Title
Optimization and integration of renewable energy sources on a community scale using Artificial Neural Networks and Genetic Algorithms

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Optimization and Integration of Renewable Energy Sources on a Community Scale using Artificial Neural Networks and Genetic Algorithms

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of the Requirements for the Degree

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by

Bron Davis

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Signature page for the Masters in MEAM Thesis of Bron Davis

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Date

Optimization and Integration of Renewable Energy Sources on a Community Scale using Artificial Neural Networks and Genetic Algorithms

Bron Davis, UC Merced

Abstract

The goal for this paper and my research is to reduce overall cost associated with electricity use at UC Merced. UC Merced presents itself as a unique opportunity for to model integration and optimization of renewable energy sources. It will be discussed exactly what makes UC Merced unique and how UC Merced has set a path towards higher energy efficiency on a community level. Furthermore, I will discuss difficulties involved with integrating renewable resources and then proceed to analyze techniques for further optimization as UC Merced continues its path towards zero net energy. One of these optimization techniques, genetic algorithms; I will discuss in some detail as it was the technique chose to verify the results of the optimization.

7KH PDLQ JRDO RI WKLV VWXG\ LV WR GHWHUPLQH

Central Plant load closer to or completely during daylight hours when there is inexpensive (solar) energy available or during the night time when energy pricing is minimum. While it seems logical to shift the cooling load, it has yet to be quantitatively shown that such load shifting would be more cost effective. Genetic algorithm (GA)-based Artificial Neural Network (ANN) models are used for demand and energy production forecasting and then GA based cost optimization is performed to find optimum time window for load shifting. We determined that loading shifting can be beneficial and the associated savings are presented for both summer and winter seasons.

ACKNOWLEDGEMENTS

I would like to take this opportunity to thank my advisor Professor Carolos Coimbra for his insight, guidance and enormous support. This work would not have started, let alone be completed, without his faith in me. He believed me and saw potential in me when others did not.

I also want to thank my committee members Professors Gerardo Diaz and Harish Bhat for their advice. Working with them has been a pleasant experience and their impact on me goes beyond research.

A special thank-you to John Elliott, Director of Energy and Sustainability at UC Merced. His knowledgeable background and advice on the topic gave a starting point to this work.

Many colleagues and friends helped me along the way. I would to thank all my lab mates for their enjoyable and invaluable discussions during my studies at UC Merced. Ricardo Marquez and Amanpreet Kaur in particular; this work would simply not have been successful without your help.

My deepest gratitude goes to my parents, my brother, and my girlfriend Jennifer. They are always there for me and never have any doubt in my abilities as both a person and an engineer. I thank my parents for their love and support, for always being there for me and believing in me as person and as an engineer. I also thank Jen for her love and support, but perhaps moreover, for her accompanying me on this journey; making it both worthwhile and enjoyable.

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1 Introduction

1.1 Motivation

Over the last decade, cause for concern grew higher over the changing climate. As the world came to realize the actuality of this concern, countries and the citizens that comprise them begin to search for solutions. It became clear in the United States and in particular, California, that becoming more sustainable with how we produce energy is a must. That is, turning to renewable energy sources (RES) and being more efficient with non-renewable sources of energy with the overall goal of achieving zero net energy. This is crucial in the buildings sector, where heating (and cooling) accounts for around 80% of WKH ZRUOG¶V HQHUJ\ FRQVXPSWLRQ (Kiely). In the US, commercial and residential buildings account for close to 40% of the primary energy use and approximately 70% of electricity (Paul Torcellini)(EIA). While efficient building technologies are expected to grow about 6% a year, electricity consumption in the commercial sector is expected to increase 50% by 2025, after already doubling consumption between 1980 and 2000 (Kiely)(EIA). These factors, coupled with growing concerns of greenhouse gas emissions produced by non-renewable energy sources, has led to many pushes in energy policy change not only in the US, but worldwide.

Policy changes also contribute to higher energy efficiency; particularly in California via Assembly Bill (AB) 32, where increases in energy efficiency are seen more as the route to the goal of AB32 which is climate neutrality. In California, the Renewable Portfolios Standards (RPS) mandates that 33% of power produced in the state must come from renewable sources by 2020 [http://www.energy.ca.gov/portfolio/]. Directly focusing on decreasing energy consumption, the Department of Energy (DOE) in collaboration with the California Public Utilities Commission (CPUC), has put in place aggressive planning to reach zero net energy. CPUC Planning LQFOXGHV WZR QHW]HUR ³ Energy Efficiency Strategies´: 1) all new residential construction will be net zero energy by 2020, and 2) all new commercial construction will be net zero energy by 2030 (CPUC). Additionally, the UC system revamped its policy on sustainability which states that every UC Campus must develop its own action plan toward climate neutrality ± specifically how each campus plans to reach the goal of reducing greenhouse gas (GHG) emissions to the levels of the year 2000 by 2014 and 1990 levels by 2020(CPUC). UC 0HUFHG UHVSRQGHG E\ LPSOHPHQWLQJ LWV SDJJUHVVLY Commitment´ which promises to achieve zero net energy, zero landfill waste, and climate neutrality by 2020 (CACS)(UCOP).

While these goals may be considered extreme by industry standards, many nations are migrating toward similar goals for environmental and economic concerns. For utility FRPSDQLHV ,62¶V DQG HOHFWULFLW\ VHUYLFH SURYLGH new challenge, which is well documented by (E.Y. Bitar) of integrating and managing renewable energy sources that are highly variable (such as solar and wind) not only efficiently, but also cost effectively.

1.2 **UC Merced's** Current Energy Management System

3(QHUJ\ HIILFLHQF\ RIIHUV WKH PRVW DIIRUGDEOH PHDQV (Hannah Gold Granade). Therefore UC Merced has placed significant importance on maintaining and improving its campus energy efficiency. As can be seen in Figure 1, provided by UCM Director of Energy and Sustainability John Elliot, shows this emphasis of energy efficiency now and projected into the future. It can also be seen that renewable sources of

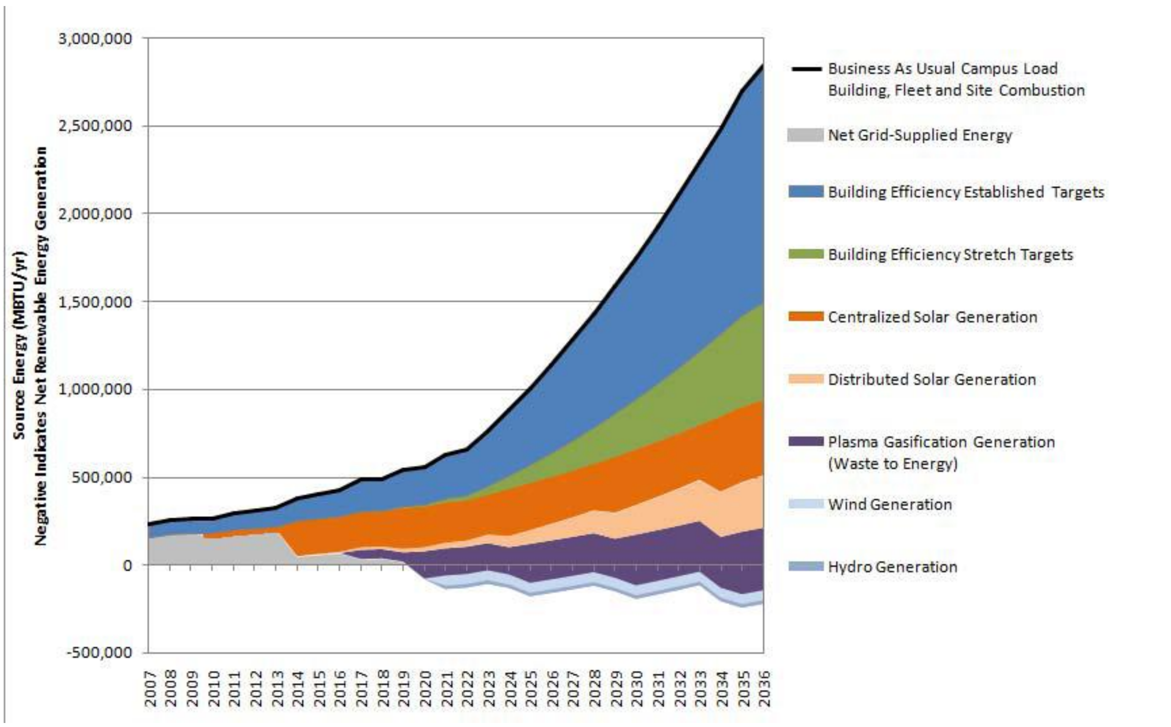

Figure 1: UC Merced example analysis showing business as usual loads to achieve Zero Net Energy (John Elliott et. al. 2010). Data for 2007, 2008, and 2009 are measured values. While renewable energy sources are an integral part of achieving zero net energy, energy efficiency is vastly more significant if UC Merced hopes to achieve its goals.

energy play a large part in the campus goal of zero net energy. To achieve this goal, the campus is focused on building independent energy resources on site. There is 1-MW single axis photovoltaic solar farm installed by a power producer in November 2009, meeting 15% - 30% of the campus energy demand. The rest of the campus demand is met by buying electricity from the grid supplied by the local utility company. The usage of intermittent energy resource, such as solar, is noticeable in the form of variability in the energy demand from the power grid which can be seen in Figure 2. Despite good SHUIRUPDQFH WKXV IDU ³VHYHUDO RSSRUWXQLWLHV U VWUDWHJLHV LQ WKH EXLOGLQJV >DW 8& 0HUFHG@ DQG (John Elliott).

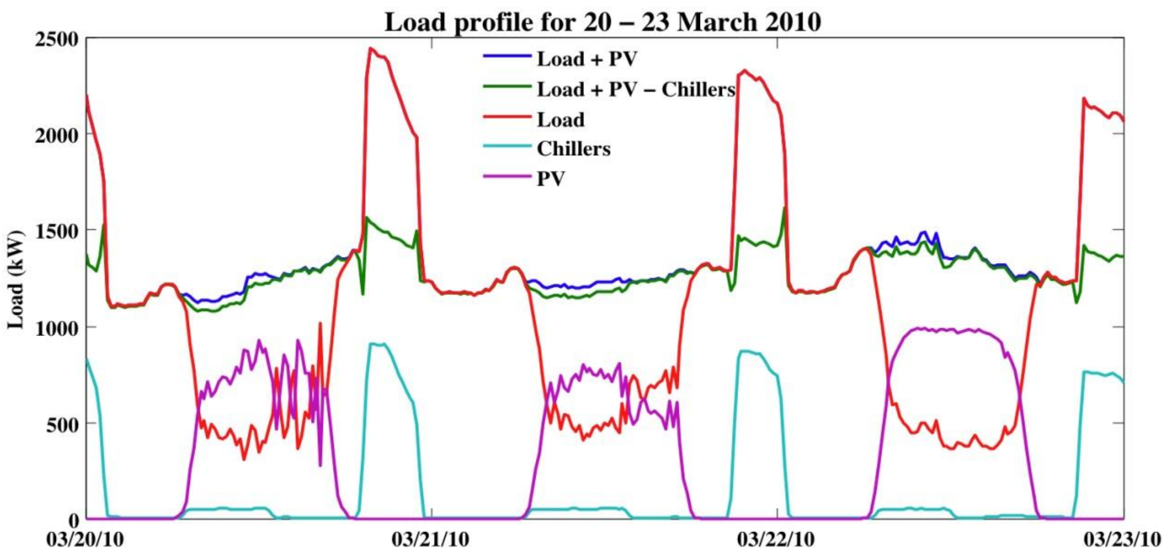

Figure 2: UC Merced campus load profile for a few days in March 2010. The campus has a unique load shape because it has shifted the majority of its HVAV loads to the night time. With the addition of PV, the ORDG VKDSH FXUYH µ/RDG¶ EHFRPHV PRUH XQXVXDO of a typical commercial building. In DOPRVW WKH this study we want to see if we can take advantage of the PV by moving the chiller closer to the peak hours thus eliminating the high spikes cause by the chillers.

