

Optimal Load Management Application for Industrial Customers

by

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Abstract

The urgent need for greater planning and operation efficiency of current and future electrical networks, as well as the reduction of environmental impact due to current levels of greenhouse gas emissions have led to the development of the Smart Grid concept. In this context, the integration of renewable sources to the transmission and distribution systems, and the management of customer's consumption through direct or indirect control methods are two important components of smart grids. The latter, in particular, has led to the emergence of Demand Side Management (DSM) programs with the main purpose of controlling demand levels considering end-user preferences or the final service quality.

In the case of developed countries, the industrial sector requires significant and growing amounts of energy year after year. For this reason, considering the special characteristics imposed by industrial processes, DSM programs that focus on rational and efficient electric consumption have been designed to improve the current operation practice of this sector. In particular, load shifting, which is part of Demand Response (DR) programs in the context of DSM, together with dynamic pricing schemes, such as Time of Use (TOU) and Real Time Pricing (RTP), are attractive approaches for demand management. With this goal in mind, the present research focuses on the development and evaluation of an optimization model to optimally schedule water-cooled chillers in industrial applications.

The proposed optimization model is capable of minimizing energy and/or peak demand costs associated with normal operation of chillers, depending on the priority of the industrial consumer, while meeting demand-supply balance, process, peak demand constraints, and operating limits at the same time. To represent the chiller active power demand at every time interval, a polynomial regression model is proposed, and estimated by means of a robust regression technique using actual load demand and process measurements at an actual industrial facility, showing that the resulting regression model determines the chiller electric consumption accurately for normal operating conditions; a Chilled Water Storage (CWS), i.e. a thermal storage device for water cooling systems, is also considered in this model. The final optimization model is tested to find the optimal scheduling of chillers in a water cooling system of an automotive frame manufacturing plant in Ontario. Two different cost minimization scenarios are simulated to determine the better operation strategy and contrasted with the actual operation to evaluate the possible monthly bill savings that can be achieved. Finally, the optimal size of the CWS is determined, to maximize savings, for the current number of chillers as well as with the possible decommissioning of one of them, as requested by the facility technical staff.

The final simulation results suggest that load shifting of chillers could be a successful strategy for industrial customers, since important electricity bill savings without affecting

the normal plant operation were attained. This was possible due to an optimal chiller scheduling and indirect incentives provided by current industry energy price schemes in Ontario. Furthermore, the optimization model presented permitted to optimally size the CWS in the water cooling system studied, so that electricity costs were minimized depending on the total chiller capacity considered. Therefore, optimization approaches to schedule industrial processes could be a powerful tool to increase the operational efficiency of industrial plants to reduce their significant energy costs.

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Dedication

I could not have finished this journey without the support of my beloved wife Mayra and my family. Thanks for being all in my life.

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List of Acronyms

AMI	Advanced Metering Infrastructure
BB	Branch and Bound
COP	Coefficient of Performance
CPP	Critical Peak Pricing
CWS	Chilled Water Storage
DER	Distributed Energy Resource
DR	Demand Response
DSM	Demand Side Management
ECP	Extended Cutting Plane
EMS	Energy Management Systems
FIT	Feed-in Tariff
GA	Global Adjustment
GAMS	General Algebraic Modeling System
GBD	Generalized Bender Decomposition
GPM	Gallons Per Minute
HOEP	Hourly Ontario Energy Price
IESO	Independent Electric System Operator

IRP	Integrated Resource Planning
LDC	Local Distribution Company
LP	Linear Programming
LS	Least Square
MILP	Mix Integer Linear Programming
MINLP	Mix Integer Nonlinear Programming
MPC	Model Predictive Control
NLP	Nonlinear Programming
OA	Outer Approximations
OILM	Optimal Industrial Load Management
PLR	Partial Load Ratio
RMSE	Root Mean Square Error
RTP	Real Time Pricing
TOU	Time of Use

Nomenclature

Parameters:

α	Energy price [\$/kWh].
β	Peak demand charge [\$/kW].
ΔT	Length of a time interval [hour].
θ	Probability function parameter.
a	Tuning constant.
p	Coefficient of polynomial regression model.
z	Independent statistical data sample.
C_{max}	Upper limit of chiller variables.
C_{min}	Lower limit of chiller variables.
C_{pw}	Specific water heat [Btu/(USgal°F)].
K_{bt}	Constant to convert heat rejection units to cooling load units.
K_{pt}	Constant to convert active power units to cooling load units.
n_{sw}	Maximum chiller switching operations.
P_{max}	Maximum power demand [kW].
Q_{er}	Rated chiller cooling load [tons].
Q_l	Total cooling system load [tons].

R_{max}	Upper limit of process variables.
R_{min}	Lower limit of process variables.
S_{cap_0}	Initial storage tank capacity [tons].
$S_{cap_{max}}$	Upper limit on the capacity of storage tank [tons].
$S_{cap_{min}}$	Lower limit on the capacity of storage tank [tons].
$S_{l_{max}}$	Upper limit on the level of storage devices.
$S_{l_{min}}$	Lower limit on the level of storage devices.

Indices:

j	Chiller number.
k	Industrial process number.
m	Number of storage device output.
nc	Storage device number.
q	Number of storage device input.
t	Time interval.
v	Storage tank number.

Variables:

c	Chiller variables: $[P_{ch} \ W_f \ T_{eo} \ T_{ei} \ T_{ci}]^T$
e	Random error.
ir	Input flow rates per hour.
or	Output flow rates per hour.
P	Process or storage power demand [kW].
r	Total set of process variables.

st	Binary status of process (1 ON, 0 OFF).
P_{ch}	Chiller power demand [kW].
P_{peak}	Total peak power demand [kW].
P_{tot}	Total process power demand [kW].
P_T	Total chiller power demand [kW].
Q_e	Chiller cooling load [tons].
s_{cap}	Storage tank capacity [tons].
s_l	Storage device level.
T_{ei}	Inlet temperature at chiller evaporator [°F].
t_{off}	Binary variable denoting process turn-off (1 OFF).
t_{on}	Binary variable denoting process turn-on (1 ON).

Functions:

$\psi(\cdot)$	First derivative of log-likelihood function.
$\rho(\cdot)$	Log-likelihood function.
$F(\cdot)$	Polynomial function to estimate power demand.
$f(\cdot)$	Probability distribution.

Chapter 1

Introduction

1.1 Motivation

Historically, power system planning has focused on investments in power generation on a large scale in order to meet the ever increasing energy demand. From this point of view, the end user has been considered a passive actor in the development of the electric system. However, the current availability of Advanced Metering Infrastructure (AMI) and communication systems, as well as the global aim to reduce the impact of fossil fuel-based generation have raised the need for dynamic demand management as an effective tool to reduce demand levels in the context of a “Smart Grid”. In this regard, various utilities have designed and introduced Demand Side Management (DSM) programs to manage and control the steady demand increase.

The sustained economic development of a country depends largely on the industrial sector, which in turn requires large amounts of energy to operate. Overall, the Major Economies Forum on Energy and Climate estimated the energy consumption share of this sector by the year 2009 at one-third [1]. In the Canadian case, the industry sector energy share was about 43% of the total energy consumption in 2013, as shown in Figure 1.1 [2].

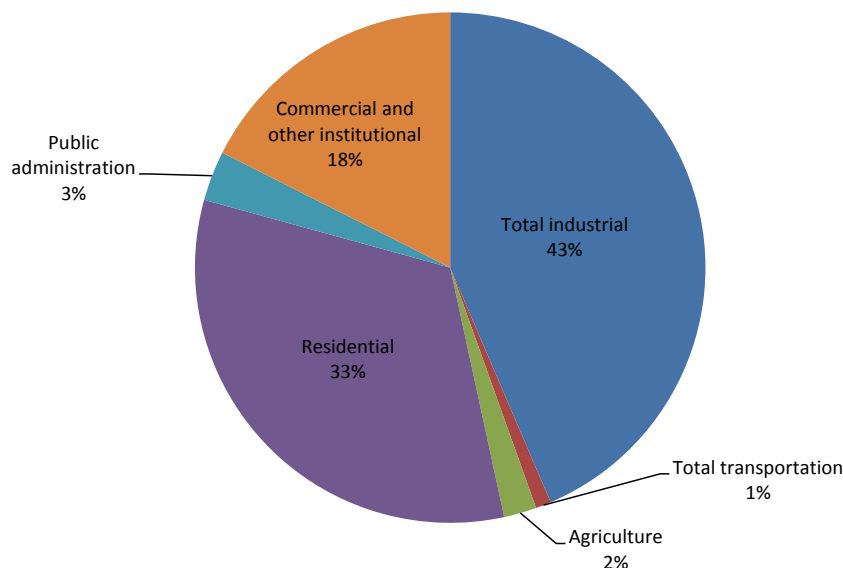


Figure 1.1: Energy consumption by sector in Canada for 2013.

The main focus of Demand Response (DR) programs, a key part of DSM, is the reduction of electricity consumption through high-efficiency equipment and the introduction of automatic systems for energy management in industrial processes. In the case of Ontario, utilities encourage customer participation through various programs, as part of the SaveOnEnergy program [3]; among these, the Retrofit and Process and Systems programs focus on small businesses and large industries respectively. The International Union for Electricity, on the other hand, has reported the successful implementation of DR programs in countries like France, Italy, and Japan, among others, including energy reductions of 10% and 15% in two industrial facilities in France, through the use of systems for demand monitoring and control [4]. Thus, the implementation of more efficient equipment and industrial processes promise a significant reduction in industry electricity consumption. Furthermore, DSM programs do not only benefit the final customers through energy demand reductions, but also improve the operational security and planning of distribution systems at the same time, since demand reductions reduce the resources needed in the delivery networks [5].

From the previous discussion, the motivation of this work is based on the potential reduction in electricity consumption and increased operating efficiency of electric networks by introducing Energy Management Systems (EMS) in the industrial sector, since it is expected that the optimal scheduling of industrial processes would reduce electricity bills

and improve the operation of electrical systems.

1.2 Literature Review

A comprehensive literature review of the state of the art regarding DSM and DR methods is provided next.

