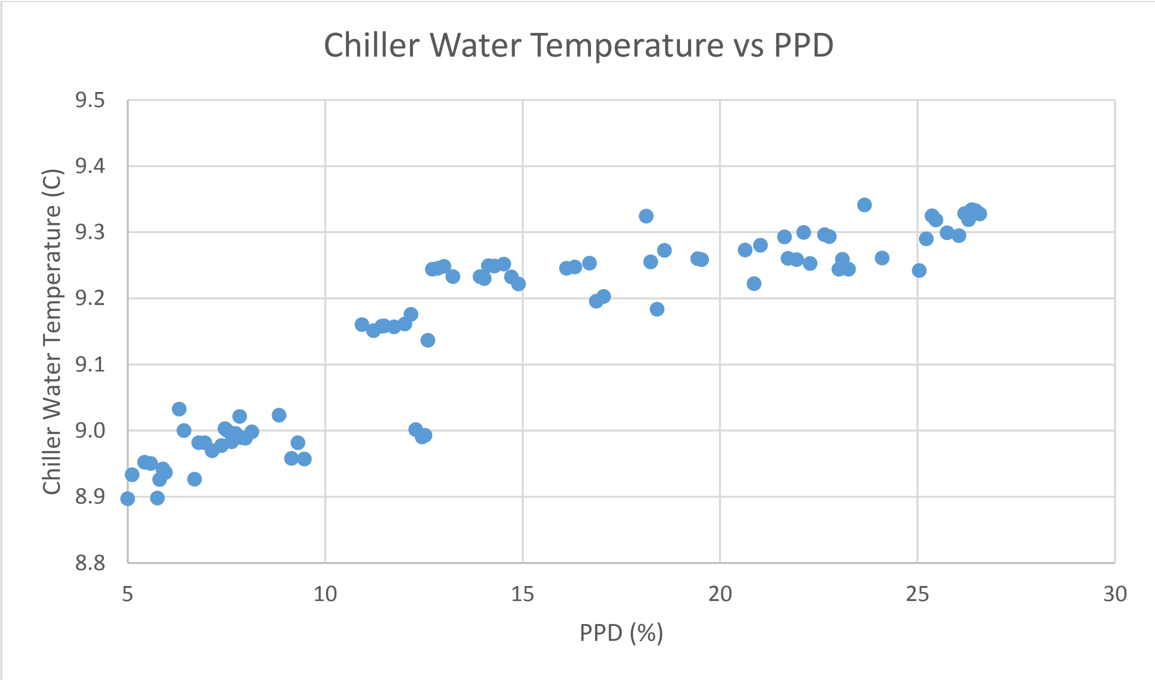

Figure 5.1817: NSGA-II with reheat - Chiller Water Temperature vs. PPD

In Figure 5.19 and Figure 5.20, we see that there is no variation in the humidifier set-point in the different optimal solutions. The reason for this maybe because of the fact the humidity does not affect the PMV and PPD much. On the other hand, Zone temperature affects PPD-PMV very much. Comparatively, we find that Relative humidity plays a minor role in thermal comfort, at least, according to the PMV-PPD equation. Thus the reason for the almost-nil variation of the relative humidity set-point.