The major component of the campus load comes from Central Plant which is the centralized HVAC system combined with thermal energy storage (TES). It has been shown by (Joseph C Lam) that centralized HVAC system with TES is very energy efficient and economical long term. The central plant consists of three chillers (of which only two operate at once) where water is refrigerated to 4 degrees Celsius at night and stored in large tanks. The water is then circulated throughout the campus by a series of pumps and air controllers during the daytime when it is needed. This allows the central plant to be operated at night (in this case study, typically around 10:00PM) when electricity prices are lower. However, with the integration of the new solar array, there is now a renewable and cheap alternative available during the middle of the day.

Additionally, independent of the time of operation, any HAVC system is largely driven by weather and other external environmental conditions which can change from month to month (even weekly or daily). However, the current energy management system is only optimized for two seasons: summer and winter.

1.3 Objectives and Methodology of Thesis

This work is focused on the economic impact of integrating a high penetration of variable renewable energy source. Such a scenario brings to light new questions and concerns about energy efficiency and load management; two of which will this work begin to explore the answers of: 1) Solar energy introduces a large amount of variability into the power load. While solar energy represents a cheaper alternative to other energy sources, will large fluctuations in power output in a high penetration scenario be too expensive to manage? And 2) would it be economically beneficial to move large electrical loads (such as those from a centralized cooling system) closer to peak operating hours where there exists relatively large amounts of cheap energy available? With these questions in mind, the objectives of this work are two-fold with emphasis placed on the latter:

1) Load smoothing

- Discuss the economic benefits and costs associated with integrating a variable renewable energy source (solar) and suggest a method to curtail the associated costs.

2) Load shifting

- Discuss and suggest a strategy for optimally managing a com P X Q LW\ ¶ V power consumption when a high percentage of the power is derived from a variable energy source (solar).

While both objectives are of importance, from a small community perspective, the variability introduced is not of high concern because of the scale. However, such a situation could be of utmost importance on a larger scale ±such from a utility perspective. Therefore, the second issue will be the main focus of this work because it allows for a more detailed and practical case study where the outcome could potentially have an influence on the current energy management system of the campus at which the study is conducted.

Thesis Outline:

In section 2, the objective that deals with load shifting is discussed. Since, from a small community perspective, the variability introduced is relatively small and therefore not of high concern. However, such a situation could be of utmost importance on a larger scale ±such from a utility perspective. A brief case study is preformed and concludes with a discussion on future work.

In section 3, the first object is covered and a detailed case study is preformed. This section includes a background in load forecasting, where ANNs is the main strategy reviewed. The background concludes with optimization strategies that are commonly used in building energy minimization focusing on Genetic Algorithms. Results of the study are presented and discussed. The thesis concludes with a section on future work.

2 Reducing Electricity C osts by Mitigating Power Output Fluctuations

2.1 Integration of Renewable Energy Source

The challenge of integrating RES is not only an engineering problem, but one that requires a multi-disciplinary approach to identify the particular R&D tasks associated with restructuring the electricity industry that will account for sustainability and energy efficiency objects currently being addressed in policy. From a technical standpoint, the main objective is to find a set of Integrated rules for component and system design and system operation that allow for the various components of an electricity industry, when connected together, to function effectively as a single machine (H. Outhred). This includes much more than optimizing electricity loads from different sources. For instance, electricity transmission lines and infrastructure would need to be upgraded to account for fluctuations in some RES. Research has found that, for the state of California, 31 transmission lines throughout the state would require additional capacity above future projected capacities in order to meet electricity demands at each hour on a typical summer day (Jacobson). This is just one of many technical challenges associated in integrating RES on a community (or larger) level. On the building level, before implementation of RES, electricity was always readily available; therefore the design of the HVAC system, etc. need not take into account where the electricity is coming from. However, now with RES, there may be more power available at different times of day, at different times of year, for different places (IEA, Empowering Variable Renewables: Options for Flexible Electricity Systems). Integration of fluctuating RES causes design and control optimization to become dependent on each other. New renewable energy technologies such as wind power or solar PV have surfaced prominently in recent discussions among policy-makers, researchers and the media for two main reasons: Firstly, the rapid growth, especially of wind power, led to significant market share in some countries within a short timeframe thus magnifying grid integration issues. Secondly, these technologies introduce a new quality of natural cycles in that they can fluctuate over short timescales intra-day and intra-hourly which requires different management strategies than previously established (IEA, Variability of Wind Power and other Renewables: Management Options and Strategies). While renewable resources such as wind and solar are becoming more popular, and in some places like the US, eventually mandated; the question still remains whether this integration can be done cost-effectively. In a recent study, primarily on the residential level, it was found that while possible, it is still currently difficult to economically integrate RES (Melissa R. Elkinton). Lastly, the evaluation of the cost of fluctuating systems can become quite complicated which is covered in detailed by Weber (Weber); who concludes management of RES is more than a problem of integration, but one that requires careful stochastic optimization in order to achieve accurate evaluations of cost.

2.2 Costs Associated with Power Load Variability

In this section, the relative cost of PV fluctuations is estimated, where the cost of the fluctuations are calculated as a fraction of the overall cost. The fluctuations of the are characterized by normalizing the with respect to the nominal capacity rating of the PV power plant, ;

$$\qquad (1)$$

where MW. The fluctuations can be summarized by computing the standard deviations,

$$- \qquad (2)$$

Power output fluctuations are compared to the cost of those fluctuations using pricing data from the utility provider. Additionally, this cost of fluctuations is compared to the variability of power output from a 1-MW PV plant. Currently, these fluctuations, and the costs associated with them are handled by the utility because on an overall basis, the fluctuations in a 1-MW plant are smaller than those currently managed by utilities. However, as variable energy resources become a larger part of a utilities portfolio, the management and mitigation of these fluctuations will become more significant. Therefore, it may be in the FRQVXPHU¶V interest to manage the fluctuations on the FRQVXPHU¶V side of electricity operation. (Omran Walid A.) suggests that the utilities should offer economical incentives for the consumer to manage these fluctuations. This section provides a quick estimate of these costs, which is to be followed by a more detailed analysis to be performed in future work.

Cost Calculations as a function of ( )

Figure 3 shows the relationship between PV power output fluctuations of a 1-MW plant and the resulting cost of those fluctuations over each of the 12 months in 2010. The total cost, and the cost of fluctuations are defined respectively as:

$$\frac{\hat{u}}{} \qquad (3)$$

and

û û û (4)

where is the price of electricity (/kWh) the cost of PV is the price of energy multiplied by the power output. In this case, the price was taken from the PG&E E-20 tariff and rounded to a tenth of a cent, and where monthly demand charges have been ignored.

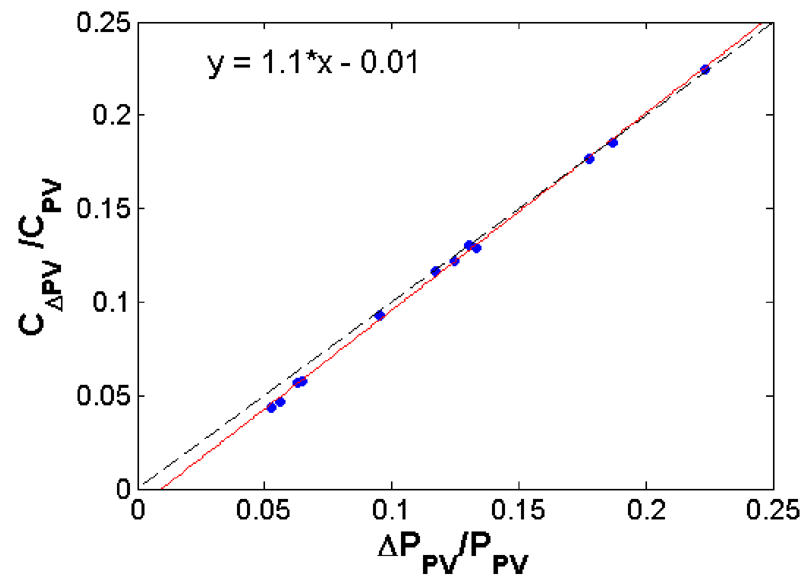

Figure 3 3RZHU RXWSXW ÀXFWXDWLRQV DQG WKHLU UHVXO

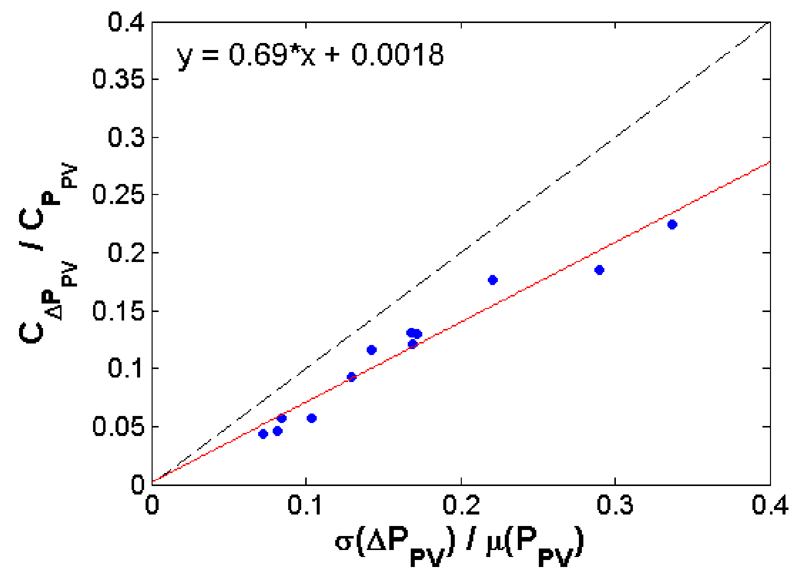

Figure 4: Power output variability compared with the cost of power output fluctuations

Cost Calculations as a function of

Figure 4 shows the cost of fluctuations as a percentage of the total cost for energy (defined as above in Eqn. (3) and (4)) as compared to the variability of power output as a fraction of the average PV power output on a monthly basis. The data displayed came from the same 1-MW PV plant over the course of a year (2010). While the percentage of cost attributed to fluctuations generally increases with increased variability of power output however, it is not the one-to-one ratio as one may have expected.