1.2.1 Load Management

The Smart Grid concept has been built assuming a complete interaction between all the energy market actors. Thus, an action taken by a utility will influence the customer response seeking to maximize their benefit. For this reason, some researchers have adopted game theory to model this complex relation. In particular, the Stackelberg game, which intends to describe a sequential game, where a leader makes the first movement and a few followers will decide their movements based on it, has been used in [6, 7]. Thus, in [6], the authors propose the aforementioned model to characterize the interactions between a retailer and customers when Real Time Pricing (RTP) is used as a DSM method. The customer behavior is modeled with a quadratic utility function and his electricity consumption as a linear function of the electricity price offered by the retailer. Even though this utility function could estimate the customer consumption due to price variations, mainly for residential customers, the electricity demand of an industrial facility is mainly driven by targeted production levels, which makes the adoption of this proposal more difficult for industrial load management. Reference [7] evaluates the influence of storage devices for residential load management. Despite the fact that these devices can help to reduce customer cost and peak-to-average load ratio, the total amount of storage capacity could create new power peaks at low cost hours due to power selling to the grid by the customers. To avoid this problem, the authors propose the Stackelberg game to model the interaction between customers and the utility. Based on the final results, it is argued that new prices created by the utility for cheap energy cost periods will prevent customers from selling energy from storage devices, thus, improving the peak-to-average load ratio and reducing energy costs, assuming already existing storage systems.

An agent-based model framework, wherein different agents are created to perform the functions of distributed generation, energy storage systems, and responsive loads, is presented in [8]. It is intended that these agents would participate in a virtual market among microgrids. This model assigns higher priority to aggregated responsive loads, and proposes

three different DR options, which basically correspond to load shifting and curtailment, to encourage customer participation. However, the model only considers DR for residential loads, without considering the commercial and industrial sectors. On the other hand, a non-cooperative game to model the interaction between multicarrier energy systems, wherein natural gas and electricity work together, is evaluated as DSM in [9]. A distributed algorithm is implemented in a cloud computing framework to solve this problem, and final results show that bill savings can be achieved and peak-to-average load ratio can be reduced. In this paper, due to the fact that finding a unique Nash equilibrium for this type of games necessitates having strictly convex functions, the electricity and natural gas price functions are built to have this property; however, Time of Use (TOU) prices do not have this property, since they are constant values per certain time periods, with the same price being charged irrespective of the energy consumption.

A model to reduce the active power consumption of a factory, when load shifting and internal generation are not available to feed the process electric requirements, is proposed in [10]. A fuzzy cognitive map and maintenance scheduling constraints are used to prioritize the process disconnection, whereas an integer programming optimization model is employed to minimize the total electric load in the plant. The model is applied to a luxury vehicle manufacturing plant, where the total demand is reduced by a DR event requested by a Local Distribution Company (LDC). This approach reflects the load curtailment methodologies used in practice in some plants. On the other hand, in the present work, and EMS-based approach is proposed for industrial load management.

1.2.2 Optimal Load Management

The optimal scheduling of furnaces for steel plants have been studied in [11, 12]. Unlike a continuous production line, these papers categorize the operation of the electric furnaces as batch production, i.e. equipment operates at fixed time periods, after which the final product is available. The first proposed model assumes full load of the furnace per operation period, so that the electric consumption is the maximum of the equipment, obtaining final savings of 5.5% due to the optimal scheduling. On the other hand, the second study focuses on the scheduling of processes under different energy price structures and on-site generation. The resulting Mix Integer Linear Programming (MILP) optimization problem becomes a very large combinatorial problem, due to the fact that a 5-min time window was used to find the scheduling of the electrical equipment. To simplify the optimization problem, this is decoupled in 4 steps, and the consumption of each electric equipment is considered constant. It is shown that the proposed technique minimizes the energy cost

of the plant, but it does not consider peak-demand charges, which can be significant for industrial facilities (e.g. in Ontario, these are the most significant costs).

To avoid negative effects of commonly used maximum load controllers to meet maximum demand contracts for industries in China, a Nonlinear Programming (NLP) multi-objective particle swarm optimization approach is applied to a smelting plant in [13]. A Least Square Support Vector Machine technique is used to estimate the production of the plant as a nonlinear function of the furnace electric consumption, without considering the interdependencies among processes in the industrial facility. A double closed loop control methodology is also proposed to reduce the deviation between the scheduled and actual electric load of every furnace. Only the scheduling of furnaces is considered for this study, and the optimization model is specific for this smelting factory.

Industrial customers can also take advantage of on-site generation facilities to reduce their electricity consumption and final electricity bill by means of an optimal approach, as proposed in [14]. This paper addresses the operation of a petrochemical factory by focusing on the impact of optimal scheduling of industrial cogeneration to balance the electric demand. Different cost models regarding gas, diesel, steam turbines, and thermodynamic equipment as well as possible electric power import and export with the grid are developed and included in the optimization model; however, minimum up and down time constraints are not considered. Monthly costs due to the optimal scheduling of the cogeneration are obtained, but the net savings amount due to the minimization of electric demand from the grid and operating costs of cogeneration are not discussed. An MILP optimization problem is proposed in [15] to deal with energy cost minimization of energy intensive enterprises, such as iron and steel production plants, obtaining the lowest cost of operation for the facility by considering optimal scheduling of processes and on-site generation. However, maximum demand charges are not considered.

The model in [16] considers the manufacturing of a single product. It is assumed the electric consumption of the processes is fixed, and only depends on the loading of the equipment, neglecting the influence of other variables. Sequential constraints are only considered as interdependency constraints between processes. The model only minimizes the energy cost without considering the cost of peak demand.

An optimal scheduling methodology, specifically a Mix Integer Nonlinear Programming (MINLP) load management model, is also applied to electrolytic process industries in [17]. Here, the efficiency and power factor of each process are expressed as functions of its actual loading by second order polynomial equations, whereas the active power varies linearly with the loading of the process. A penalty factor is introduced to account for violations of peak demand contracts in the context of the Indian market. The overall effect of this factor

over the reduction of peak demand depends on the variable tariff chosen; estimated annual savings of 9% under TOU tariffs are achieved. However, only series process operation is modeled for an electrolytic plant, and hence the possible application of the proposed methodology to other industrial processes and facilities is yet to be determined.

In [18], optimal oil refinery process scheduling is performed to minimize the energy cost. The interdependencies among processes are modeled through a directed graph. The nodes and edges of this graph represent the processes in the factory and the time each process needs to finish a specific task, respectively. However, active power consumption is fixed every time period whenever a process is turned on, and associated storage devices and peak demand charge minimization are not considered in the optimization model. Final energy cost savings of 14% are reported.

Finally, in [19], an optimal control approach is suggested to reduce the energy consumption of conveyor belts in a colliery, in South Africa. The model assumes the electric machinery works at full capacity when operating, and no peak charge minimization is considered in the objective function. Promising results show energy cost could be reduced by almost 49% of actual operation. Likewise, Model Predictive Control (MPC) is employed in [20] to minimize energy costs of a water purification plant. Although the number of maximum demand periods over a time horizon is limited, an upper bound for the maximum demand within every period is not provided; moreover, the pumps operation are assumed independent, and only full load pumps are considered. A hypothetical study of energy cost minimization using TOU tariff, instead of the fixed energy prices currently employed by the LDC, is carried out, noting that the same amount of savings is achieved with open loop or closed loop optimization, and no specific advantage of MPC over optimization methods is mentioned when disturbances are considered.

1.3 Objectives

Based on the previous detailed literature review, there is a need to enhance mathematical models and scheduling methodologies for industrial facilities in the context of DSM. Thus, the following objectives are the main drivers of the present work:

- Further application, demonstration, and validation of the previously proposed generic methodology for energy management of industrial loads discussed in [21].
- Propose a parametric regression based polynomial model for water-cooled chillers (referred as chillers, hereafter), which are prevalent in several industries, to estimate

their active power needs within normal operation conditions, from actual measurements in an industrial facility.

- Propose an optimization model to schedule these chillers to minimize both energy and peak-demand costs for the industrial customer.
- Test through simulations the proposed optimization model to schedule chillers and determine the possible savings that can be achieved through the modification of the current operating practices.
- Use the proposed optimization model to determine improvements to the existent chiller system to attain further electricity cost reductions.

1.4 Contents

Chapter 2 describes the mathematical background required for the development of the presented research. Thus, first, a brief introduction to general and industrial-oriented DSM programs is given. Second, regression techniques to estimate the active power of industrial loads during normal operating conditions are discussed; in this context, robustness of Least Square (LS) and M estimator methodologies are analyzed, and the bisquare method, which is a robust regression method, is explained in detail. Third, an overview of the general industrial optimization model upon which the present work is based is discussed. Finally, some basic optimization concepts, mainly focused on MINLP problems and related currently available commercial solvers, are briefly reviewed.

A parametric regression model to determine the active power consumption of chillers, based on measured data of a water cooling system in an automotive manufacturing plant, is developed in Chapter 3. In order to establish the relations between outputs and inputs, the basic operation of chillers is reviewed first. Then, a polynomial regression model is developed by using the bisquare method to reduce the influence of possible outliers. Finally, the obtained model coefficients are discussed, and the associated regression statistics are summarized and evaluated.

In Chapter 4, the Optimal Industrial Load Management (OILM) model developed to minimize electricity costs for May 2013 of an industrial water cooling system is tested and demonstrated. This model is also used to determine the optimal size of the system's storage tank by analyzing different storage capacities for the current water cooling system demand; the final monthly bill savings with respect to storage tank size are presented and discussed.

Chapter 5 summarizes the main findings of the current research, highlighting the advantages of the proposed OILM implementation for the optimal scheduling of industrial processes. Finally, the main contributions of the present research are presented, and future research work to improve the proposed model is discussed.

Chapter 2

Background

This chapter describes the concepts and analytical tools used for the presented research. First, the most common DSM/DR programs are briefly reviewed. Second, a discussion regarding load management programs for industrial facilities is discussed. Third, the foundations of robust regression are presented. Finally, a detailed explanation of optimization model on which the proposed approach is based is presented, followed by a general discussion on optimization types of algorithms and commercial solvers currently in use.

2.1 Demand Side Management (DSM)

In a broader context, DSM is a planning process of activities oriented to modify energy consumption of customers to increase the efficiency of electrical networks. It is a part of an Integrated Resource Planning (IRP) process, which should evaluate supply-side (generation units, storage devices, etc.) against demand-side alternatives. Multiple objectives such as customer satisfaction, reliability and quality indexes can be accomplished through DSM programs. First, the objectives of DSM should be defined; energy and investment reductions are just a few examples of objectives. Moreover, DSM has to be able to predict future behavior of customers due to related programs to evaluate the costs and benefits of DSM implementation. Thus, the adoption of a DSM program encompasses several important steps to modify efficiently the load pattern of a utility.