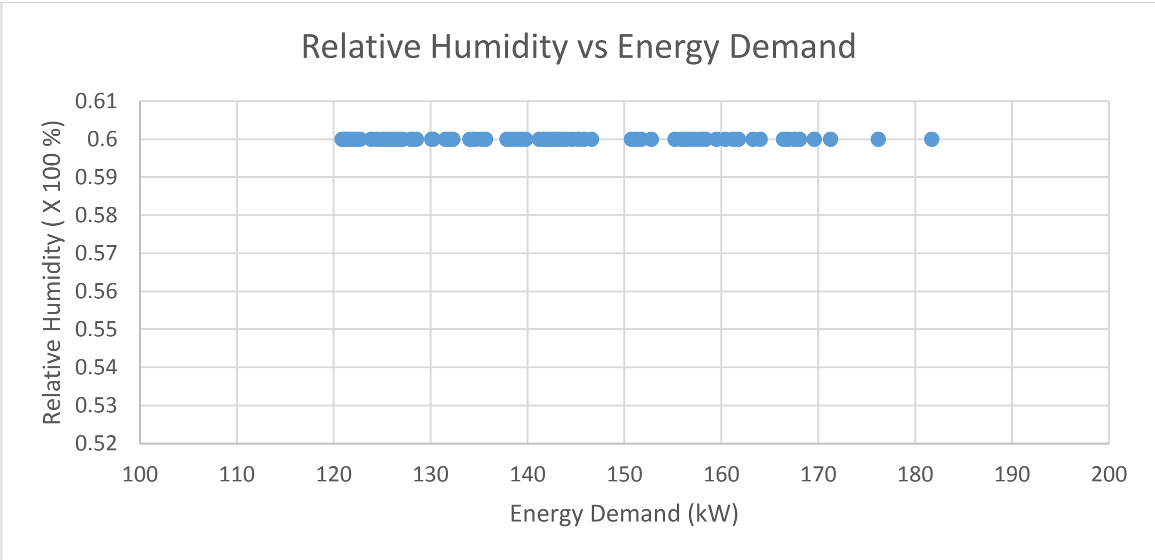

Figure 5.1918: NSGA-II with reheat - Relative Humidity vs. Energy Demand

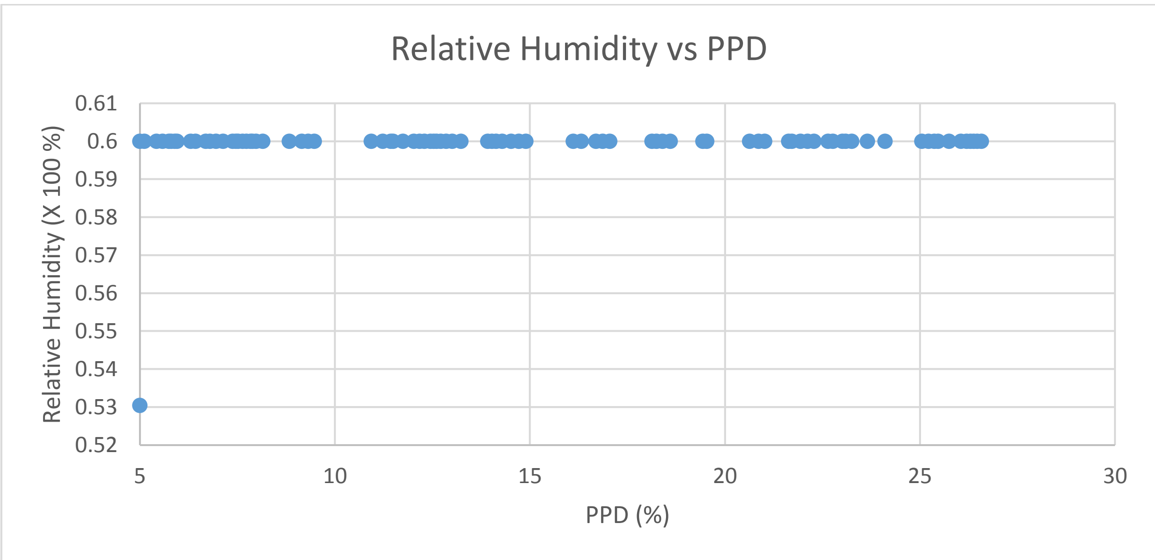

Figure 5.2019: NSGA-II with reheat - Relative Humidity vs. PPD

From these results, we notice that as the reheat was added, along with zone temperature, the chiller water temperature also starts to affect the variation of the energy demand and PPD of the system.

5.3 The Existing HVAC model optimized using Omni-Optimizer

The use of a new algorithm, Omni-optimizer was also tested and analyzed. The Omni-optimizer is useful because, if at any point, the HVAC system was to be optimized for either Thermal comfort (minimum PPD) or Energy Demand, but not both, NSGA-II would not work. As Omni-optimizer is able to handle a variety of different problems, especially single objective optimization problems, the potential flexibility it offers for real world problems far exceeds the flexibility offered by NSGA-II.

After analyzing the Optimal Solution obtained using Omni-optimizer, we see that Omni-optimizer produced results (Figure 5.21 to Figure 5.23) that were very similar, or even identical as that of the solutions obtained using NSGA-II. This was expected as the authors of Omni-optimizer had mentioned that the results obtained would be almost identical as that of NSGA-II.