The costs calculated here are not the costs associated with the utilization of a PV system; but rather, represent the costs of having additional fluctuations than those already present in . Figure 3 shows that with larger fluctuations in output, higher costs ensue; which is an intuitive result. However, Fig. 4 shows that there is also a strong correlation between variability and the costs of fluctuations. These correlations imply that, if the variability in solar irradiance that leads to the variability in is known, it is possible to estimate the costs associated with having a PV plant at the given location.

Estimation of the cost of variability

The cost of variability of 1 MW PV plant at UC Merced can be estimated from the slope in Figure 4. Mathematically, it can be expressed as:

(5)

where is the total cost of the variability for the total solar energy produced by the PV. Thus, based on the cost incurred by variability, power purchasers and utilities can give incentives to renewable energy producers to limit variability. UC Merced buys solar energy from SunPower at a contracted fixed price of 12 cents/ kWh. Using this value, cost for variability per unit energy produced is tabulated as follows:

Table 1: Estimated cost of variability

Variability (%)	Cost (c/ kWh)
10	0.84
20	1.67
30	2.50
40	3.33
50	4.16

2.3 Discussion and Future Work

One methodology that could be adopted here was recently formulated and employed by (Omran Walid A.) for the case of reducing fluctuations of 10-MW PV plant using either LA or NA batteries, as well the option of dumping energy. The objective carried out (Omran Walid A.) was to make an evaluation of the most cost effective ways for reducing fluctuations by considering the use of two different types of batteries and also the options of dumping loads.

3 Reducing Electricity Costs via Chiller Load Shifting

3.1 General Methodology/Strategy

The steps followed in this study are listed as follows:

1. Compiling data
2. Power demand and production forecasting
3. Cost optimization
4. Shift chiller load to optimal start time

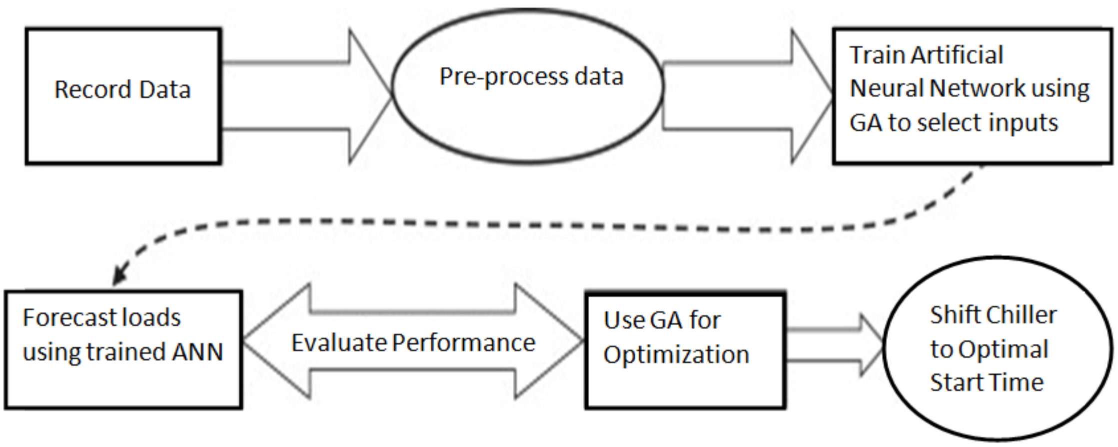

Figure 5: Block diagram that outlines the general energy management procedure presented in this study. Data comes from multiple sources so processing the data is an important step. Once the inputs are defined, they are fed through an ANN/GA hybrid in order to forecast power loads. These power loads, combined with a detailed price structure are then optimized using another GA. The desired output of this optimization is the start time of chillers that provides the minimal cost.

3.2 Compiling Data

Input data used for forecasting models can be classified as raw and processed data. Raw data is directly downloaded from a source and processed data is generated by applying some operator on the raw data available.

The first step is to compile and synchronize data from various sources. Power demand from the grid is provided by the utility company. The power output produced by

1-MW solar farm is downloaded from the SRZHU SURGXFHU¶V servers. This data consists of solar irradiance (W/m^2), temperature (degree C), wind speed (m/sec) and power output (kW). Lastly, all the power consumed by the Central Plant is downloaded from UC 0HUFHG¶V HQHUJ\ PDQDJHPHQW SODWIRUP $XWRPDWLF / (ALC). All the data is synchronized and processed using Matlab. In addition, the population present on campus HDFK GD\ LV PRGHOHG XVLQJ GDWD SURYLGHG E\ WKH and according to academic calendar for the school. Finally, weekday and hourly information is added because campus population flux depends on office and class hours.

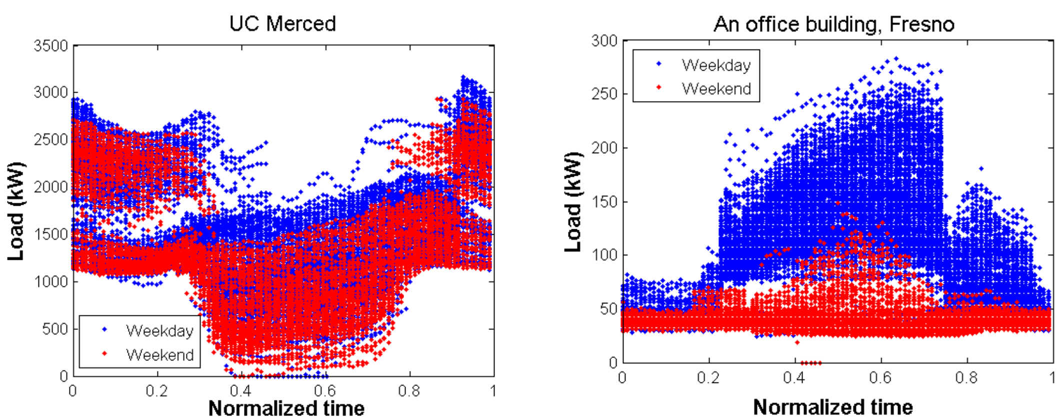

Figure 6: (a) UC Merced campus load in Merced, CA. (b) An office building load in Fresno, CA.

Generally, most office buildings have a high correlation between weekly data which can be explored to create the forecasting model. With the central plant operating at night and the 1-MW solar farm producing energy during the daylight hours, the current overall campus load has a very interesting load shape as shown in Figure 6 (a). This load profile is very different than standard office buildings as exemplified in Figure 6(b) where higher demand period coincides with the working hours.

3.3 Load Forecasting Overview

While not the focus of this paper, it is important to mention this aspect of electricity load profile optimization. As integration of RES continues to grow, load forecasting has become more prominent because of fluctuations in energy generation. With fluctuating RES such as solar and wind, it is necessary to be able to predict how much energy will be generated at different time steps (hours, days, months). Before RES, it was still important to know this information from a utilities standpoint so they would know exactly how much energy to produce without having to store, leading to large cost savings (J. Stuart McMenamin)(Lacir J. Soares). Without knowing this information, it is impossible to optimize a building or community accurately.

ANNs have been used to make very good predictions of energy consumption as shown in a study by (Pedro A. González). However, in building load management, only a few have combined ANN forecasts with a GA as the optimization tool. Nonetheless, a few studies have shown that this combination can successfully evaluate complex systems with high efficiency. This study is quite similar one conducted by (Laurent Magnier) in how the ANN and GA interact, whereas in studies by (Liang Zhou) and by (T.T. Chow) the implementation of the ANN and GA differ in that they are more intertwined.

ANNs are modeled after the human brain; electric pulses that deliver information travel through complex networks made up of neurons. That is, in the most basic terms, an ANN is an attempt at a mathematical representation of how the human brain learns. This model maps the inputs of the process to the output via units called neurons. The neurons are arranged in a minimum of two layers - an input and output layer. However, it is typical for a network to be made of many layers, the middle layers being referred to as hidden layers. The input neurons receive the weighted sum of external information which is decided by the operator of the network. These neurons then process the information and produce an output by applying an activation function to the weighted sum. If there are hidden neurons in the network, this output is now acts as an input to a neuron in the next layer and the procedure repeats until the output neurons are reached. In most neural networks, the information travels in one direction (from inputs to outputs) and is defined as a feedforward neural network. A feedforward neural network, such as the one adapted here, with N inputs and N_h neurons in one hidden layer with a linear output activation function can be expressed mathematically as

where are sigmoidal functions, such as the hyperbolic tangent function. Once the ANN structure (number of layers, number of neurons in each layer, and type of activation function) has been established, the ANN undergoes a training process in which the weights of the activation functions are adjusted so that minimization of some performance measure is achieved. One such method used in this study is the mean square error (MSE) defined as

$$- \qquad (6)$$

where y is the function being approximated by the ANN and a is the target value; the measured electricity load in this case.

However, the mentioned studies all use simulated data to train the ANN. In this study, actual data is used to train the ANN, and also for validation. This is significant VLQFH $11¶V KLJKO\ GHSHQG RQ WUDLQLQJ GDWD VHWV loads, but the studied HVAC system was poorly designed or is operating inefficiently, the ANN will continue to forecast those same loads (albeit with high accuracy).

Prior to the installation of the solar array at UC Merced, model predictive control (MPC) studies had been conducted by (Brian Coffey) (MPC studies are covered in more detail in the section 4). Therefore, it is presumed in this work, that the present cooling system is already quite energy efficient. The focus of this work is on studying the effects of integrating a renewable energy source have on the overall load and investigate whether this load shape can be manipulated to achieve maximum cost savings. To do this, an ANN/GA hybrid model is used to predict energy loads coupled with a separate GA to optimize the system for minimal operating costs. The objective of the optimization is to find the optimal start time for the centralized HVAC system. The accuracy of the minimized cost depends directly on the performance of the ANN; however, it is shown that a high performing ANN may not be needed to achieve optimal start times. Furthermore, this study gives an insight into how variable energy production from the ~20% integration of renewable energy impacts load shifting from a cost point of view.

3.4 Forecasting UC Merced's Electricity Loads Using ANN

The second step in our approach is to build a forecasting model. Predicted data is needed for the user to make a decision about shifting their load. Very recently, a study was done to build a forecasting model based on end-uses (Guillermo Escrivá-Escrivá).