Within the DSM framework, many programs have been designed to achieve reduction of energy consumption. Load management and strategic conservation, for example, are activities within a DSM program. The next sections present a survey of the available programs currently used by utilities for load management.

2.1.1 Demand Response (DR)

DR encompasses all methods focused on the modification of the load demand curve of an LDC, and they can, in general, be divided into direct and indirect methods. Direct methods allow direct control over the equipment by the LDC operators, so that preventive or corrective actions can be applied; load shedding, for instance, could be used to avoid overloading of primary feeders of the local utility or energy price spikes in competitive power markets. On the other hand, indirect methods encourage final customers to change consumption patterns. In this regard, differentiated tariffs through the day have been introduced successfully; TOU and RTP are just two examples of variable tariffs schemes to promote load shifting.

Load shape modification goals can be achieved by six load management methods, as mentioned by [22]. Thus, peak clipping focuses on reducing the peak load, and is mainly considered as a direct load control method used by a utility. Valley filling, on the other hand, considers using off-peak loads to reduce the average energy price. Moving load from on-peak to off-peak periods to fulfill peak clipping and valley filling objectives at the same time is achieved by means of load shifting. Consumption patterns can also be reduced by energy efficiency measurements, which can be considered part of strategic conservation techniques. Strategic load growth, on other side, looks to increase load; for example, the deployment of new technology such as electric vehicles will increase the electricity consumption. A utility can take advantage of flexible load shape methods to modify the final load shape, providing incentives to customers in order to meet, for example, reliability constraints. Figure 2.1 shows a graphical representation of the aforementioned load management methods [22].

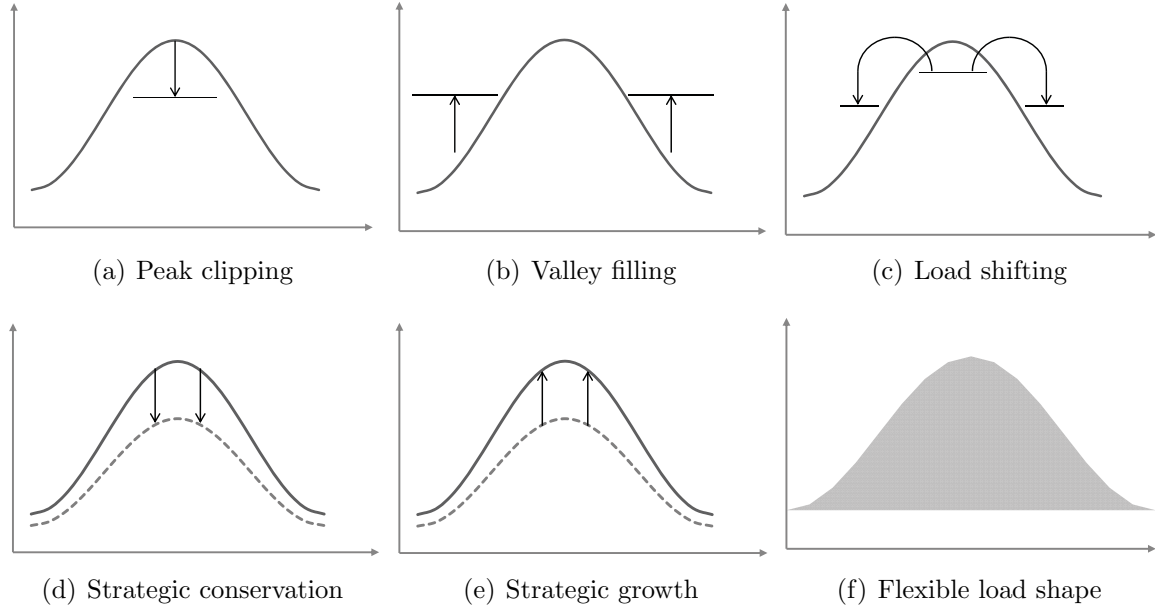


Figure 2.1: Most common DR programs.

All possible alternatives of load shape adjustment should be explored based on the general objectives and current operational conditions of a utility, employing appropriate technologies to achieve the desired load pattern modifications. For instance, if the utility is interested in shifting load demand, storage devices are useful to accomplish this objective; however, if peak clipping is desired, a direct control method would be a better option. At the end, suppliers and customers should evaluate together all the possible options for load management, considering that the mutual benefit for both should be the main goal. Finally, after implementation of the most beneficial decision, monitoring should be performed to enhance the performance of the chosen DR program, thus providing feedback to reduce deviations from the designed objectives.

2.1.2 Industrial DR Programs

Due to the special characteristics of industrial facilities and processes, not all the DR programs available for residential customers can be applied to or are appropriate for the industry sector. Most of the industrial processes have to operate in a coordinated manner to get a final product, in contrast to residential loads, where the loads can operate independently. Moreover, stringent quality standards and target production levels, main-

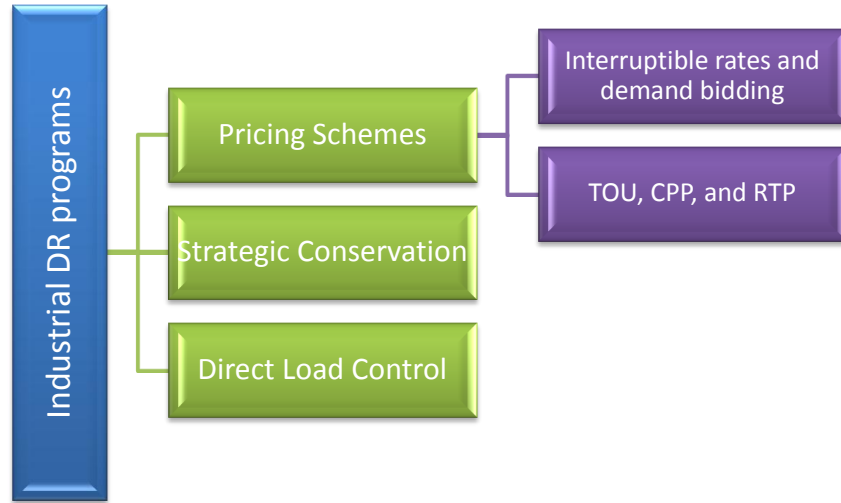


Figure 2.2: Industrial DR programs.

taining adequate equipment operation practices at the same time, are some characteristics of industrial facilities which must be strictly met to be successful in competitive markets. Figure 2.2 shows a broad classification of industrial DR programs implemented in some North American utilities.

The following is a brief description of industrial DR programs [22, 23]:

- Utilities employ interruptible rates as a means of reducing system peak demand. In this case, an energy price reduction is usually offered to incentivize the customer participation to maintain a contracted load demand during peak periods, and penalties are charged if the customer does not attain this load reduction.
- Demand bidding, whose principle is very similar to interruptible rates, is an optional DR program where the customer can bid an amount of load reduction, without any penalty if this reduction is not achieved. The main goal of a utility for adopting this type of program is to maintain its operational security during peak demand periods.
- Direct load control refers to on/off control of the main electric machinery of a customer, such as air conditioning systems and water heaters, carried out by the utility during peak demand periods. As a reward, the utility grants a differentiated rate or discount to the participating customer.

- Dynamic pricing schemes have been designed to provide economical benefits to customers who participate in this type of DR. The most common schemes used so far are TOU, Critical Peak Pricing (CPP), and RTP. In the case of TOU and CPP, the day is split in two or three periods wherein different rates are assigned. However, the rate during critical peak hours for CPP, which are around 1% of the total number of hours in the year, is higher than the corresponding TOU on-peak rate. On the other hand, RTP is an hourly pricing scheme which is usually settled by active power market rules.
- An important operational characteristic of an industrial process is its efficiency, which can be improved by conservation programs, which focus on the enhancement of current industrial technology to reduce electric consumption. High efficiency motors, heat recovery systems, and variable speed drives are just some examples of new technologies that can be used to reduce industrial energy demand.

Most of the current industrial DR programs employed by LDCs are based on variable price schemes to incentivize the participation of industrial customers. Therefore, the smart operation of industrial facilities should take advantage of low cost periods and prevent operation on peak demand periods.

2.2 Robust Regression

Some important assumptions such as independence and randomness of predictor variables, as well as the normal distribution of data, are generally taken as satisfied by data sets used in regression processes. Indeed, classical regression methods, like the LS approach, have been developed based on these assumptions. However, this normal distribution assumption, being the most critical, can lead to biased regression models if not satisfied due to the presence of outliers. Some practitioners and researchers argue that a careful review of the data quality could remove corrupted information, thus avoiding the necessity of robust methods, but the successful identification of outliers, as mentioned in [24], is not a trivial task. In fact, one outlier could be hidden by another outlier preventing a successful data filtering. Additionally, it is difficult to identify outliers for multiparameter regression models. For these reasons, a robust statistical regression method, which is to some extent insensitive to outliers, is used for the current research.

Many estimators have been developed due to the necessity of outlier effect reduction. Thus, M estimators (maximum likelihood type estimators), L estimators (linear combinations of order statistics), and R estimators (derived from rank tests) have been proposed

in the literature. Among these, the former is preferred due to the fact that its performance can be easily adjusted in contrast with the other two estimators. Additionally, L and R estimators do not perform well for multiparameter estimation, whereas M estimators can properly handle these types of problems. Furthermore, the breakdown point, which can be considered an asymptotic quantitative measurement of robustness and is defined as the maximum fraction of outliers that does not affect the overall estimator performance, is 0.5 for M estimators, whereas for LS is 0 [24, 25], thus reflecting the advantage of robust regression over classical methods. For these reasons, M estimators that are explained next are used here for the parametric regression model proposed in Chapter 3.