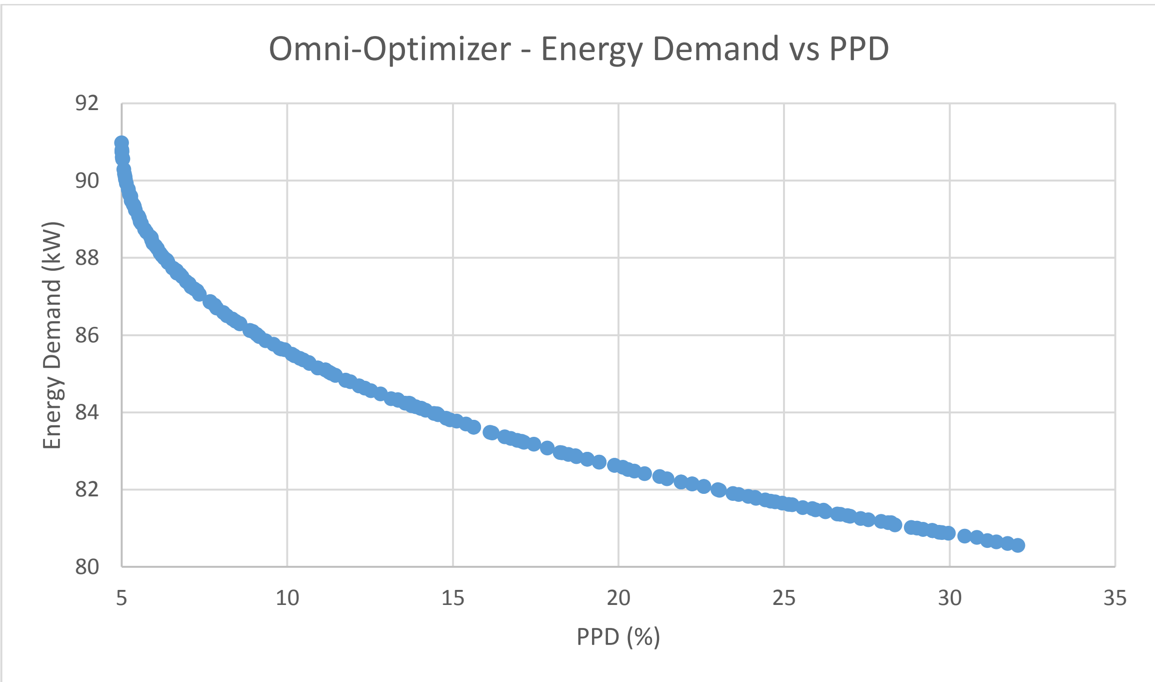

Figure 5.2120: Omni-optimizer - Energy Demand vs. PPD

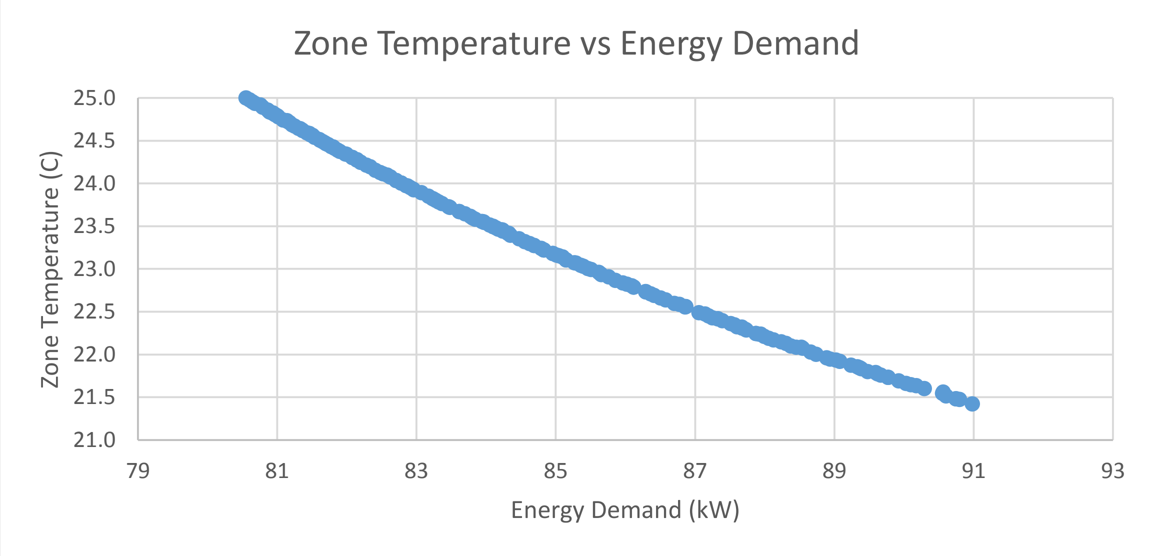

Figure 5.2221: Omni-optimizer - Zone Temperature vs. Energy Demand

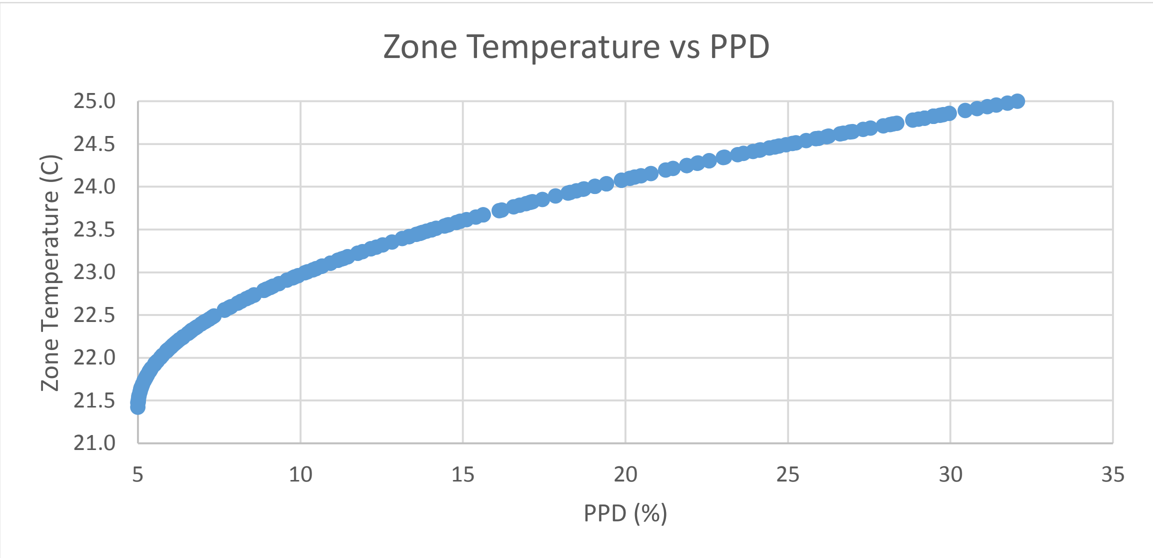

Figure 5.2322: Omni-optimizer - Zone Temperature vs. PPD

An advantage of Omni-Optimizer above NSGA-II that was mentioned in the literature [6] was that it tried to maximize diversity in the decision variable space also. This is evident in Figure 5.24 to Figure 5.29. But the variation, although there, is at a very small level. We also see that there is a small deviation of some of the obtained solutions from the optimal-front, the optimal front assumed to be the front generated by using NSGA-II This maybe because of the abovementioned part of the algorithm attempting to increase diversity among the solutions at the decision variable space also.