Similarly, for this study, the focus was on time dependent demand and production forecasting and time independent load forecasting (Central Plant). For UC Merced load management three types of forecasting are required:

a) Total campus load
b) Solar farm power output
c) Central plant load

For all these forecasts, only one forecasting model based on ANNs was used. Previously, these models have been used for forecasting irradiance and PO from 1 MW solar farm (Ricardo Marquez). ANNs are well suited for problems in classification and pattern prediction - even more so in cases where the underlying processes are complicated or difficult to formulate, VLQFH $11¶V GR QRW UHTXLUH H[SO the system/process being analyzed. In addition to (Ricardo Marquez), the ANN/GA methodology utilized here was recently formulated by (H.T.C. Pedro).

In this methodology, the inputs for each model are selected using a GA, with the max number of inputs being defined at the beginning. In this research, the forecasts are required for the aforementioned electrical loads. Every forecast shares the same meteorological inputs (temperature, wind speed, irradiance, and humidity). Also, up to four lagged values (meaning an hour back) of demand are included as inputs from which the GA can select. Additionally, a population model is also added as an input along with day type and month. For instance, in forecasting the UC Merced campus demand there may be up to 11 inputs available. The genome of the GA will be something like [0 1 0 0 1 0 1 1 0 0 1]. That means that the ANN will use only the 2^{nd}, 5^{th}, 7^{th}, 8^{th}, and 11^{th} inputs. The other inputs are not discarded; they are kept in memory because they may be needed for other ANNs. The optimization in GA is based on root mean square error (RMSE) between the forecasted and actual data. Over fitting is avoided by applying the same ANN to several testing sets. Once the RMSE error is calculated for each set, we calculate the standard deviation from all the average RMSEs. If the standard deviation is too large, the ANN is over fitted for a particular set. The forecast is well generalized if the standard deviation of the average RMSE is low. Meaning the ANN should perform independently of the input dataset and therefore insuring the ANN is not over fitted. Inputs selected by the GA are then used to train the ANN model for forecasting. This way one generalized ANN forecasting model can be used for three different applications. In this study, Short Term Forecasting (STF) is performed i.e. a day ahead for 15 minute time intervals.

For testing the ANN forecasting model, March 2010 is selected as the winter month and August 2010 as the summer month. March contains Spring break, when majority of students and staff are on vacation. Similarly, Fall semester begins in the middle of August, where campus population suddenly rises. Though these qualities make March and August more difficult to forecast, if high accuracy forecasts can be achieved with these month, it implies that forecasting for other months should not be worse. Therefore, these months are taking representatives of their respective seasons. The results using the GA based ANN forecasting models for August and March are shown below.

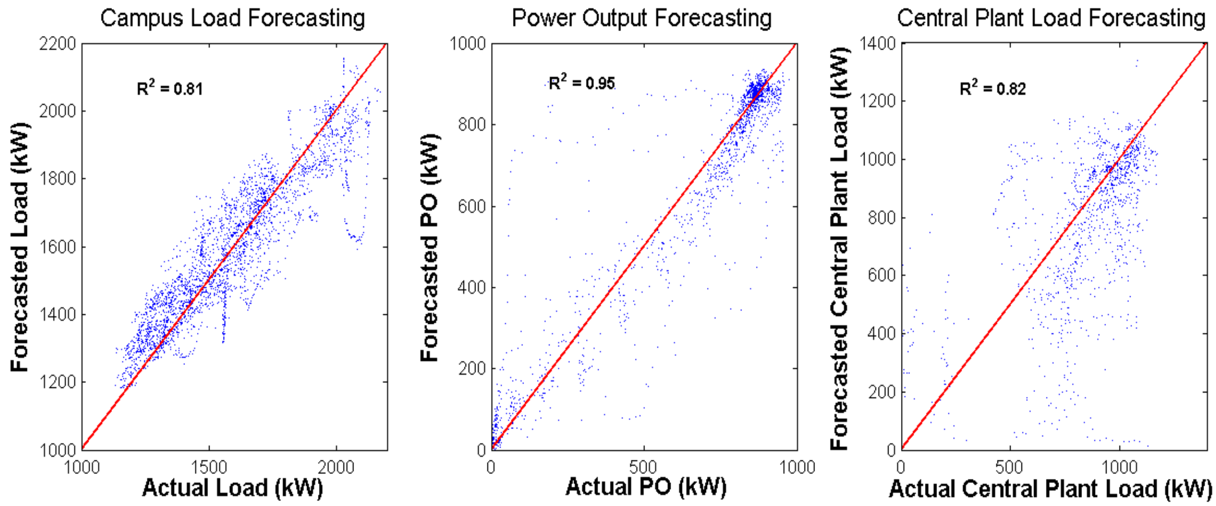

Figure 7: ANN forecasting results for a summer month (August 2010). Forecasting was done daily (24-hour ahead) for the entire month with 15-minute intervals. The feed forward ANN had 11 input neurons (meteorological data, a number of lagged values, and day type information) in the input layer and 20 hidden neurons in the single hidden layer with only one neuron in the output layer. The ANN was trained using back propagation and only 2010 data used for training with August 2010 used as the validation set.

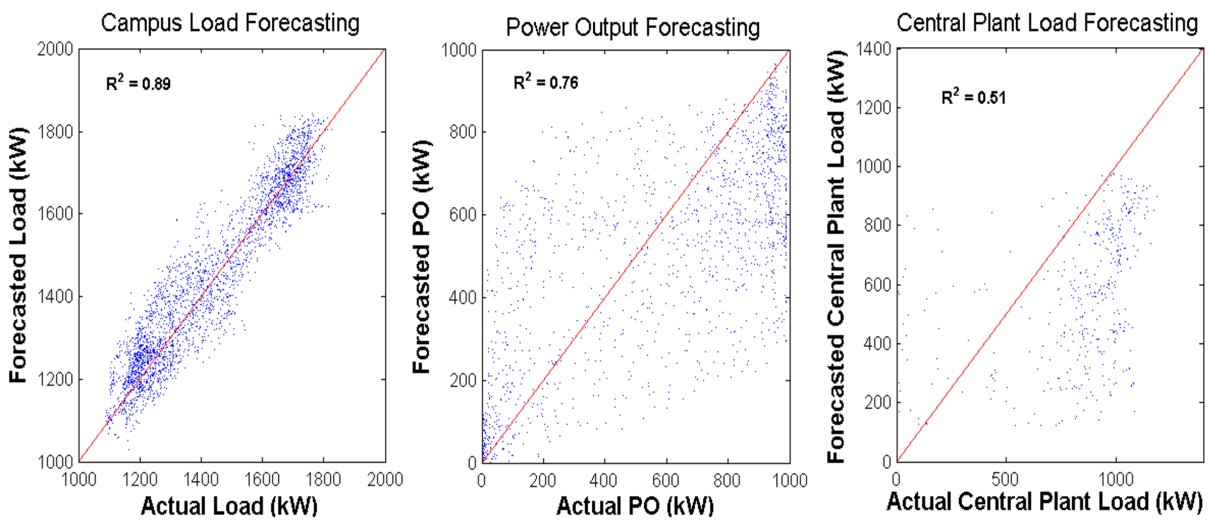

Figure 8: ANN forecasting results for a winter month (March 2010). Forecasting was done daily (24-hour ahead) for the entire month with 15-minute intervals. The feed forward ANN had 11 input neurons (meteorological data, a number of lagged values, and day type information) in the input layer and 20 hidden neurons in the single hidden layer with only one neuron in the output layer. The ANN was trained using back propagation and only 2010 data used for training with March 2010 used as the validation set.

From the above results, it can be observed that for summer, PO from the solar farm can be forecasted with relative high accuracy (0.95). This is due to clear sky conditions and minimal fluctuation in the irradiance reaching the ground. Expectantly, the results for winter are comparatively worse; mainly due to volatile nature of the weather (a mixture of rain and clouds, but also clear days).

Forecasting for the net campus load should be relatively consistent throughout the year with the chiller loads removed and solar energy generated added in. This is generally depicted in the above figures; however, the months chosen do have aforementioned peculiarities. In addition to the sudden rise in campus population, some of the hottest days of the year occurred, which adds to the uncertainty in the load. In March, where the population is relatively consistent, Spring break could cause an increase in forecasting error, especially considering the training data has no such occurrence.

Lastly, the forecasting for the Central Plant load was better for August, as it was operated at very regular schedules except for a few days where it operated during the day. On the contrary, due to the Spring break in March, there were many variations in the scheduling of the Central Plant cooling load, which affected the forecasting for the Central Plant load. Since the operation of Central plant can be controlled by scheduling fixed times, the impact of the error in chiller load forecasting could be avoided.

3.5 Optimization Strategies for Minimizing Costs due to Electricity Use

³7KH IXQGDPHQWDO DSproach to optimization is to formulate a single standard of measurement ±a cost function ±that summarizes the performance or value of a decision and iteratively improve this performance by selecting from among the available DOWHUQDWLYHV´ (Fogel). The optimization route one chooses typically depends on the type of problem being solved. Even then, it can sometimes be difficult to measure the effectiveness of one strategy over the other. For this case, many studies and methods have

been proposed for optimizing energy use in the past, even more so recently, with and without the integration of RES. Moreover, while it is typical to optimize for cost, this is not always done directly for building optimizations. Optimizing with respect to thermal comfort is quite common throughout the industry because it is believed if the occupants are comfortable they are less likely to change temperature settings, thus reducing cost in that form (Lomas)(Jonathan A. Wright).

Load shifting, or other forms of load management, has been performed on a variety of levels from single factories (B. Ostadi) to power producers (J.M. Godoy-Alcantar) usually involving the HVAC system. Indeed, the majority of optimization techniques employed in an effort to save costs and energy associated with buildings are applied to the HVAC system (Armstrong) (G.A. Floridesa). Central plant load shifting is typically achieved on two bases: cost efficiency or energy efficiency. For instance, it is usually more energy efficient to operate chillers when there is a smaller temperature difference between the surrounding environment and the cooling fluid. In study (Joseph C Lam), load shifting involves implementing centralized HVAC in order to shift large heating and cooling loads into the nighttime which has already been successfully implemented at UC Merced. Centralized HVAC also has the benefit of being somewhat time independent - it allows for the cooling load to be initiated at any time of the day or night which makes it uncomplicated to shift.

When considering load management, many studies (which will be discussed here) have constructed or utilized detailed physical model simulations combined with dynamic (i.e. mixed/binary, linear/nonlinear) programming to predict energy loads and optimize this system based on operating costs. In(Middelberg), Middelberg developed an optimal control model for load shifting and applied it to the energy management of a colliery. Middelberg uses binary integer linear programming to optimize energy efficiency. (G.B. Sheble) models a non-linear objective function by using approximate linear segments and then uses integer linear programming. Also, Sheble performs the optimization for two separate objectives, the first objective being with the traditional minimization of operating costs, and then goes to the second which is a more utility helpful profit-based objective. (B. Ostadi) shows the benefits of not simplifying the model and uses non-linear programming to optimize electrical energy consumption. However, the case study presented by Ostadi is not overly complex and other may have difficulty in adopting the methodology to a more complicated scenario. (Ashok) concludes that significant reductions in electricity cost (about 5.7%) are possible with optimal-load schedules.