2.2.1 M Estimators [24, 25]

As already mentioned, an M estimator is a maximum likelihood estimator which can be obtained by minimizing the following expression:

$$\min \sum \rho(z_i, \theta) \quad (2.1)$$

where the $\rho(z_i, \theta)$ function is defined as:

$$\rho(z_i, \theta) = -\log f(z_i, \theta) \quad (2.2)$$

and $f(z_i, \theta)$ is a known probability distribution. The minimization of (2.1) can be expressed as

$$\sum \psi(z_i - \theta) = 0 \quad (2.3)$$

which can also be rewritten as:

$$\sum \omega_i(z_i - \theta) = 0 \quad (2.4)$$

where the weight function ω is defined as:

$$\omega_i = \frac{\psi(z_i - \theta)}{(z_i - \theta)} \quad (2.5)$$

This weight function iteratively assigns greater importance to measurements closest to the estimated ones, and reduces the effect of remote measurements.

It is useful, for convergence improvement, to introduce an estimate of scale s , and an expression commonly used for this is suggested in [25], as follows:

$$s = \frac{\text{median } |e_i - \text{median}(e_i)|}{0.6745} \quad (2.6)$$

Thus, for the case of the bisquare function, the equations corresponding to ρ , ψ , and ω , expressed as functions of the new scaled variable $r = (z_i - \theta) / s$, are [25]:

$$\rho(r) = \frac{r^2}{2} - \frac{r^4}{4a^2} \quad (2.7)$$

$$\psi(r) = r \left(1 - \frac{r^2}{a^2} \right) \quad (2.8)$$

$$\omega(r) = 1 - \frac{r^2}{a^2} \quad (2.9)$$

These equations define the bisquare function that will be used to find the parametric regression model, proposed in Chapter 3, to represent the active power demand of industrial processes.

2.3 Optimal Industrial Load Management (OILM) Model

The optimization model employed in this work is derived from the OILM model proposed in [21], which is capable of scheduling industrial processes to minimize energy costs and/or peak demand charges, while various process constraints are met. The following is a brief explanation of the equations that make up this model:

1. *Electricity cost function:* The main goal of optimal process scheduling is to reduce the electricity costs associated with the plant operation. For this reason, the energy and peak demand costs resulting from the process operation are included in this function as follows:

$$J = \sum_t \alpha_t P_{tot_t} + \beta P_{peak} \quad (2.10)$$

2. *Process coordination constraints:* A process may or may not depend on the previous operation of another process, so these constraints describe the possible interdependency between processes. First, independent processes are scheduled within a time window, and minimum up-time and down-time requirements are considered. Second, different dependent processes are modeled. For instance, when the operation of one process depends on the previous operation of another, they are categorized as sequential processes; on the other hand, if two or more processes are required to operate at the same time, they are considered parallel processes. The equations that maintain proper coordination of processes, which are relevant to this thesis, are integer constraints as follows:

$$t_{on_{k,t}} + t_{off_{k,t}} \leq 1 \quad (2.11)$$

$$t_{on_{k,t}} - t_{off_{k,t}} = st_{k,t} - st_{k,t-1} \quad (2.12)$$

3. *System constraints:* In this work, system requirements are imposed using a supply-demand balance constraint. Thus, this equality equation, that also includes the storage device operation, ensures that the demand is always met by the system, as follows:

$$s_{l_{nc},t-1} + \sum_m or_{m,nc,t} + \sum_q ir_{q,nc,t} = s_{l_{nc},t} \quad (2.13)$$

4. *Power demand constraints:* As already mentioned, the main objective of the optimal industrial operation is to minimize the electricity costs of an industrial facility. These constraints, therefore, take into account the individual as well as the total power demand required for the equipment and storage devices. Furthermore, peak demand constraints are provided to control the maximum demand as required by the customer. These equations are as follows:

$$P_{k,t} = F_k(or_{k,t}, ir_{k,t}) \quad (2.14)$$

$$P_{nc,t} = F_{nc}(or_{nc,t}, ir_{nc,t}) \quad (2.15)$$

$$P_{tot_t} = \sum_k P_{k,t} + \sum_{nc} P_{nc,t} \quad (2.16)$$

$$P_{tot_t} \leq P_{peak} \quad (2.17)$$

$$P_{peak} \leq P_{max} \quad (2.18)$$

5. *Operating constraints:* The following inequality constraints keep all the process variables within limits:

$$R_{min,k} \leq r_k \leq R_{max,k} \quad (2.19)$$

$$S_{lmin,nc} \leq s_{lnc} \leq S_{lmax,nc} \quad (2.20)$$

This OILM model provides a comprehensive framework for optimal industrial operation. Note that these equations are general, and hence they can be adapted for the actual operating conditions of a given industrial facility. Therefore, this model is the foundation for the model proposed in this work.

2.4 Optimization Methods and Solvers

An optimization problem basically focuses on finding the set of continuous and discrete variables that minimize or maximize an objective function satisfying a set of equality and inequality constraints. These problems, depending on the formulation of the objective function, the constraint equations, and the type of decision variables, can be mainly categorized into Linear Programming (LP), MILP, NLP, and MINLP problems. The latter, whose computational complexity is considered NP hard, is of great theoretical and practical importance, since many real problems can be modeled as MINLP problems. A detailed description of the methods developed to deal with these problems, as well as related optimization solvers currently available are discussed next.

Formally, an MINLP problem can be represented by the following set of equations:

$$\min \quad g(x, y) \quad (2.21)$$

$$\text{subject to:} \quad d(x, y) \leq 0 \quad (2.22)$$

$$h(x, y) = 0 \quad (2.23)$$

$$x \in X, y \in Y$$

where $g(x, y)$ is the objective function, $d(x, y)$ is the set of linear and non-linear inequality constraints, $h(x, y)$ is the set of linear and non-linear equality constraints, and X and Y are the set of continuous and discrete decision variables, respectively. Notice that MINLP problems are composed of MILP and NLP subproblems, and global optimality cannot be guaranteed due to the integer constraints, even though the nonlinear constraint could be convex.

To solve the aforementioned optimization problem, many algorithms have been proposed in the literature. Broadly speaking, these methods can be classified in mathematical and heuristic approaches. In general, the mathematical algorithms focus on solving relaxed NLP subproblems, which set lower bounds for the original MINLP problem, whereas feasible solutions to the MINLP problem set the upper limits. A comprehensive description of these methods can be found in [26]. The state-of-the-art algorithms for solving these type of optimization problems are Branch and Bound (BB), Outer Approximations (OA), Generalized Bender Decomposition (GBD), and Extended Cutting Plane (ECP). On the other hand, heuristic search methods such as genetic algorithms, particle swarm optimization, ant colony, and simulated annealing have been used to solve MINLP problems.

Currently, there are a variety of commercial software packages to solve complex optimization problems. Among these, the General Algebraic Modeling System (GAMS) [27], used in this research, is very versatile for the mathematical modeling of large optimization problems. In addition, the model and the algorithm are independent of each other, thereby allowing flexibility for the use and evaluation of different solvers. Table 2.1 summarizes the methods for each MINLP solver available in GAMS. The present work uses DICOPT to solve the optimization problem introduced in Chapter 4.

Table 2.1: GAMS solvers and algorithms for MINLP problems.

Solver	Algorithm
AlphaECP	ECP
BARON	BB
COINBONMIN	BB,OA,ECP
COINCOUENNE	BB
DICOPT	OA
KNITRO	BB
LINDOGLOBAL	BB
SBB	BB

2.5 Summary

The background required to develop an optimization model for industrial process scheduling was introduced in this chapter. DSM programs, especially DR programs oriented to modify the load curve patterns such as valley filling, load clipping, and load shifting, were reviewed. Robust regression was briefly introduced as a method to reduce the outlier effect in a final regression model, and the bisquare method, an M estimator used to develop a parametric regression model in Chapter 3, was described in detailed. The general OILM model was briefly described as the basis for the optimization model proposed in Chapter 4. Finally, optimization problems mainly focused on MINLP problems and the mathematical algorithms commonly used to solve them were presented.

Chapter 3

Industrial Load Modeling

In this chapter, a polynomial regression model is introduced and developed for industrial loads. In particular, this parametric model is determined for the case of a chiller, which is a thermodynamic equipment used to chill sensitive machinery in industrial processes. Hence, a chiller system is described in detail first, followed by its mathematical model for load management purposes.

3.1 Chiller Fundamentals

Before a feasible model can be proposed to estimate the active power consumption of chillers, a detailed review of its basic operating principles as well as the main components of this equipment should be properly understood. Thus, this section discusses the basic operating principles of a chiller system.

The refrigeration cycle, wherein a chemical substance called primary refrigerant can change from liquid to gas and vice versa, by increasing or decreasing its internal energy or enthalpy, can be mainly carried out using vapor compression or absorption refrigeration cycles [28]. Nowadays, thermodynamic machinery employs the former to chill water as the secondary coolant for water cooling systems. The first step of this cycle increases the enthalpy of the primary refrigerant without pressure and temperature variations; then, the pressure and temperature are increased by adding external energy to the refrigerant. Afterward, energy is released, thus decreasing the enthalpy, maintaining temperature and pressure constant, and at the same time, the temperature of the primary refrigerant is reduced. At the end, the pressure of the refrigerant decreases before a new refrigeration cycle begins again. This thermodynamic cycle is shown in Figure 3.1(b) [28].

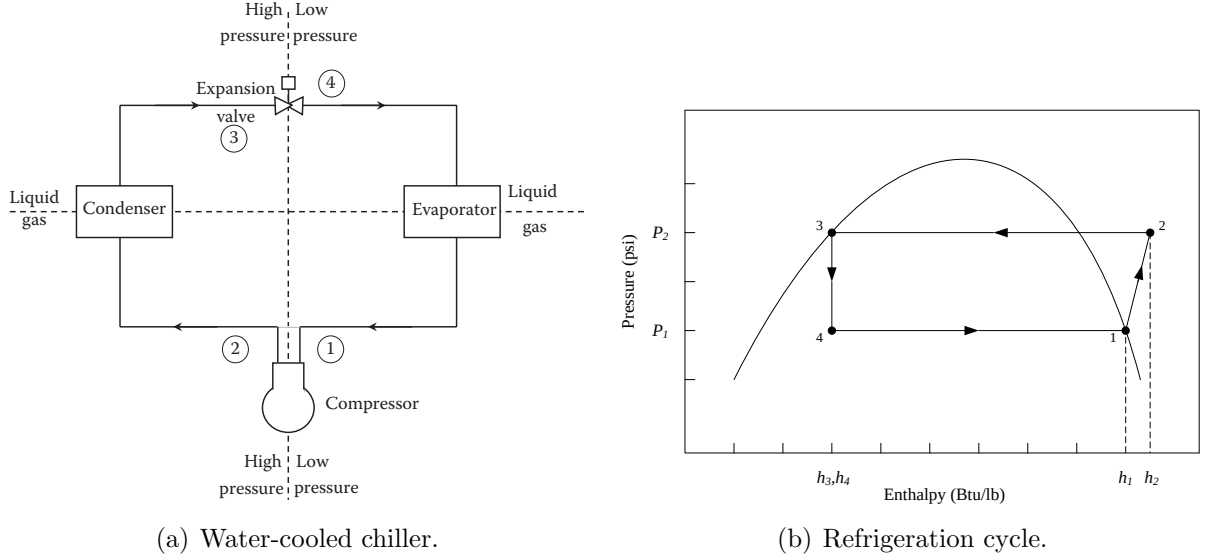


Figure 3.1: Basic operating principles of water-cooled chillers.