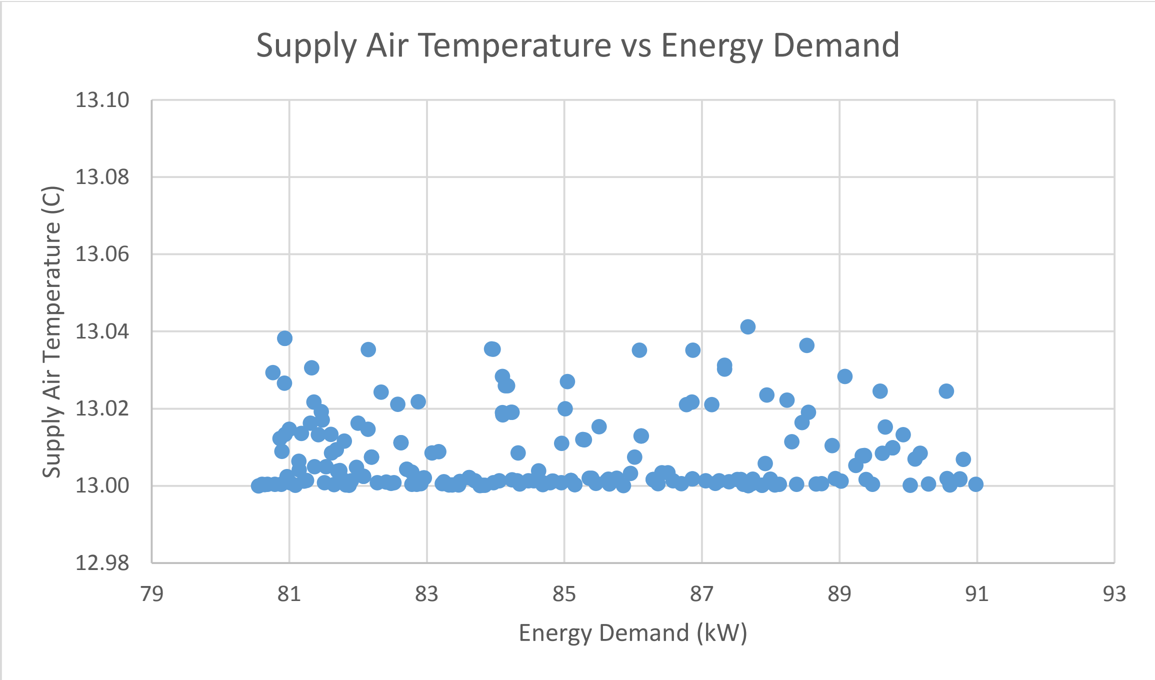

Figure 5.2423: Omni-optimizer - Supply Air Temperature vs. Energy Demand

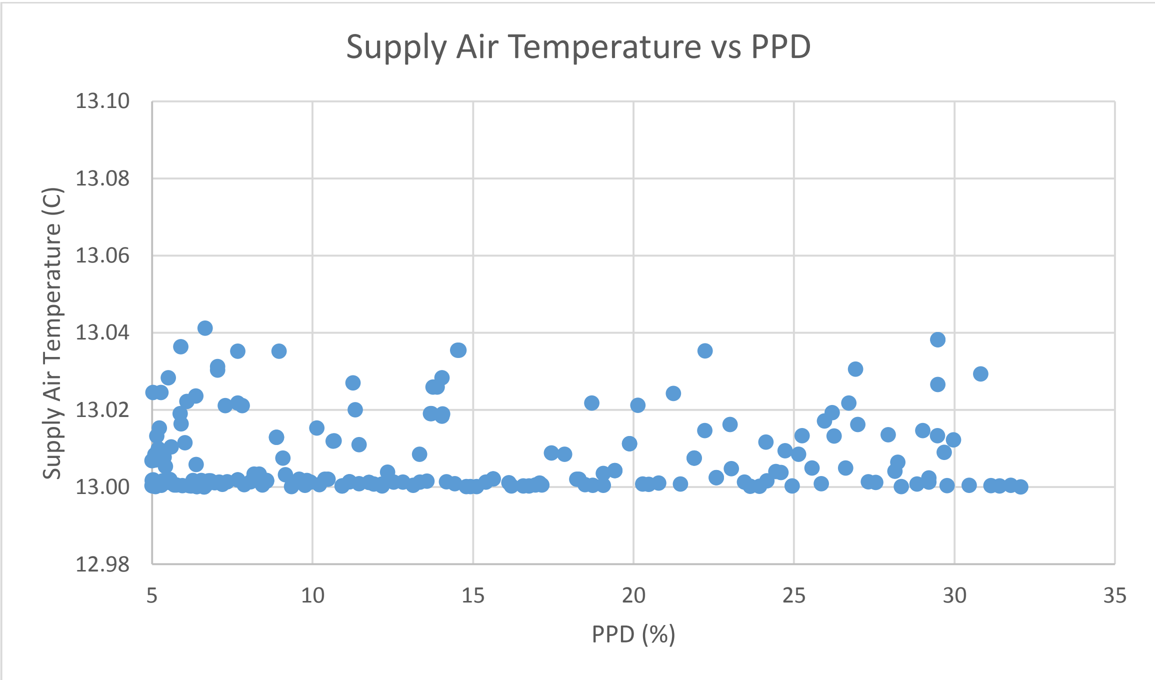

Figure 5.2524: Omni-optimizer - Supply Air Temperature vs. PPD

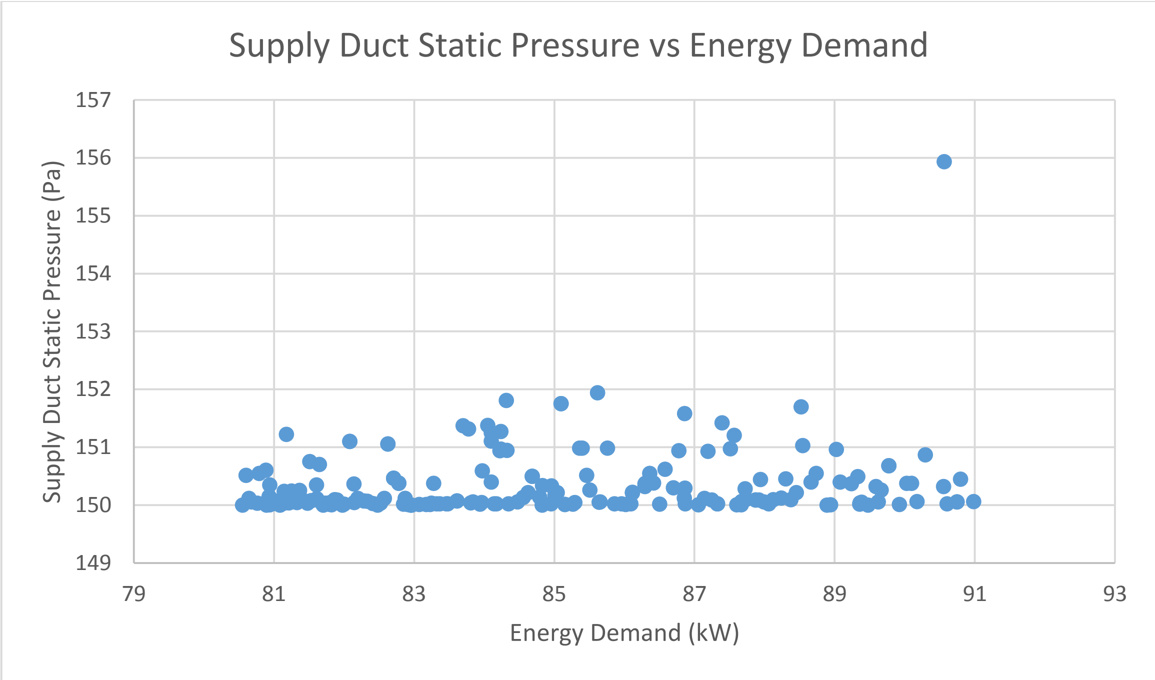

Figure 5.2625: Omni-optimizer - Supply Duct Static Pressure vs. Energy Demand

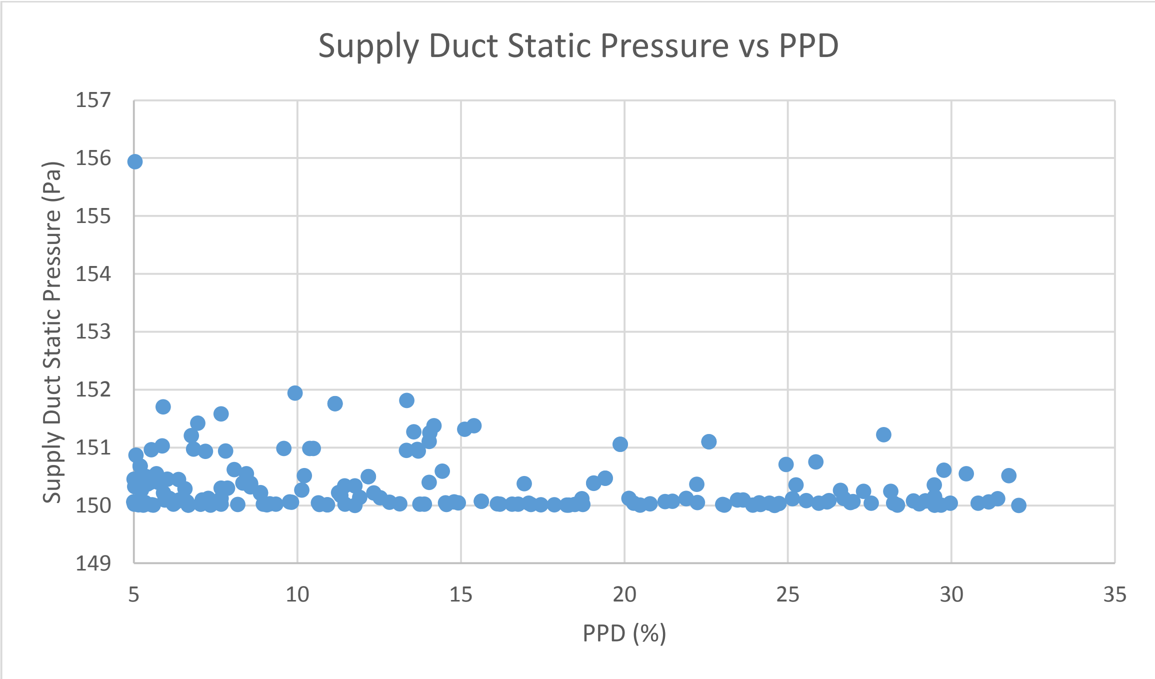

Figure 5.2726: Omni-optimizer - Supply Duct Static Pressure vs. PPD

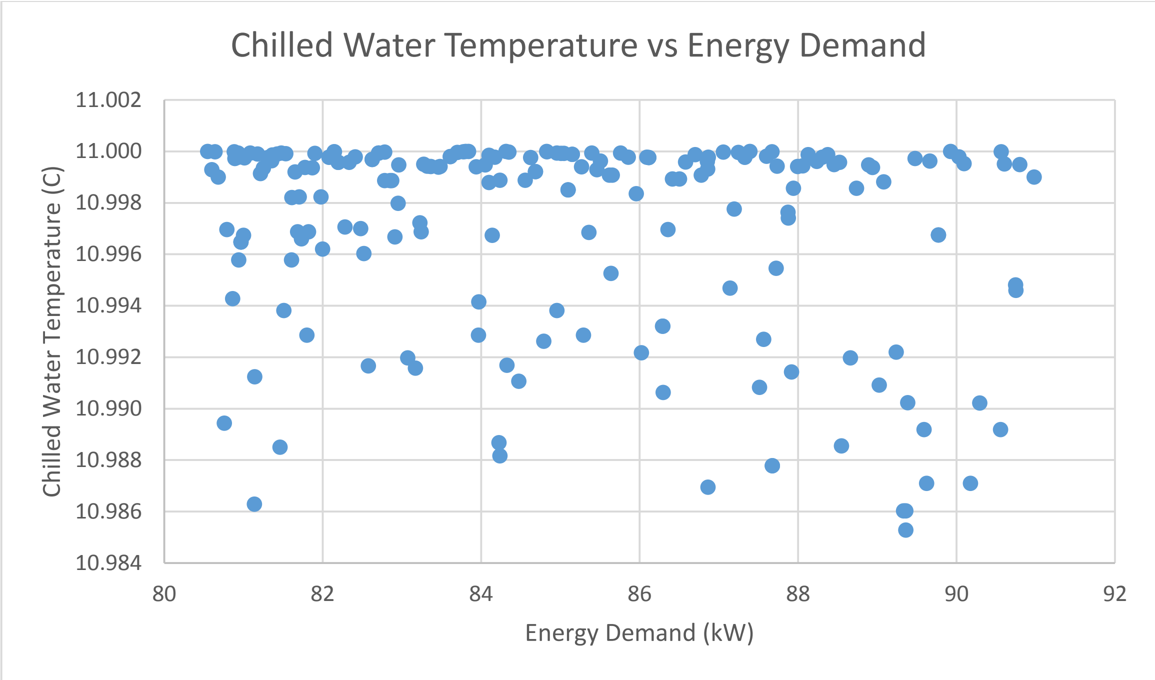

Figure 5.2827: Omni-optimizer - Chilled Water Temperature vs. Energy Demand

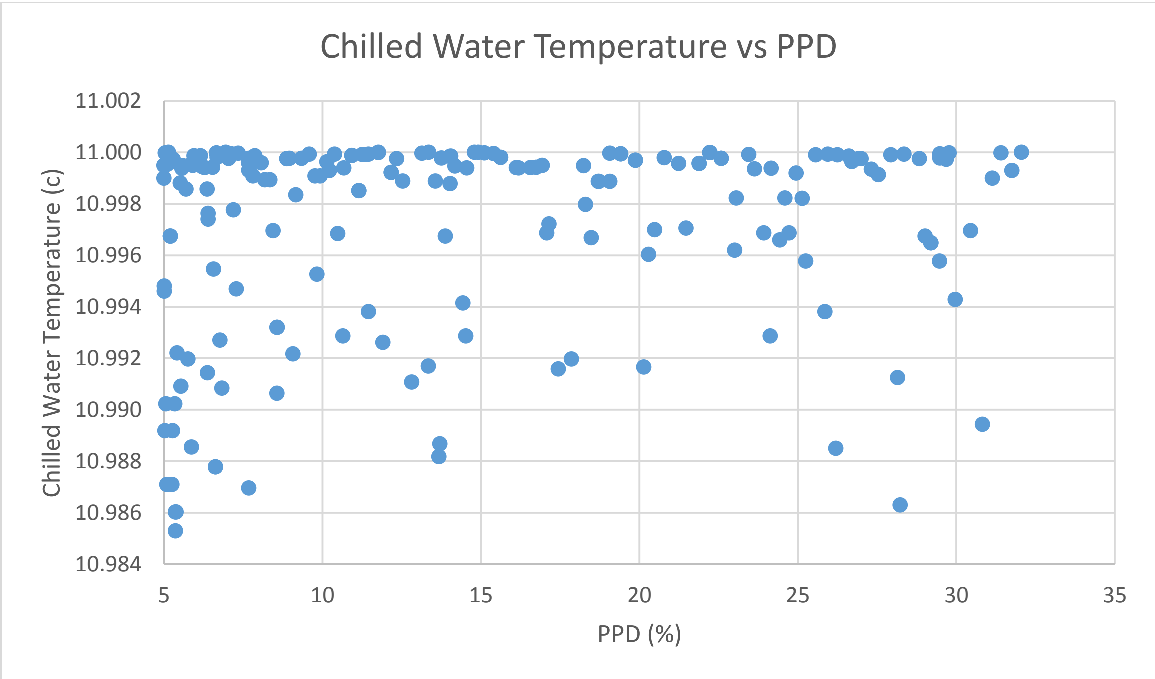

Figure 28.29: Omni-optimizer - Chilled Water Temperature vs. PPD

5.3.1 Comparison of Convergence of solutions in Omni Optimizer and NSGA-II

In the literature on Omni-optimizer [6], the authors claim that there are changes in the procedure (Restricted Selection) of Omni-optimizer that bring about better and faster convergence of solutions. The populations of the first few generations created by Omni-optimizer and NSGA-II are shown in Figure 5.30 and Figure 5.31 to analyze how the solutions converge to the pareto-optimal solution. We find that both algorithms almost converge to the pareto-optimal solution by generation 15. But upon closer inspection of the graphs, we find that the solutions in Omni-optimizer tends to clump together in the 5th and 10th generations compared to the solutions of NSGA-II in 5th and 10th generations. But, as the Genetic algorithms advance to later generations, we find that the results become more equally spaced for both the algorithms. This clumping that is observed might be due to the few changes between the two algorithms such as restricted selection and ε-Dominance or it may be due to the nature of this specific problem.