The main advantage of a detailed model simulation is that information is known at many steps in the process and thus presents itself with more opportunities to reduce energy loads. In a study conducted about UC Merced, in accordance with Lawrence Berkeley Labs (LBL), the researchers used a model-predictive-control (MPC) to model the schools energy system. MPC is very useful in the optimization of buildings because once you have a complete model; the system is able to give you multiple outputs of information; whereas using a more stochastic/probabilistic method (such as ANNs/GAs) may not be able to give you information at every level (Brian Coffey).

In this research, a GA is formulated and is the tool used for the cost optimization. GAs use concepts from evolutionary biology to find exact or approximate solutions to optimization problems, mimicking the Darwinian process of evolution, but in a statistical solver form. Starting with an initial generation of chromosomes (possible solutions), the

GA tests these possible solutions against some fitness (objective) function in order to select the next generation. This next generation evolves through the typical processes of evolution, selection (elitism), crossover, and mutation. The individual that performs the best (has the highest fitness, usually minimizing or maximizing the objective function) is returned as the ideal solution(McCall). For this study, three processes of evolution are used:

¶ Elitism: In this method of reproduction, a certain number or percentage of the population that shows the best fitness in a generation is kept. This increases the likely hood that the best solution remains in the population. Other methods, such as fitness-proportional selection as used by (Conraud) where a more fit individual is given a higher probability of making it into the next generation.

¶ Crossover (or recombination): crossover requires at least two parents from the current generation to create new individuals in the next generation. In a 1-point crossover, the chromosomes of the parents are sectioned off at the same point in the chromosome. The beginning section of one parent is appended to the end section of the other and vice-versa. This particular method then produces two new chromosomes. The probability of crossover typically ranges from 0.6 to 0.95 (Y.J Cao).

¶ Mutation: mutation acts by altering the genes of a single individual in order to a slightly change individual in the next generation. The altered gene is usually chosen randomly and the probability of it occurring on an individual is usually set to be low (Y.J Cao).

GAs make a great optimization tool for the issue at hand for a few distinct reasons. First, GAs are very adaptable to complicated considerations (Fogel). Most of the current uses of genetic algorithms deal the optimization of input parameters for the building HVAC system (Ryozo Ooka)(L.G. Caldas) (W. Huang). Even though these studies valuate primarily HVAC systems, many of them all have the similar objections functions: minimize cost, fuel, or GHG emissions. In all these cases GAs were chosen because of the complexity of HVAC systems. Additionally, GAs are quite efficient at finding a solution, whereas a method like MPC can take relatively long, even if it arrives at the same solution (Brian Coffey). Meaning, if you get new equipment or make changes to the building, sometimes the whole model needs to be reevaluated in MPC, however; using a method like GAs, this is not a significant issue. For instance, UC Merced has only integrated one RES, that being the 1-MW solar array, though they are soon to integrate plasma gasification of campus waste. Within the next few years, more solar (possibly concentrated) will be integrated along with the possibility of electricity generation from wind. Each of these generates electricity differently and can create a complicated load profile. In this situation, the chromosomes of the algorithm are the load profiles and the best solution would be the load profile that minimizes total cost according to some pricing index for electricity.

Moreover, while an economic solution is desired, there may be other criteria on which to base the objection function on. These criteria could range from minimization of fossil fuels or minimization of GHG to maximizing operation efficiency. Conceivably, the goal could be optimize a combination of the above objectives, giving each a certain weight of importance. GAs are particularly useful in multi-objective optimization (McCall).

One such study successfully uses GAs in the design process of green building design, taking into account factors mainly attributed to the envelope of the building. However, the study proceeds to admit that more variables, such as the mechanical system that operates the building could be included in the optimization (Weimin Wang). In another study, a different multi-criterion GA is used to guide energy efficient design of buildings. Their focus is more on cost of the HVAC system in particular, along with minimizing thermal discomfort, instead of having an objective function just focused on cost(Jonathan A. Wright). Both of these studies conclude that GAs show great potential for the solution of multi-criterion building efficiency optimization with respect to different objectives.

3.6 Optimization Methodology for UC Merced Case Study

Price Structure:

As mentioned in Section 1, UC Merced purchases energy from utility provider where the cost of electricity is comprised of two components: 1) the price of energy ($/kWh), and 2) amount of energy used (kWh) i.e. Demand cost. The amount of energy XVHG LV DGGUHVVHG LQ WKH SUHYLRXV VHFWLRQV YLD C Merced falls under is provided in Table 1. The utility splits the year into a summer season (May-October) and a winter season (November-April). Hourly break down the price structure on a daily basis for each season into Time-of-Use (TOU) periods is as follows:

Table 2: Summer TOU Period

Peak Hours	12:00pm 6:00pm, Monday-Friday (except holidays)
Partial Peak Hours	8:30am to 12:00pm AND 6:00pm to 9:30pm, M-F (except holidays)
Off-Peak Hours	9:30pm to 8:30am, M-F (except holidays); All day on weekends and holidays

Table 3: Winter TOU Periods

Partial-Peak Hours	8:30am to 9:30pm, M-F (except holidays
Off-Peak Hours	9:30pm to 8:30 m, M-F (except holidays); All day on weekends and holidays

$GGLWLRQDOO\ WKH XWLOLW\¶V WDULII LQFOXGHV WKUH minute interval in which the maximum energy is demanded in certain TOU periods (peak, partial-peak, and one charge) for overall maximum energy demanded. In order to accurately determine the daily cost (or monthly average), this demand charge needed to be broken down into days, and then from days, into TOU periods. Therefore, breaking down the utiliW\ V ³'HPDQG &KDUJH´ FRQVWLWXWHG transforming the monthly ($/kW-month) demand charge into an hourly ($/kWh) demand FKDUJH FRPSDUDEOH WR WKH X ³(QHUJ\ &KDUJH´[1] Traditionally, demand charges are neglected from this type of analysis for instance, in a study by (Alireza Khotanzad) demand charges were not considered in VLPXODWLQJ D SULFH VHQVLWLYH ELOOLQJ VWUXFWXUH demand charges can contribute anywhere from 10-25% of the final energy bill (depending on time of the year). Therefore an effort is made to account for them in the analysis of this study. Since it is impossible (with plausible accuracy) to forecast the above mention electricity loads for an entire month, some approximation is required. The utility Demand Charges will be charged to the maximum demands throughout the day of

[1] $P_{DP}(x)$ ($/kWh) = PG&E Monthly Peak Demand Charge ($/kW-month) / (# of Weekdays/Month)*(# of Peak Hours/Day)

$P_{DPP}(x)$ ($/kWh) = PG&E Monthly Partial Peak Demand Charge ($/kW-month) / (# of Weekdays/Month)*(# of Partial Peak Hours/Day)

$P_{Dmax}(x)$ ($/kWh) = PG&E Monthly MAX Demand Charge ($/kW-month) / (# of Days/Month)*(24 hrs/Day) prediction (DOP), instead of from the whole month. This will add error and propagate uncertainty to the calculated minimized cost, but this added error is always smaller than neglecting the utility Demand Chargers altogether.

The price of energy use, P_E, (as in separate from the energy demand charges) is VLPSOH EHFDXVH LW FRPHV VWUDLJKW IURP WKH WDULII
Lastly, UC Merced has a power purchase agreement with a solar power producer which FKDUJHV 8& 0HUFHG SHU N: RI HOHFWULFLW\ XVHG VLP
For the dates of this study, the amount charged, P_s, was about 0.12 \$/kWh. The total price is then

$$P_T(x) = P_E(x) + P_s(x) + P_{PD}(x), \quad (7)$$

where $P_D = [P_{DP}(x) + P_{DPP}(x) + P_{Dmax}(x)]$,

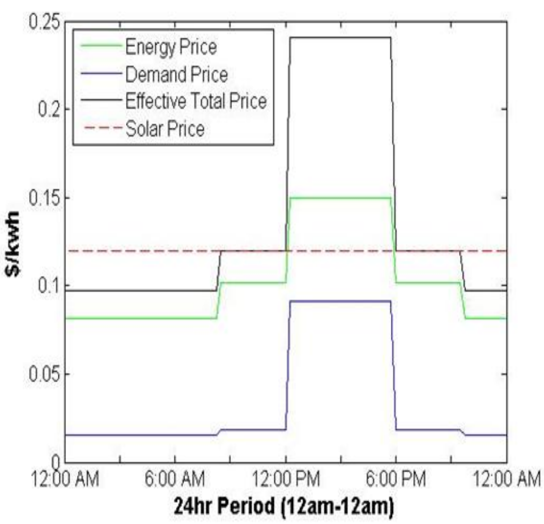

Figure 9: Representation of the daily price structure for UC Merced in summer 2010. The Energy price is straight from the utilities tariff, where the demand price is the utilities monthly demand charges (\$/kW) transformed into (\$/kWh) charges. The combination of these charges constitutes the total price charged by the utility. Also included is the price charged by the power producer.

Table 4: Price structure for utility and power producer

Rate Schedule	**Season**	**Time-of-Use Period**	**Demand Charges** (\$/kW)	**Energy Charges** (\$/kWh)
Utility	**Summer**	Max Peak	\$12.02	\$0.14958
		Part-Peak	\$2.78	\$0.10197
		Off-Peak	-	\$0.08140
		Maximum	\$7.12	-
	Winter	Part-Peak	\$0.72	\$0.08794
		Off-Peak	-	\$0.07753
		Maximum	\$7.12	-
Power Producer		-	-	\$0.12

Peak Demand Loads:

In addition to multiple different charges, we are also forecasting three different loads, as mentioned earlier. For the current optimization, we treat the forecasted power demand from the grid, L_C, and the power generated by the solar array, L_{PV}, as fixed loads. The only variable load is the electric load required to run the chillers, L_{Ch}, for the FDPSXV¶ FRROLQJ GHPDQGV :KLOH WKHVH DUH WKH RQ demand, L_{Dmax}, and peak TOU demands, L_{Dp} and L_{Dpp}, must also be accounted for. The total load can be represented as

$$L_T(x) = L_C{*}(x) + L_{PV}{*}(x) + L_{Ch}(x\text{-}i) + L_D(x,i), \tag{8}$$

$$\text{where } L_D(x,i) = [L_{Dp}(x,i) + L_{Dpp}(x,i) + L_{Dmax}(x,i)]$$

and

(summer only)

(for summer)

for winter)

While the max and peak TOU demands are per kilowatt; here they have been manipulated to kWh in a similar manner the demand charges were converted from $/kW-month charges to $/kWh charges.