All the stages of the refrigeration cycle previously described are carried out by the different components of a chiller, which are shown in Figure 3.1(a). First, the evaporator, which is a heat exchanger, increases the enthalpy of the primary refrigerant by removing heat from the secondary refrigerant. Second, the pressure and temperature are increased by the compressor, which is responsible for most of the electrical consumption of this equipment. Then, the enthalpy of the primary refrigerant is reduced by the secondary refrigerant flowing through the condenser. Finally, an expansion valve decreases the pressure of the refrigerant.

3.2 Chiller Modeling

As stated before, the OILM requires the modeling of electric equipment using a feasible model to estimate the equipment's active power demand. Two physical models to determine the electric power required by a centrifugal chiller to reject heat to a secondary refrigerant are presented in [29, 30]. These models consider internal variables of the primary refrigerant, which are not commonly measurable during normal operation, to characterize the active power consumption needed. On the other hand, a comprehensive regression model, developed by Lawrence Berkeley National Laboratory, introduces, as predictor variables, the inlet and outlet water temperatures at the condenser and evaporator of the chiller

Table 3.1: Variations of the general polynomial model.

Model	p_{00}	p_{01}	p_{02}	p_{03}	p_{11}	p_{22}	p_{33}	p_{12}	p_{13}	p_{23}
1		X	X	X						
2		X	X	X	X					
3		X	X	X		X				
4		X	X	X			X			
5		X	X	X	X			X	X	
6		X	X	X	X	X	X	X	X	X

respectively [29]; the water flow rate, however, is considered constant in this model. Based on these ideas, the following parametric polynomial regression model, as per [21], is proposed to account for chiller's active power consumption in this research, considering that the water flow rates change:

$$\begin{aligned}
 P_{ch}(W_f, T_{eo}, T_{ci}) = & p_{00} + p_{01}W_f + p_{02}T_{eo} + p_{03}T_{ci} + p_{11}W_f^2 + p_{22}T_{eo}^2 \\
 & + p_{33}T_{ci}^2 + p_{12}W_fT_{eo} + p_{13}W_fT_{ci} + p_{23}T_{eo}T_{ci} + \epsilon
 \end{aligned} \quad (3.1)$$

where ϵ is the error, and W_f , T_{eo} , and T_{ci} are the water flow rate and outlet water temperature at the evaporator, and inlet water temperature at the condenser, respectively. These variables, also known as predictor variables, determine the chiller's active power requirement for normal operation.

3.2.1 Polynomial Model Fitting

In order to determine the most suitable regression model to estimate the power consumption of the aforementioned chillers, six variants of the general model (3.1), which are shown in Table 3.1, have been evaluated. The different options are ranked based on the results obtained for the square of the correlation coefficient (R^2), Root Mean Square Error (RMSE), and energy error. The latter is defined as the prediction error of the regression model due to the fitting process for a normal day of operation of the chillers.

Based on measurements of the relevant chiller model variables obtained from a measuring campaign at an automotive frame manufacturing facility in Ontario, between April 27 and June 19, 2013, the bisquare approach explained in Section 2.2.1 is applied to estimate

Table 3.2: Polynomial fitting statistics.

Model		1	2	3	4	5	6
Chiller 1	R^2 [pu]	0.7688	0.8559	0.7696	0.7695	0.8596	0.8623
	RMSE [kW]	18.64	9.49	18.67	18.65	9.50	10.13
	Energy Error[%]	-4.78	-3.29	-4.96	-4.86	-3.62	-4.34
Chiller 2	R^2 [pu]	0.8686	0.9524	0.8688	0.8689	0.959	0.9618
	RMSE [kW]	18.70	10.38	18.71	18.69	9.08	9.14
	Energy Error[%]	-10.83	-5.72	-10.91	-10.82	-5.71	-6.39
Chiller 3	R^2 [pu]	0.7652	0.8809	0.7678	0.7677	0.8855	0.8865
	RMSE [kW]	13.85	9.30	14.47	14.50	9.08	10.25
	Energy Error[%]	-5.97	-4.07	-6.44	-6.46	-3.91	-4.52
Chiller 4	R^2 [pu]	0.8365	0.9645	0.8363	0.8365	0.9629	0.9691
	RMSE [kW]	20.21	6.74	20.24	20.26	6.93	7.55
	Energy Error[%]	0.77	-1.39	0.80	0.77	-0.81	-2.45

the coefficients of (3.1) for every chiller so that the influence of possible outliers in real data for demand and process is reduced [25]. This results in the statistics and non-zero chiller polynomial model coefficients for the fitting process presented in Tables 3.2 and 3.3, respectively. Observe that the best results were obtained for Models 2, 5, and 6. These models include second degree terms of the water flow rate, which significantly influences the chiller power demand. Therefore, Model 5, based on the statistics in these tables, is chosen to estimate the power consumption of the chillers. Figures 3.2 to 3.5 show how effectively the electric power estimated by the computed polynomials matches the actual consumption for each chiller for a normal day of operation (June 7, 2013). Note also that the bisquare function reduces the effect of the outlier shown in Figure 3.5. This is possible due to the fact that the regression method assigns a low weight to this measurement in comparison with the remaining data available for Chiller 4.

Table 3.3: Polynomial coefficients for Model 5.

Chiller	1	2	3	4
p_{01} [kW/GPM]	0.118937048	-0.378962631	-0.264400077	0.087629535
p_{02} [kW/°F]	-0.644322437	-0.684596166	-0.264656196	-0.13625212
p_{03} [kW/°F]	0.428700392	0.463760361	0.177507725	0.09307501
p_{11} [kW/GPM ²]	-0.00074433	-0.000618612	-0.000680398	-0.000902843
p_{12} [kW/(GPM)(°F)]	0.006840054	0.019393174	0.012305408	0.005273654
p_{13} [kW/(GPM)(°F)]	0.001388705	-0.000704116	0.003165732	0.003987419

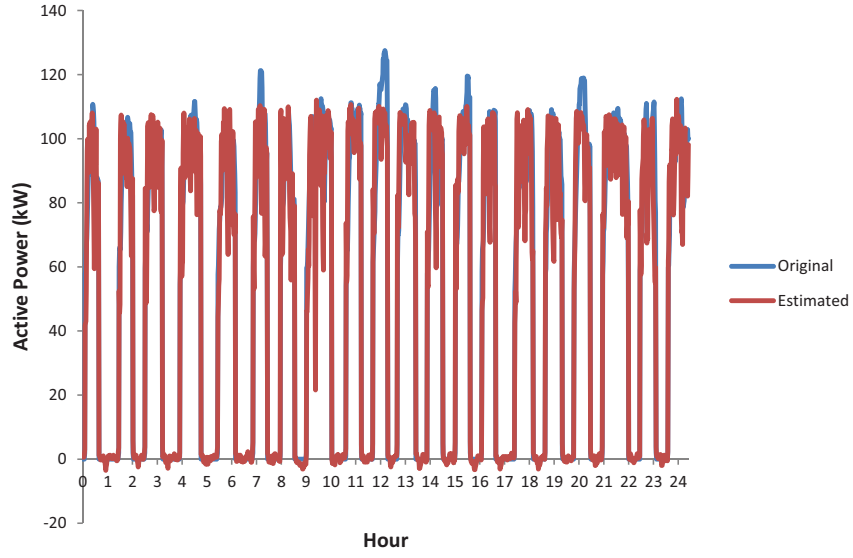


Figure 3.2: Original and estimated active power demands of Chiller 1.

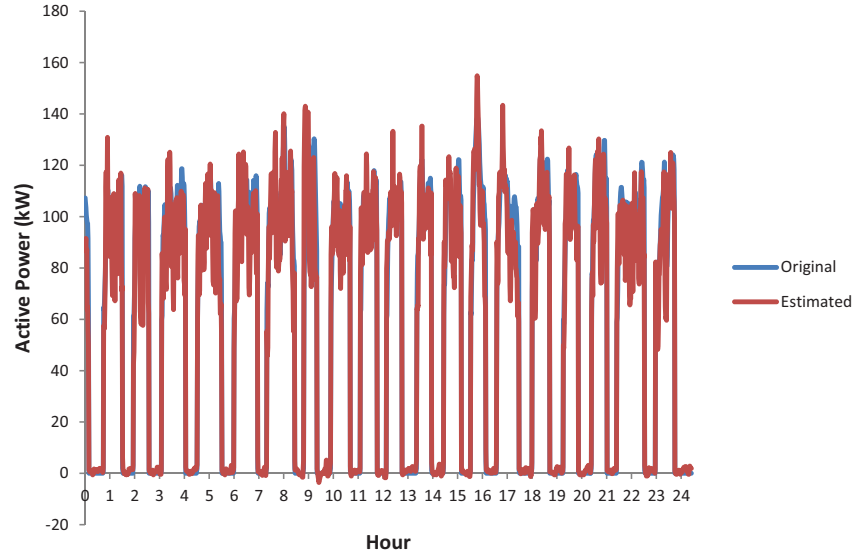


Figure 3.3: Original and estimated active power demands of Chiller 2.