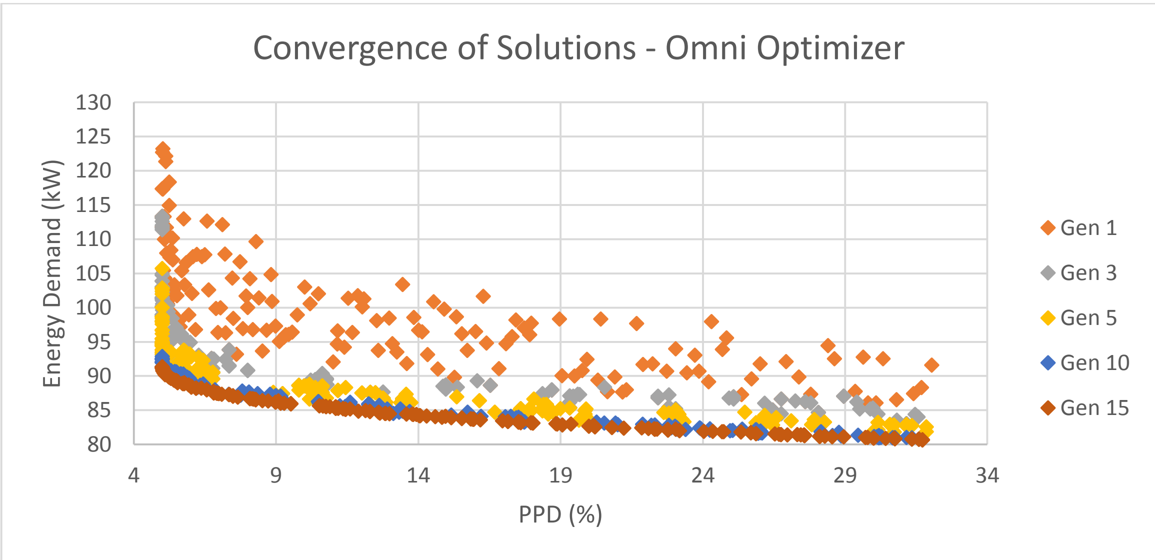

Figure 5.3029: Omni-optimizer - Convergence of Solutions

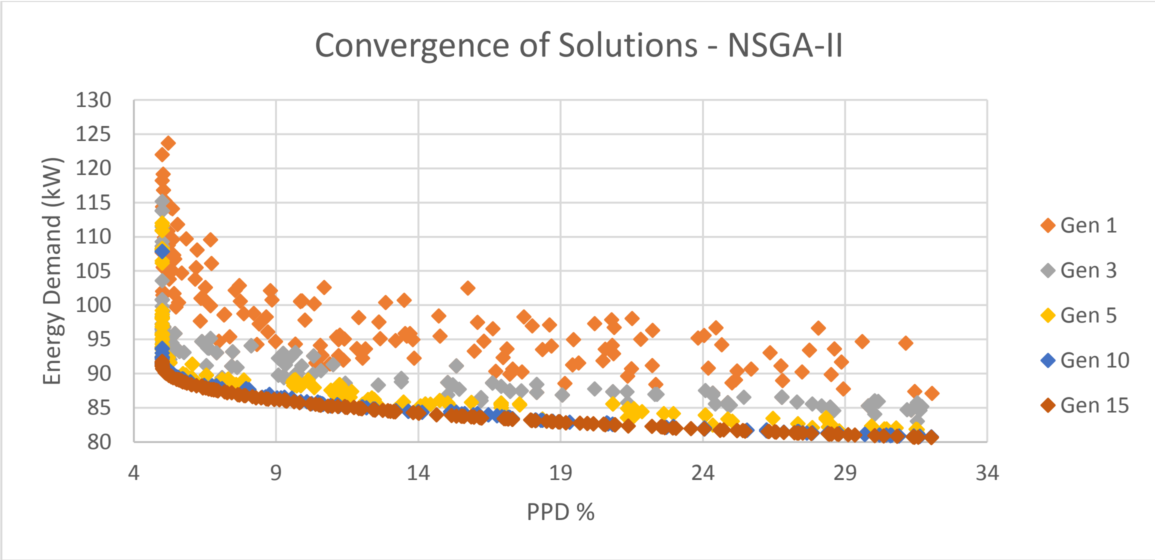

Figure 5.3130: NSGA-II - Convergence of Solutions

Chapter 6

Conclusion

From the literature survey conducted, it was realized that there is significant work being done in the fields of Genetic algorithms and of Optimization of HVAC systems. A study on optimization of the control system strategy using a two-objective genetic algorithm was conducted. Models of HVAC systems were made from elementary equations, one model with reheat and one without reheat. The energy demand and PPD for these models were used as the objective functions for the multi-objective genetic algorithms

It is concluded that Multi-objective genetic algorithms are found to be effective in optimizing HVAC systems. Each solution which corresponds to a set of values for the HVAC system set-points can produce the minimum energy demand for the given PPD. It was also concluded that better results in terms of energy savings could be achieved by the addition of reheat to the HVAC model. Addition of reheat helped to optimize the humidity in the HVAC system. The modified HVAC system, after including Relative Humidity as an additional control parameter, becomes more realistic. For the modified system, it was found that by sacrificing the thermal comfort by 5% PPD results in an energy saving of 32 kW or an energy saving of 17.5% can be obtained

A different genetic algorithm, Omni-optimizer, was also used to try and optimize the first HVAC model. Omni-Optimizer was found to be slower as compared to NSGA-II. This is because Omni-optimizer scans for more diverse solutions and hence takes more time to converge. This may be due to the fact that the procedure of Omni-optimizer emphasizes more on diversity preservation and this feature has not yet been perfected. It is also inferred that this feature may be the reason for the clumping together of solutions in the initial generations when compared to the initially used genetic algorithm.

Chapter 7

Future Work

During the process of doing this work, a large number of ideas were generated for future work. A few of these are discussed below.

1. Changing more parameters to variable set-points with upper and lower ranges. This would increase the amount of control that could be set on the HVAC system and thus help in decreasing energy demand without sacrificing thermal comfort.
2. Adding more constraints to the model so as to change the model from a generic one to a specific one.
3. Simulating the optimization process for a whole year to quantify the energy savings.
4. Changing the component models to more realistic models so that the realistic solutions are obtained.

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