Objective function:

To get total cost (C_T), the above equations must be combined in a specific way, with most RI WKH FRPSOH[LWLHV DULVLQJ IURP XWLOLW\¶V GHPDQG

$$C_T(i) = [P_E(x) * (L_C*(x) + L_{Ch}(x-i))] + [P_s(x)L_{PV} \quad [\quad @ \quad « \tag{9}$$

$$[P_{DP}(x)\ L_{DP}(x,i)] + [P_{DPP}(x)\ L_{DPP}(x,i)] + [P_{Dmax}(x)\ L_{Dmax}(x,i)],$$

which is a function of start time (i). Also, in all the above relationships, real time is UHSUHVHQWHG DV ³[´ DQG ³L´ 7KH 1 SS LV WKH QXPEHU RI VWHSV calculated on a 15-minute basis, therefore time intervals of 15-minutes - or 96 time steps were used; any time interval could have been chosen.

The problem as described is unconstrained, so the chillers have no scheduling restrictions. This is an effort to find the absolute minimal cost according to the daily price structure provided.

For this to be the case, the following assumptions have been made:

- Each horizon period is independent from the next. For instance, if the optimizer chooses 11PM WR VWDUW WKH FKLOOHUV WKLV LV QRW WD optimization. 7KXV LI WKH QH[W GD\¶V 1AM, it would be not VWDUW W be a good choice, since the chillers would still be running. As of now, this distinction would need to be made by the operator and the optimization would need to be run again with a constraint that would force the GA to select an optimal start time from say, the latter part of horizon. This constraint would be dependent on the cooling load needed by the campus for the day, but this is not taken into account in the current work.

- The chiller loads for the month are of similar size. This assumption has some interesting implications. Since the chiller currently starts operation at 10PM, this implies some of the chiller load occurs in the next day. In this study, any chiller load that would occur in the next day is instead shifted to the beginning of day being analyzed. This implies that if the start time of current day is chosen in this way, the start time of the previous day is also assumed to have the same start time. This coincides with the forecasting, that was also only done on a 24-hr basis.

- It should be noted again that starting the chillers midday in summer (high temperatures) is probably not at option as the efficiency of the chillers can decrease greatly. However, in this study is assumed that starting the chiller midday would have no adverse effects on cost.

Since practicality requires discrete time intervals, a solver capable of handling discrete data was also required. Even though, for this relatively simple scenario, the objective function can be easily minimized using numerous methods, a GA is adopted with future research in mind.

For the single chiller load analysis presented here, the GA was created using the MATLAB Optimization Toolbox. Many of the default parameters were kept intact and are presented in Table 2. . For the purpose of the GA, the genotype is a vector of real numbers whereas the parameter to be optimized, start time, is an integer. The conversion is done simply by rounding the elements of the genome to the nearest integer within the established bounds. The algorithm runs until the weighted average change in the fitness function value over stall generations (50) is less than function tolerance of 1e-6

Table 5: GA parameters for cost optimization

Population size	Crossover type	Crossover fraction	Elite count	Mutation type	Initial Population Range	Bounds on variable	Generations
50	Scattered	0.8	2	Gaussian	[0,NT]	[0,NT]	50

While the population size and number of generations may appear small for a typical GA, keep in mind that the above optimization problem is fairly simple. With 15-minute intervals and only one chiller load, there are only 96 possibly solutions. Therefore, if a population size of 96 was chosen, the optimal solution would appear in the first generation with the following generations simply converging to the optimal solution. It is apparent then, that even a population size of 50 is not needed for this particular scenario. However, in the case of UC Merced, there are typically two chillers running at the same time but the data has been combined. If this power consumption were to be dissected into their original forms, as two loads, the solution space would increase to 9,216 possibilities (NT^2). While it is still possible to run through all of the solutions for this case as well, after two loads, it becomes difficult to graphically represent the solution space as is done in the next section for the 1-load scenario. Moreover, if we were to include multiple objectives in addition to multiple variables, the methods in which to efficiently solve the problem dwindle and the GA becomes a very attractive method as mentioned in the literature review.

The dual chiller load (2-variable) case is and the multi-objective cases are discussed in future work.

3.7 Results

Cost optimization is applied independently on a daily basis for the entire month of March and August of 2010. Emphasis is placed on the classification of three different day types (weekday, Saturday, and Sunday), since cooling and overall campus loads vary for each type. Currently, it would be difficult to manually start the chiller at different times each day. This is another reason for looking at the different day types, to investigate if patterns exist and if a practical rule or set of rules could be determined. Despite the current and ongoing difficulties, installation of a more automated Central Plant control operation is undergoing development. Therefore, it is still important for this study to evaluate the optimal start time of the chillers on a daily basis and thus essentially assume daily operation is possible. Though the months of August 2010 and March 2010 are analyzed; some March days are missing due to incomplete data.

The goal of the optimization is to find the time at which to start the chillers (ST) that minimizes the operating cost of the campus. Savings are computed by comparing the operating cost of the bench case (the bench case being starting chillers at 10:00PM) with the solutions obtained by the simulated optimization model. The savings are calculated in two ways: 1) using the forecasts above (Eq.12), and 2) assuming a perfect forecast (Eq.13) which implies finding the optimal ST using the actual past data instead of the forecast.

Actual savings in this sense means savings that could accrue using the actual forecasts. However, the perfect savings would reflect the maximum savings possible.

3.7.1 Summer Results and Discussion

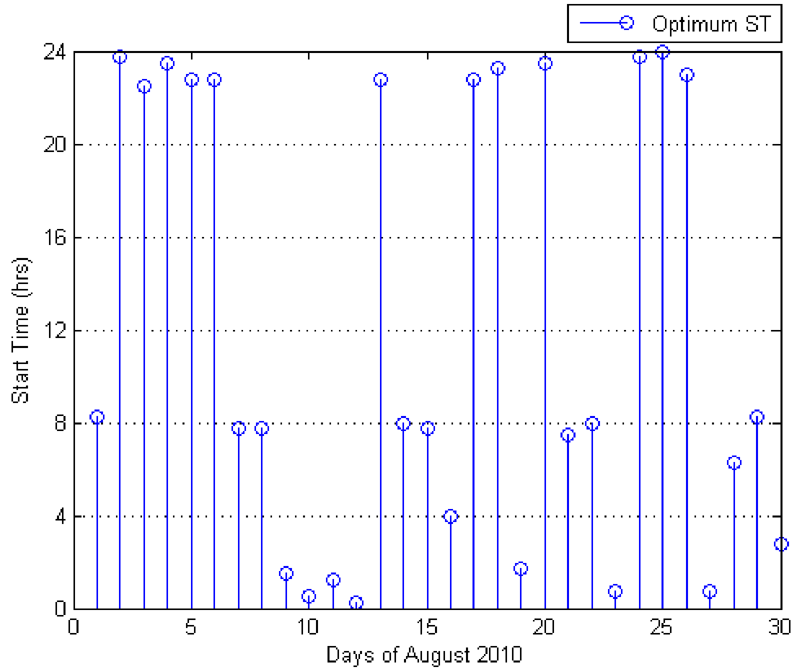

Figure 10: Optimal times to start chillers for August 2010 based on actual forecasts. Each day, and therefore start time, is independent of previous and next day. Weekends occur on the 7th, 8th, 14th, 15th, 21st, 22nd, 28th, and 29th. The only day missing from this data set is the 31st. The average optimal start time for weekends is 8:00am and the average optimal start time for weekdays is 10:45pm.

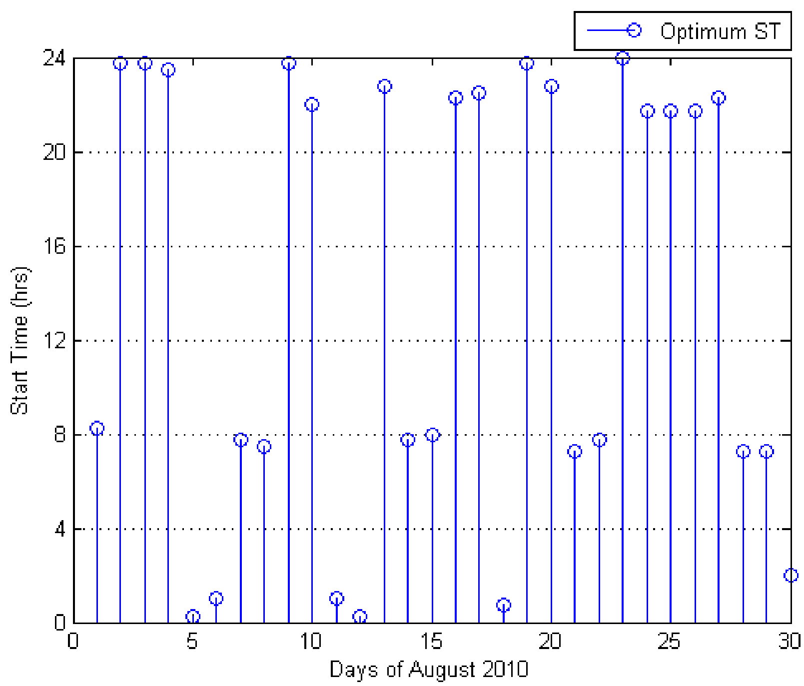

Figure 11: Optimal times to start chillers for August 2010 based on perfect forecasts. Each day, and therefore start time, is independent of previous and next day. Weekends occur on the 7th, 8th, 14th, 15th, 21st, 22nd, 28th, and 29th. The only day missing from this data set is the 31st. The average optimal start time for weekends is 7:45am and the average optimal start time for weekdays is 10:15pm.

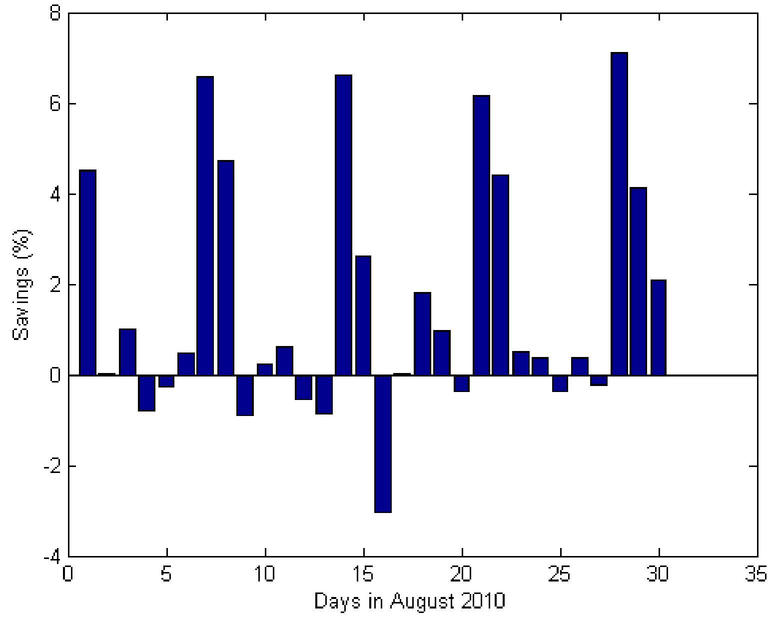

Figure 12: Percentage of savings for August 2010 based on actual forecasts. Percent savings is calculated by using the known cost to operate the chillers with a start time 10:00pm as the bench mark. Negative savings imply that the bench case of 10:00pm would have been more economical. Weekends occur on the 7^{th}, 8^{th}, 14^{th}, 15^{th}, 21^{st}, 22^{nd}, 28^{th}, and 29^{th}. The only day missing from this data set is the 31^{st}. The average weekend savings is calculated to be 6.45% and the average weekday savings is calculated to be 0.92%.