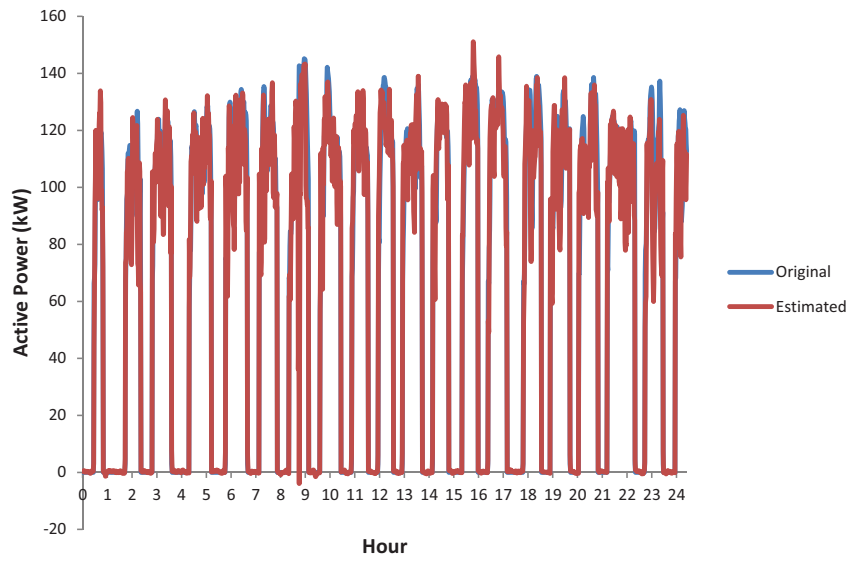


Figure 3.4: Original and estimated active power demands of Chiller 3.

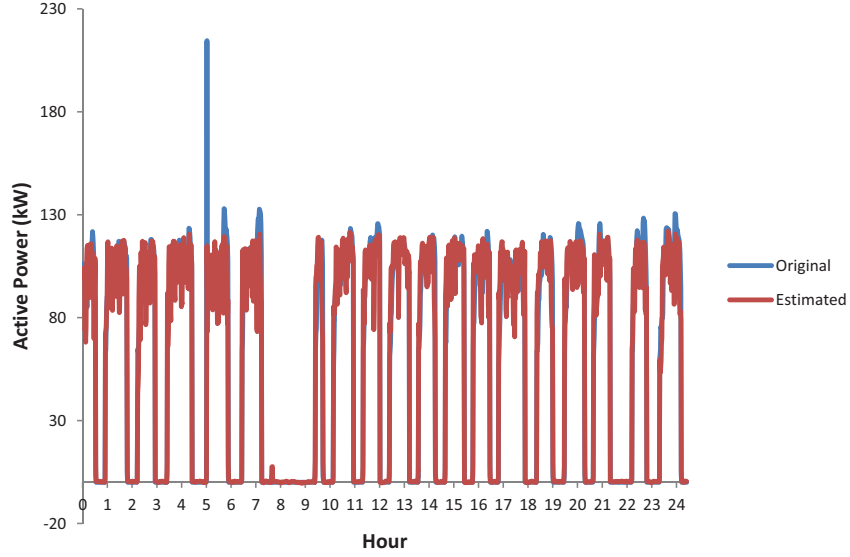


Figure 3.5: Original and estimated active power demands of Chiller 4.

3.3 Summary

The basic principles of chiller operation, and the methodology carried out to find the best suitable polynomial model to estimate the active power consumption were presented in this chapter. First, a brief review of chiller's components and their relation with the vapor compression refrigeration cycle were presented. This information was used to propose a parametric polynomial regression model as a function of outlet water temperature and water flow rate at the evaporator, and inlet water temperature at the condenser. The fitting of six different alternatives of a general regression model using available measured data from an actual industrial facility was then carried out, and the final model for every chiller was explained, based on the statistics determined using a regression technique. It was shown that accurate results were obtained for all chiller models in the plant. These results are used in Chapter 4 in the proposed OILM model of the chiller system.

Chapter 4

Optimal Operation of an Industrial Process

The optimization model described in this chapter focuses on the minimization of energy and/or peak demand costs for the chiller system of an automotive frame manufacturing plant, based on the general OILM model described in Section 2.3. This model is used to optimize the scheduling of 4 chillers in the plant water cooling system. The results of applying this model to the chiller system operation are compared with actual data and costs obtained for the plant. Finally, improvements to the water cooling system based on the proposed model are determined, so that higher electricity bill savings can be achieved.

4.1 Optimization Model for Chiller System Scheduling

The goal of the optimal scheduling of industrial loads is to minimize the monthly electricity costs, through increasing the efficiency of operation. Therefore, the following objective function, which takes into account the energy and peak demand costs, charged to industrial customers by an LDC, is used here:

$$J = \Delta T \sum_t \alpha_t P_{T_t} + \beta P_{peak} \quad (4.1)$$

where the parameters α , β , and ΔT can be adjusted depending on the main objectives of the plant operation.

Constraints associated with the operation of the chiller process starting with the active power required by the process, estimated from the following equation, need also be considered. This corresponds to the second-order polynomial model developed in Section 3.2, for the case of the chillers studied here:

$$P_{ch_{j,t}} = F_j (W_{f_{j,t}}, T_{eo_t}, T_{ci_t}) \quad \forall j, t \quad (4.2)$$

The required chiller cooling capacity is obtained from:

$$Q_{e_{j,t}} = W_{f_{j,t}} (T_{ei_t} - T_{eo_t}) K_{bt} \quad \forall j, t \quad (4.3)$$

Additionally, considering the current operating practices, the Partial Load Ratio (*PLR*) and Coefficient of Performance (*COP*) of the chillers must be considered, as follows:

$$PLR_{j,t} = Q_{e_{j,t}} / Q_{er_j} \quad \forall j, t \quad (4.4)$$

$$COP_{j,t} = Q_{e_{j,t}} / (P_{ch_{j,t}} K_{pt}) \quad \forall j, t \quad (4.5)$$

The water cooling system must be able to supply the requirements of the cooling load at every time period. To ensure the system demand-supply balance, the following constraints are needed:

$$S_{cap_{v,0}} + \sum_j Q_{e_{j,t}} st_{j,t} - s_{cap_{v,t}} = Q_{lt} \quad \forall v, t = 1 \quad (4.6)$$

$$s_{cap_{v,t-1}} + \sum_j Q_{e_{j,t}} st_{j,t} - s_{cap_{v,t}} = Q_{lt} \quad \forall v, t \geq 2 \quad (4.7)$$

The initial storage capacity of the Chilled Water Storage (CWS) is considered in (4.6), and (4.7) to match the cooling supply, demand, and storage for the next time intervals. Hence, these two constraints ensure the system demand-supply balance at every instant of time.

To properly account the total amount of power required by the industrial processes, three additional constraints are needed. Thus, the following constraint determines the total chiller active power in the water cooling system:

$$P_{T_t} = \sum_j P_{ch_{j,t}} st_{j,t} \quad \forall t \quad (4.8)$$

whereas the following constraints enforce the maximum active power limit imposed on the industrial customer to reduce peak demand costs:

$$\beta P_{T_t} \leq \beta P_{peak} \quad \forall t \quad (4.9)$$

$$\beta P_{peak} \leq \beta P_{max} \quad (4.10)$$

The coordination of chiller equipment in the industrial process is accomplished by:

$$t_{on_{j,t}} + t_{off_{j,t}} \leq 1 \quad \forall j, t \quad (4.11)$$

$$t_{on_{j,t}} - t_{off_{j,t}} = st_{j,t} - st_{j,t-1} \quad \forall j, t \quad (4.12)$$

where (4.11) prevents turn-on and turn-off decisions to be activated at the same time interval, and turn-on and turn-off decisions are coordinated through (4.12). Additionally, number of switching operations are limited by:

$$\sum_t t_{on_{j,t}} \leq n_{sw} \quad \forall j \quad (4.13)$$

Finally, all the variables used to characterize the chiller system have upper and lower bounds. Hence, the feasible ranges for the chiller and storage tank variables are represented as follows:

$$C_{min,j} st_{j,t} \leq c_{j,t} \leq C_{max,j} st_{j,t} \quad \forall j, t \quad (4.14)$$

$$S_{cap_{min,v}} \leq s_{cap_{v,t}} \leq S_{cap_{max,v}} \quad \forall v, t \quad (4.15)$$

The optimization model (4.1)-(4.15) considers active power requirements of the processes, supply-demand balance, interdependency between processes, and lower and upper limits of the process variables. Depending on the cost reduction priority for the industrial facility, the proposed optimization model permits the optimal chiller load scheduling by

minimizing the energy cost, peak demand charge, or both at the same time. For instance, choosing a zero value for the energy price parameter α would allow the minimization of the peak demand charge only, whereas a zero value for peak demand charge β would optimally schedule the chillers to reduce the associated energy costs. Thus, an industrial consumer is able to select an objective function that fits its specific concerns.

4.2 Study Case and Simulation Results

In this section, the aforementioned OILM model (4.1)-(4.15) is applied to the water cooling system of an automotive manufacturing company, which is described in some detail first. The goal is to determine the optimal scheduling of chillers, which are part of the water cooling system of the factory, in order to minimize the electricity costs for two different cases:

- Case 1: Energy cost minimization.
- Case 2: Energy and peak-demand cost minimization.

4.2.1 Plant Description

One vital part of the normal operation of the automotive manufacturing company considered is the cooling of certain processes and equipment. The industrial facility studied here has a water cooling system whose schematic representation is shown in Figure 4.1, which consists of four chillers, a cooling tower, and a CWS. The water cooling process is carried out by the chillers, whose detailed operation was described in Section 3.1. The main job of these chillers is to chill the inner water flow (stored in the CWS) by removing the heat towards the outer water flow loop (through the cooling tower). The actual capacity of heat disposal of this equipment depends on the inlet and outlet water temperature of the condenser and evaporator, respectively. The total evaporator water flow output of the chillers is sent to the CWS, which helps to decouple instant demand requirements from chiller operation, resulting in a more flexible chiller scheduling. Table 4.1 presents the main characteristic of the water cooling system. Additionally, a fixed temperature difference of 7.5 °F between inlet and outlet water temperature at the evaporator is assumed.