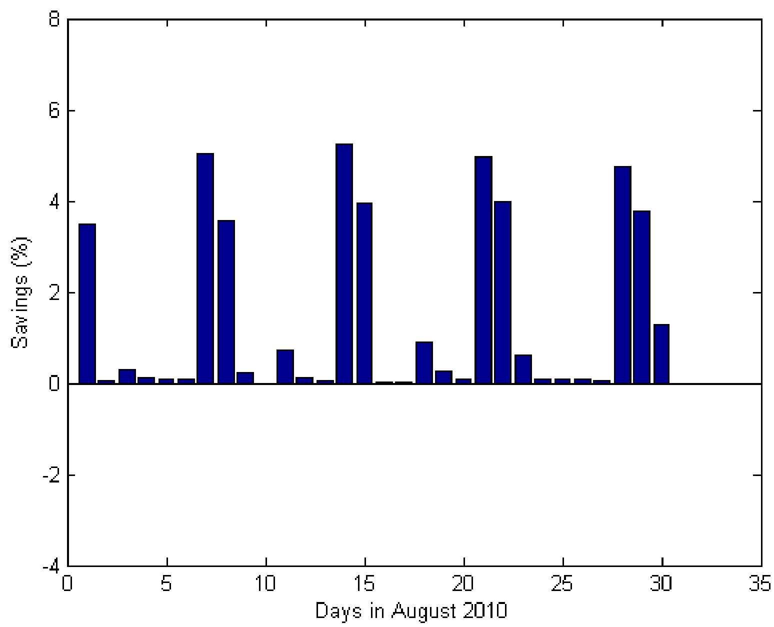

Figure 13: Percentage of savings for August 2010 based on perfect forecasts. Percent savings is calculated by using the known cost to operate the chillers with a start time 10:00pm as the bench mark. Weekends occur on the 7^{th}, 8^{th}, 14^{th}, 15^{th}, 21^{st}, 22^{nd}, 28^{th}, and 29^{th}. The only day missing from this data set is the 31^{st}. The average weekend savings is calculated to be 5.26% and the average weekday savings is calculated to be 0.92%.

Weekday:

From Fig. 13, the maximum savings possible are very small meaning the current chiller start time is close to, if not, optimal. When using the actual savings formula, some values of savings are negative implying the optimal cost selected was higher than the bench case scenario. This is entirely due to poor forecasting. However, it is apparent there is very little to savings to be gained in this scenario.

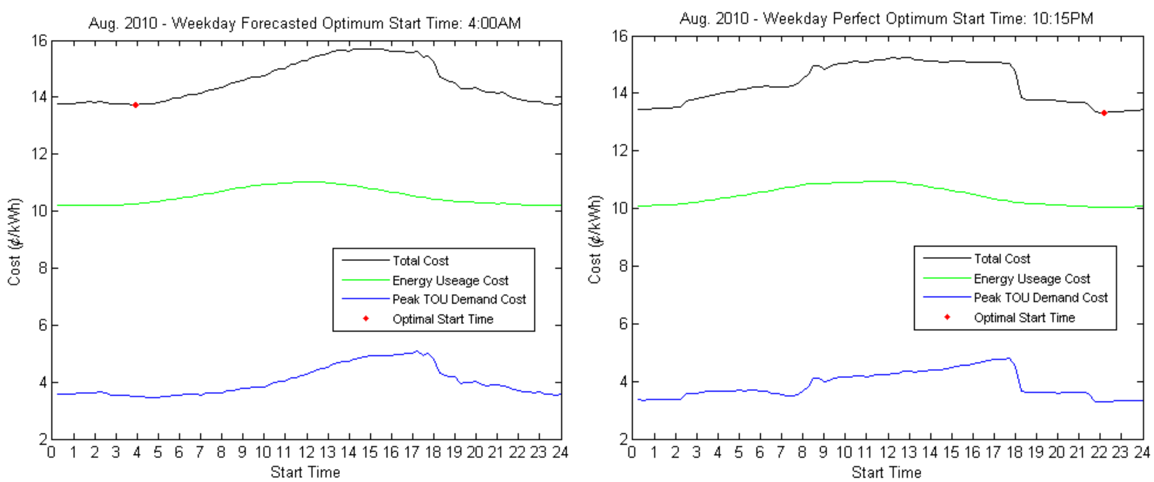

Figure 14: August 16, 2010, Forecasted cost function vs. Perfect cost function. Since there is only one chiller load, it is simple and straightforward to plot the cost function. From this figure it is evident that the demand costs drive the optimization. This is true for any case (summer or winter). However, it summer it is more predictable, whereas, in winter the demand costs can change dramatically from one day to the next.

The perfect forecast simulation leads an optimal start of what is in essence the bench case start time. While not nearly identical, the cost functions do share some similarities. For the most part, any time between 10PM-12PM, and 12PM-2AM, when using the perfect forecast is a fairly optimal start time to start the chiller. For the actual forecast, this time period is extended further into the early morning where the optimal value at 4:00AM is only slightly more cost effective than any start time in the time frame of 1AM up to 4:00AM. Outside of August 16, this time interval gets tighter. This trend continues for most of the weekdays in August, as can been observed when comparing Fig. 10 and Fig. 11. August 16, the day shown in Fig. 14, is more an outlier with respect to this trend. UC

Merced was designed with this scenario in mind as evidenced by the investment in TES. It appears that the campus operates at an exceptionally optimal level during this time of the year.

Weekend:

Relatively high savings are observed from the simulation for weekends. This is likely contributed to the fact that minimal cost on the weekend is even more dependent on the shape of L_D than weekdays. The consumption of energy is treated as a constant in this study (just shifting loads, not altering the size) so it is of no consequence. The price structure on weekends is different than during the week with P_E being completely flat during the weekend. Also, there is only one TOU period during the weekend (off-peak), so P_D is attributed just one peak demand for that day. While it appears there are moderate savings during the weekend, this can be misleading. Energy consumption is considerably lower on the weekend in addition to energy prices typically being cheaper. Weekends only account for slightly more than a quarter of the total number of days in a month. For a summer weekend, there is not much of an increase of savings to be gained during the weekday ±there are only four occurrences in August where the maximum possible savings is greater than 0.5%. Taking into account the considerations above, weekend savings would have to be anywhere from 4-5.5 times higher than the weekday savings for them to be of equal importance. From Fig. 13, most of the savings on the weekend fall into this range. Even if that were not the case, the average optimal start time on the weekend is 8:00AM, as can be seen in Fig. 10. It is highly likely that any savings gained by shifting the load to this start time would be counteracted by the decrease of efficiency in the chillers due to high ambient temperature in Merced at that time during the summer.

3.7.2 Winter Results and Discussion

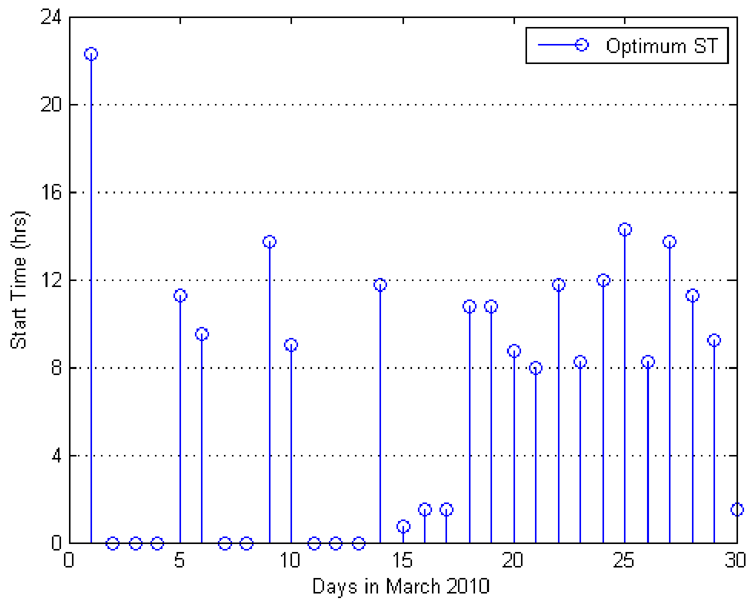

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Figure 15: Optimal times to start chillers for March 2010 based on actual forecasts. Each day, and therefore start time, is independent of previous and next day. Weekends occur on the 6th, 7th, 13th, 14th, 20th, 21st, 27th, and 28th. The 2nd, 3rd, 4th, 7th, 8th, 11, 12th, and the 13th were removed from the data set due to incomplete or corrupted data. The average optimal start time for weekends is 10:30am and the average optimal start time for weekdays is 9:15am.

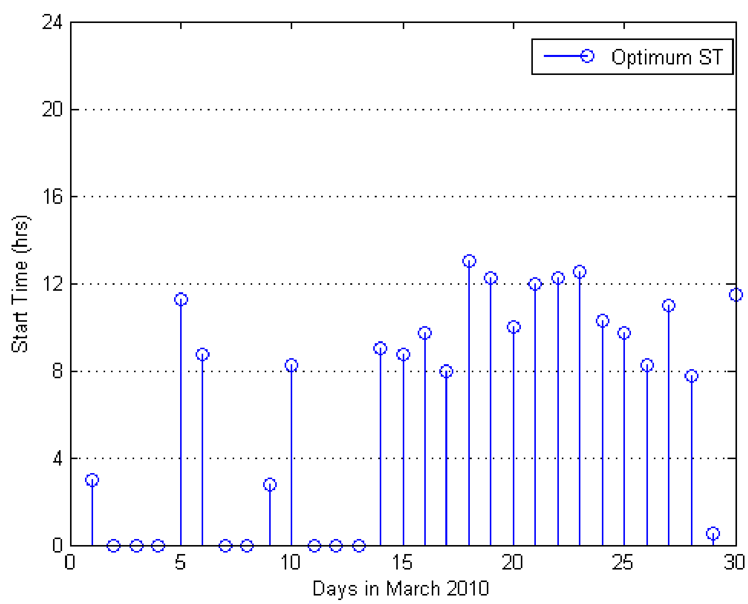

Figure 16: Optimal times to start chillers for March 2010 based on perfect forecasts. Each day, and therefore start time, is independent of previous and next day. Weekends occur on the 6th, 7th, 13th, 14th, 20th, 21st, 27th, and 28th. The 2nd, 3rd, 4th, 7th, 8th, 11, 12th, and the 13th were removed from the data set due to incomplete or corrupted data. The average optimal start time for weekends is 10:30am and the average optimal start time for weekdays is 9:15am.

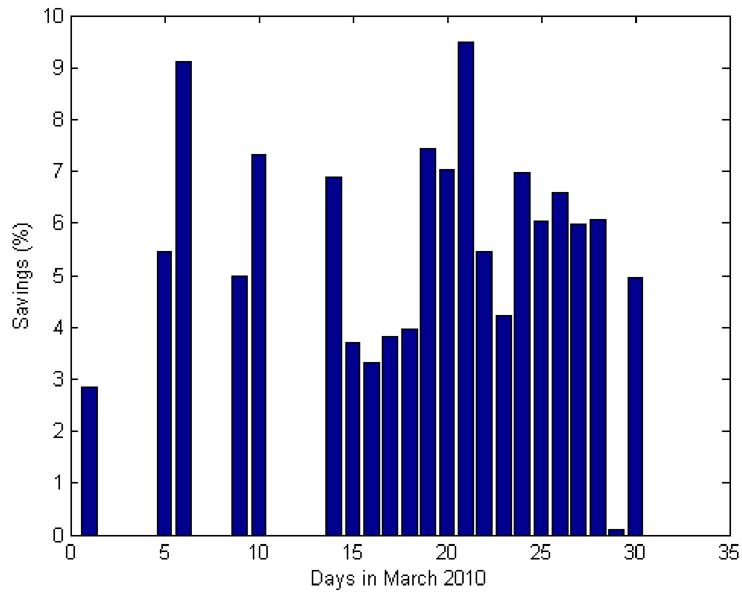

Figure 17: Percentage of savings for August 2010 based on actual forecasts. Percent savings is calculated by using the known cost to operate the chillers with a start time 10:00pm as the bench mark. Negative savings imply that the bench case of 10:00pm would have been more economical. Weekends occur on the 6th, 7th, 13th, 14th, 20th, 21st, 27th, and 28th. The 2nd, 3rd, 4th, 7th, 8th, 11, 12th, and the 13th were removed from the data set due to incomplete or corrupted data. The average weekend savings is calculated to be 7.42% and the average weekday savings is calculated to be 4.83%.

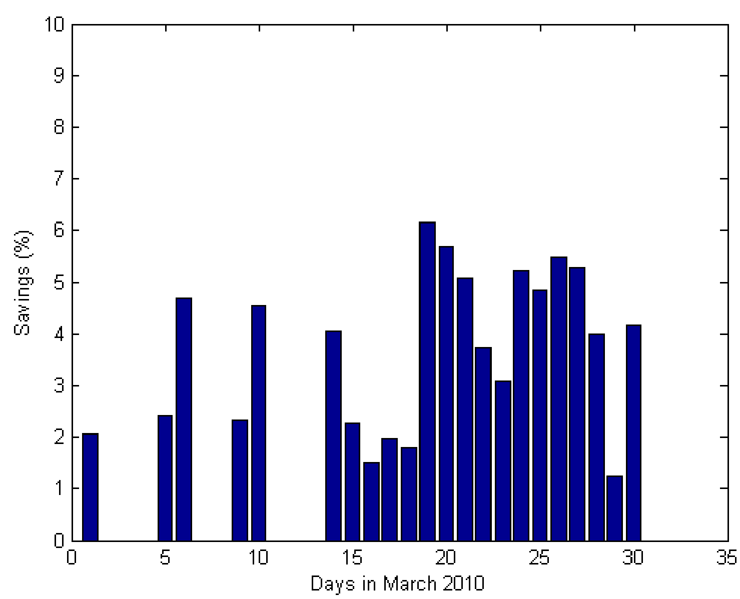

Figure 18: Percentage of savings for August 2010 based on perfect forecasts. Percent savings is calculated by using the known cost to operate the chillers with a start time 10:00pm as the bench mark. Negative savings imply that the bench case of 10:00pm would have been more economical. Weekends occur on the 6th, 7th, 13th, 14th, 20th, 21st, 27th, and 28th. The 2nd, 3rd, 4th, 7th, 8th, 11, 12th, and the 13th were removed from the data set due to incomplete or corrupted data. The average weekend savings is calculated to be 4.79% and the average weekday savings is calculated to be 3.30%.

Weekday and Weekend:

While it is true that for summer that the cost functions are drastically different largely due to the price structure of the utility, for a winter month, it appears this is not the case. From the results of the optimization alone, it is difficult to distinguish weekdays from weekends.

Moreover, what is very interesting is that despite poor load forecasting for this month, the results are noticeably more consistent than those of the summer season. This falls back on the discussion of the summer results, were great load forecasting (high accuracy) may not be needed for an accurate prediction of optimal start time. This raises the question, how much uncertainty in the error of the forecast is being propagated through to the optimization? Instead of focusing on the R^2 values or other statistical metrics typically used to determine the quality of the forecast, it may be more important to quantify the uncertainty in the error of the forecast. If this could be quantified, then perhaps increased accuracy in load forecasting would not be needed. For instance, the cost optimization for March (Fig. 17) consistently over shot the true (or perfect) percent savings (Fig. 18). This must be a results two factors:

1) Uncertainty in the monthly peak TOU demands
2) Uncertainty in error of the forecasts

Both of these factors propagate through the optimization. The amount of uncertainty in the peak TOU demand could probably be approximated to some extent based on past YDOXHV RI SHDN ORDGV DORQJ ZLWK D GHHS XQGHUVWD FDPSXV¶ ORDG +RZHYHU WKHU e is no easy way to measure or quantify the uncertainty,

HVSHFLDOO\ LQ WKH FDVH RI $11¶V ZKHUH PRVW RI W complicated and very characteristically do not express a physical relationship. One method, mentioned earlier is that the work of (Weber). Weber uses stochastic optimization, which in the case, would imply modeling the error of the forecasts as (constrained) probability density functions instead of modeling the load as discreet values. Though, this is beyond the scope of this work.

Summarization of Results:

Table 6: Averaged cost optimization results for August 2010

		Weekday			Weekend		
2010		Start time	Cost (c/kWh)	Savings (%)	Start time	Cost (c/kWh)	Savings (%)
August (actual forecast)	Min.	10:45 PM	15.91	0.92	8:00 AM	12.05	6.45
	Current	10:00 PM	16.11	-	10:00 PM	12.62	-
August (perfect)	Min.	10:15 PM	15.91	0.92	7:45 AM	12.17	5.26
	Current	10:00 PM	16.02	-	10:00 PM	12.72	-

Table 7: Averaged cost optimization results for March 2010

		Weekday			Weekend		
2010		Start time	Cost (c/kWh)	Savings (%)	Start time	Cost (c/kWh)	Savings (%)
March (actual forecast)	Min.	9:15 AM	10.34	4.83	10:30 AM	9.70	7.42
	Current	10:00 PM	10.63	-	10:00 PM	10.11	-
March (perfect)	Min.	12:00 PM	10.53	3.30	10:00 AM	9.97	4.79
	Current	10:00 PM	10.90	-	10:00 PM	10.48	-

4 Conclusions

4.1 General Remarks on Study

The overview that begun this study suggested many methods for energy control and load management. This field of efficiently integrating RES into the standard portfolio of electricity generation will only grow as policy continues to take effect, as it is advancing and changing rapidly. Much research in this area has been done over the past years, even more so recently, and various successful methods for load management have been implemented in small communities, factories, and buildings alike. While GAs have long since been used and proven to solve optimization problems of all kinds, only recently have they been thought of a way to manage energy. In the same way, ANNs have been proven to be great tools for pattern recognition and curve fitting. Moreover, they have been implemented as power output forecasters to great avail in the past. In this study, they were shown to be adequate for the task at hand.

This research showed that ANNs and GAs could be a powerful combination manage and optimize a variable and uncertain energy source such as solar. The end result of this research showed the ANN/GA can yield similar results to that of more traditional simulation based methods. However, the method has not been directly implemented and may face many more hurdles. It also shows that the GA, while very flexible, may be excessive in certain respects. Such as using it to optimize inputs to the ANN when perhaps there may be easier ways to increase forecasting accuracy.

4.1 Specific Findings of Study

¶ While the forecasting could always be improved, one of the most significant conclusions of this study is that the chiller start times should be automated to start at a known time every day. If this time was known in advance, and run on a schedule, instead of operated manually, this would greatly increase the consistency of the optimization.

¶ Along the same lines, while minimizing the error in forecasted is encouraged, it may be more beneficial to quantify what level of correctness provides consistent and accurate results in the optimization. A quantification of the uncertainty in the error of the forecasts are needed. The only way to achieve this is through scholastic optimization, which was beyond the scope of this study.

¶ It was found for the specific case study presented, that shifting the chiller loads from their current start time in the summer would be unnecessary. The current configuration is the most cost-effective. To garner savings, forecasting would need to be excellent and expected savings is still likely to be <1%.

¶ While the summer season did not leave much room for improvement in optimizing operating costs, there may be significant savings in shifting the load during the winter seasons, on the order of 2-3%. The optimization here suggests that the start time of the chillers be shifted to late morning or early afternoon. While there is concern over efficiency deficiencies of the chillers to operate at temperatures typical of mid day, it is not unreasonable to expect that later morning temperatures in the cooler winter months could be lower than the operating temperatures of the chillers at night during the summer months.

5 Recommendations for Further Work

One of the first things that could be done is to adapt the problem to a new price structure. Moreover, it may be more interesting to determine an optimal price structure based on to fit the load management system ±or in a sense ±work backwards. This would be extremely useful, especially as it is becoming more common for utility ¶V WR provide some flexibility on the tariff. This may even include a demand response model.

Throughout this study, the energy efficiency of the chillers and the Central Plant was brought to light on many occasions. One next step would be to define a separate objective function as a function of efficiency and include this in the optimization. Additionally, other objective functions, such as those based on GHG emissions, or thermal comfort, could also be included. Pareto analysis could be preformed, in which the GA should be able to handle admirably. It would also be interesting to try to convert a aforementioned objective functions into functions of cost and perform the optimization through that route.

Along the same idea of multi-objectives, is multi-variable. This would not be too difficult to achieve in the near future. For instance, the chiller system on the UC Merced campus is actually comprised of three separate chillers, which opens up a lot of possibilities for optimization.

Lastly, but perhaps most importantly, are the issues of variability and uncertainly. Gaining a clearer understanding that these factors have on the forecasting and optimization, major improvements could be achieve with many changes to the current method. Quantifying uncertainty in the load forecasts would be instrumental in achieving consistently near optimal start times.

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