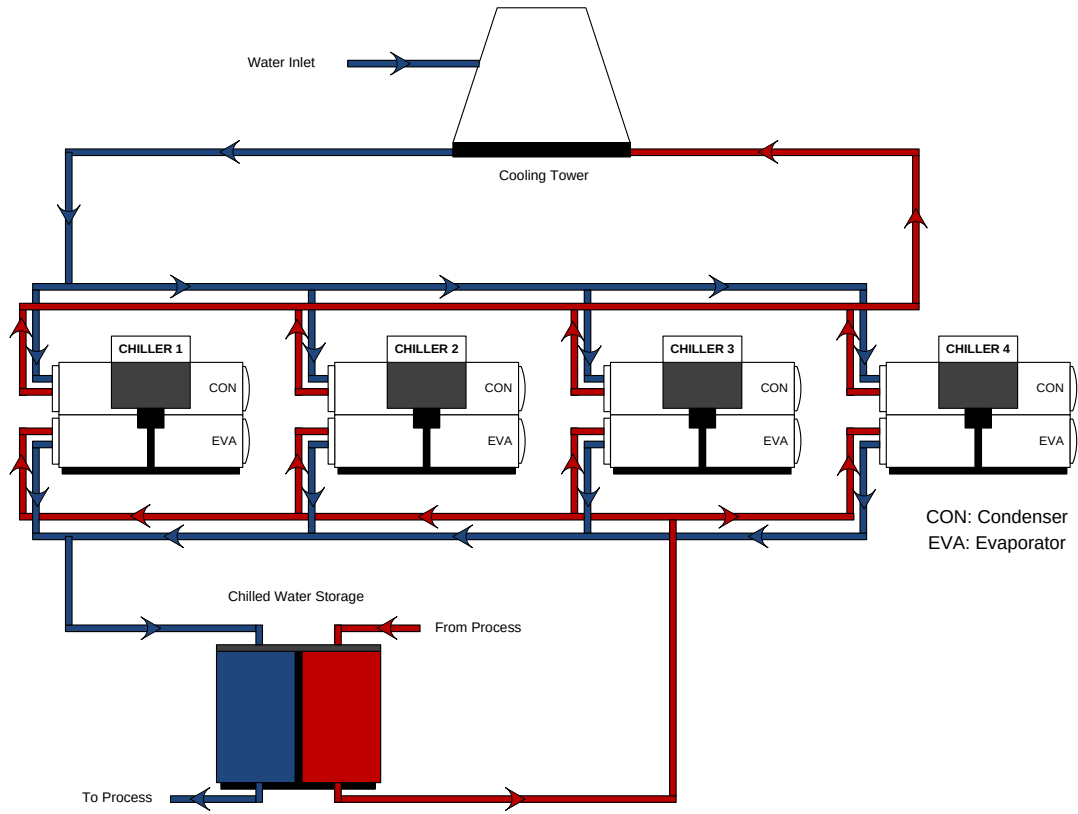


Figure 4.1: Water cooling system of the automotive manufacturing plant under study.

Table 4.1: Water cooling system equipment data.

Number of Chillers	4
Compressor Power	180 Hp
Compressor Type	Centrifugal
Chiller Capacity	156 tons
Minimum Water Flow Rate	50 GPM
Maximum Water Flow Rate	500 GPM
Maximum Chiller Switching Operations	200/month
Storage Capacity	3456 gallons 35 tons

Table 4.2: Base and Case 1 comparison for May 2013.

		Base Case	Case 1	Savings [%]
Energy	[\$]	2,391.29	2,330.30	2.55
	[kWh]	91650	94548	-3.16
Peak	[\$]	4,551.36	8,197.65	-80.11
	[kW]	284	512	-80.11
Total	[\$]	6,942.65	10,527.96	-51.64

The Independent Electric System Operator (IESO), which is responsible for clearing the wholesale market in Ontario, splits the energy price in two components [31]: Hourly Ontario Energy Price (HOEP) and Global Adjustment (GA), with the HOEP corresponding to an hourly energy price, and the GA corresponding to a variable monthly charge to account mainly for transmission congestion plus Feed-in Tariff (FIT) and DSM programs. In Ontario, an industrial customer with a peak demand greater than 5 MW is considered a Type A customer by an LDC, and GA is charged to power demand during peak hours.

For simulation purposes, the HOEP used here is based on the information published for May 2013 in [31], which coincides with the measuring campaign dates, and it is assigned to the parameter α for both cases. The GA value used, for this type of customer and based on the information for July 2013 (the May 2013 bill was not available) provided by the industrial customer, is 13.08 \$/kW. In addition, Type A customers are also charged for peak-demand, which was 2.93 \$/kW for July 2013. A sample data set, for May 30, 2013, is provided in Table A.3 in Appendix A, for reference.

4.2.2 Case 1: Energy Cost Minimization

The optimization model described in Section 4.1, considering a zero value for the parameter β , was used to obtain the optimal dispatch of the chillers for May 2013. Note that peak-demand minimization is not considered in this case. The results of this simulation are shown in Table 4.2. Observe that the energy cost is effectively reduced with respect to the original energy cost; however, the peak-demand charge is almost twice the base cost. Hence, the final cost to operate the cooling system is more expensive than the current (base) operation.

Figure 4.2 shows the supply-demand balance in the water cooling system for May 30, 2013. Notice the complementary operation of the storage tank to match the cooling demand

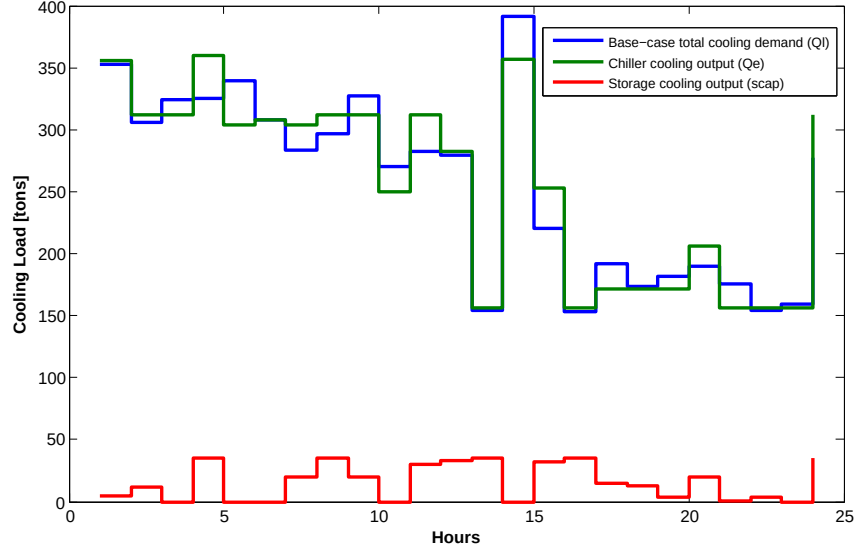


Figure 4.2: Water cooling system load and storage capacity for May 30, 2013.

requirement, which is the same for all cases since this represents process output (demand), and to store the chiller's cooling output when it exceeds the system cooling demand.

The total active power profile of the chillers is presented in Figure 4.3. Due to the fact that the present case does not minimize the peak-demand charge of the water cooling system, the optimization model tries to schedule the chillers considering the most economical time intervals only. Thus, for hours 4 and 6, when the HOEP is negative, the chiller active power requirements are the highest of the day.

The *PLR* and *COP* of every chiller are shown in Figures 4.4 and 4.5 for May 30, 2013. Note that, for the negative energy prices at hours 4 and 6, the increasing active power demand reduces the *COP*, i.e., the compressor requires more power for the same cooling load supplied by the corresponding chiller.

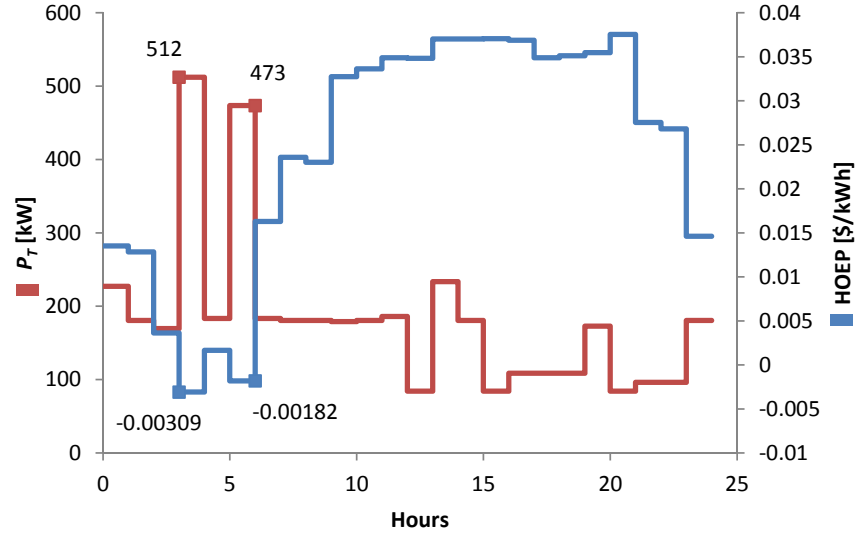


Figure 4.3: Power demand profile of chillers and HOEP for May 30, 2013.

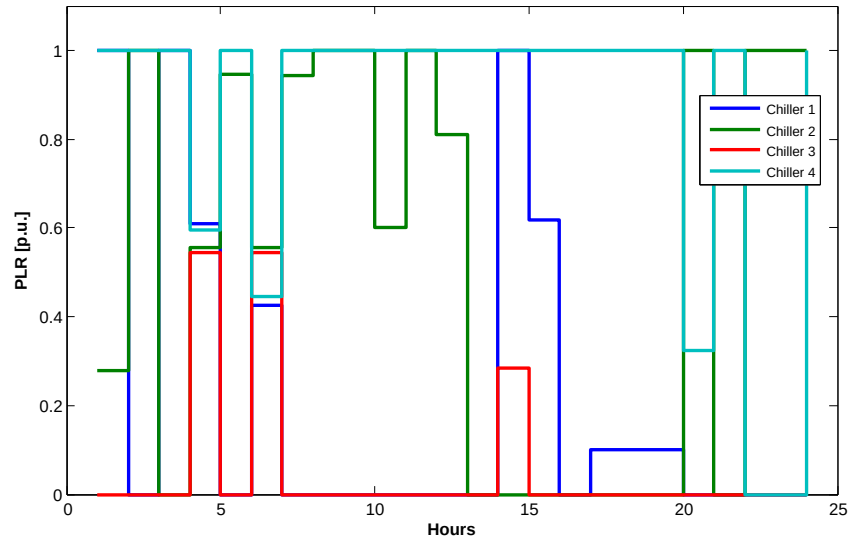


Figure 4.4: *PLR* of chillers for May 30, 2013.

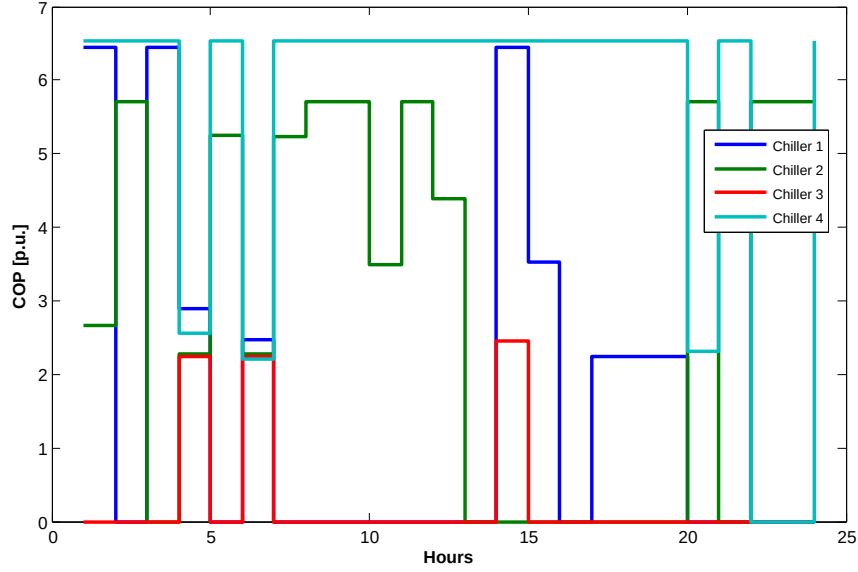


Figure 4.5: *COP* of chillers for May 30, 2013.

Even though the optimal chiller scheduling successfully minimizes the energy costs, it does not accomplish the overall reduction of electricity costs. Hence, peak-demand cost minimization needs to be included, as shown in the next section.

4.2.3 Case 2: Energy and Peak-Demand Cost Minimization

Energy and peak-demand costs are both minimized for May 2013 by the optimal chiller scheduling in this case. A value of 16.01 \$/kW, which is equal to GA plus peak-demand consumption charge, is considered for parameter β . Since the peak charges are higher than the energy costs for this type of customer, by reducing peak demand during chiller operation, final monthly savings should be attained. The final results for this case are presented in Table 4.3. Observe that, even though the energy costs are higher than Case 1, the total cost is less than that obtained for the base operation.

Table 4.3: Base and Case 2 comparison for May 2013.

		Base Case	Case 2	Savings [%]
Energy	[\$]	2,391.29	2,375.22	0.67
	[kWh]	91650	92313	-0.72
Peak	[\$]	4,551.36	4,246.98	6.69
	[kW]	284	265	6.69
Total	[\$]	6,942.65	6,622.20	4.62

The combined operation of the CWS and chillers for May 30, 2013, are shown in Figure 4.6. Again, observe that the CWS complements the chiller operation to match the required system cooling demand for that day, achieving the aforementioned savings.

Due to the fact that Case 2 minimizes not only energy cost but also peak charge, the peak demand is reduced in comparison with Case 1, as shown in Figure 4.3. Note that the total active power profile of the chillers demand no more than 230 kW, which is the main reason for the savings.

Figures 4.8 and 4.9 show the results for the *PLR* and *COP* variables. Observe that these variables do not drastically vary due to negative energy prices, unlike in Case 1; thus, the operation of Chiller 2 and Chiller 4 are more stable during these hours.

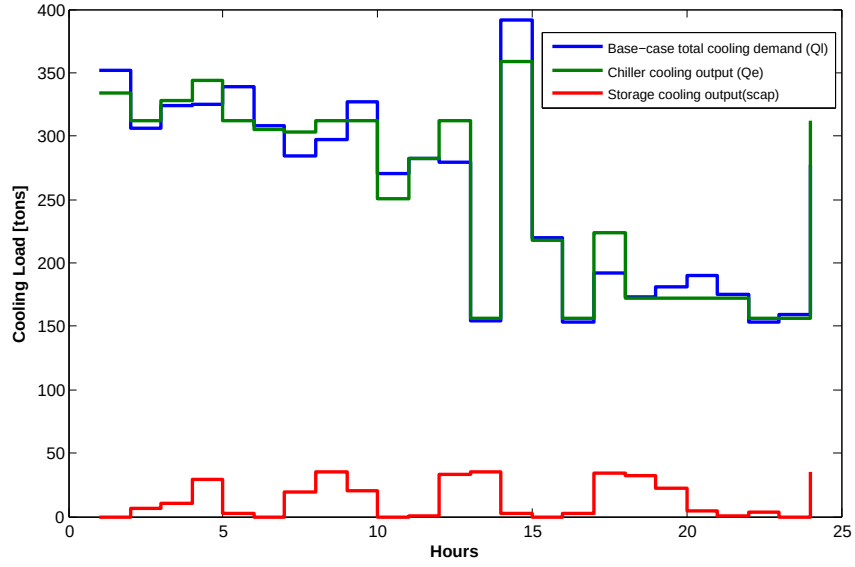


Figure 4.6: Water cooling system load and storage capacity for May 30, 2013.

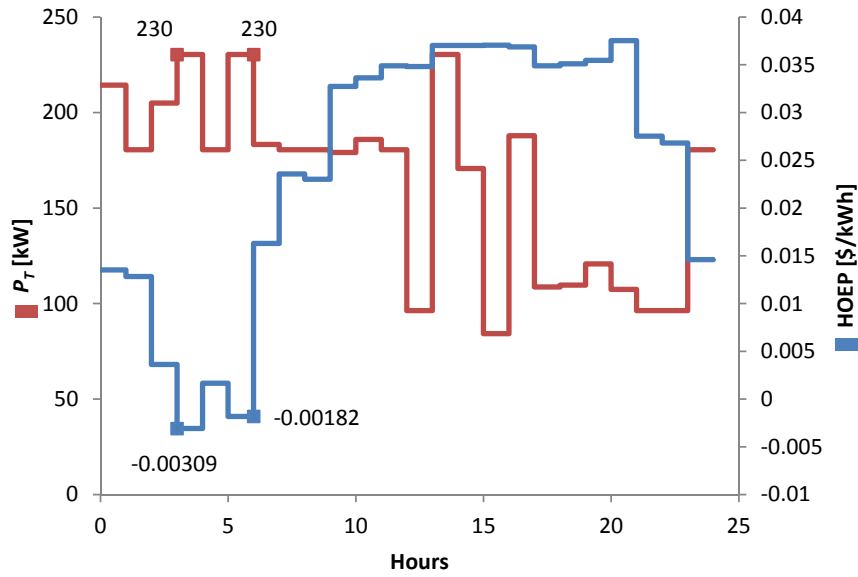


Figure 4.7: Power demand profile of chillers and HOEP for May 30, 2013.

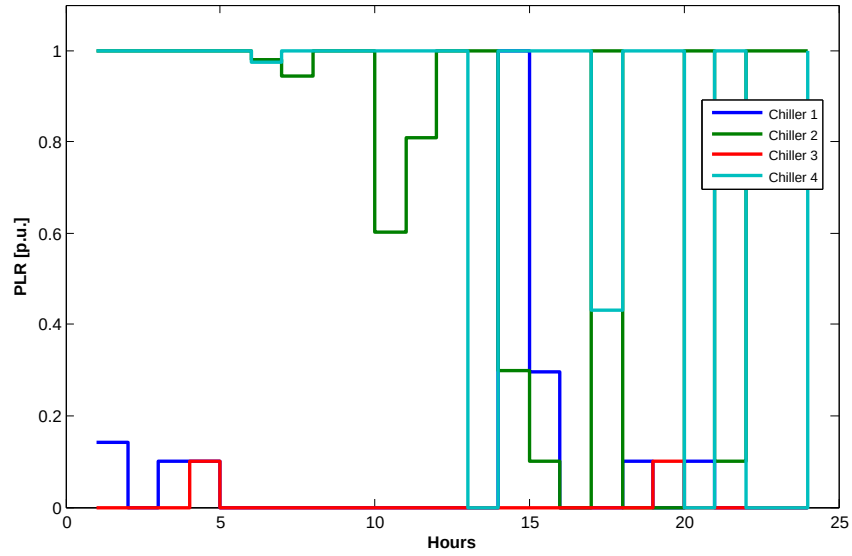


Figure 4.8: *PLR* of chillers for May 30, 2013.

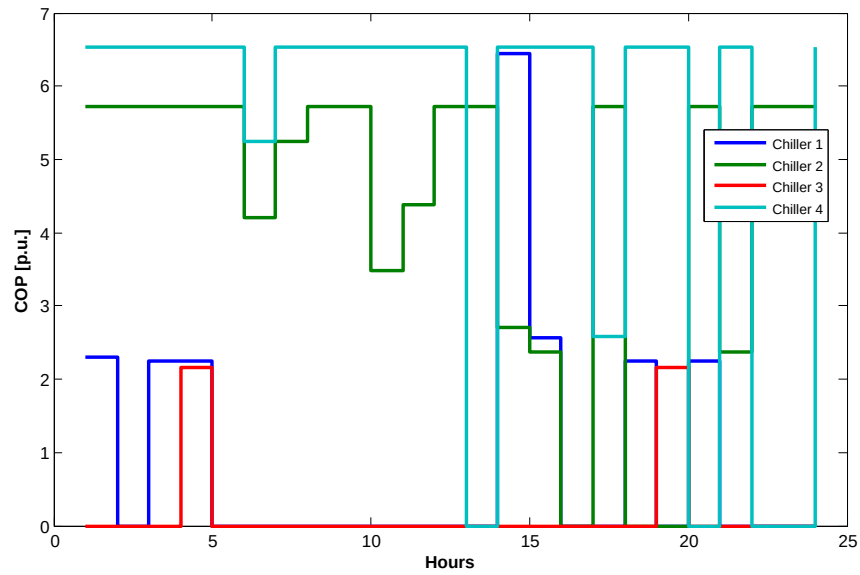


Figure 4.9: *COP* of chillers for May 30, 2013.

Table 4.4: Electricity cost savings for Case 1 and Case 2 for May 2013.

Cost Savings	Case 1 (%)	Case 2 (%)
Energy	2.55	0.67
Peak	-80.11	6.69
Total	-51.64	4.62

4.2.4 Comparison

Table 4.4 summarizes the final electricity cost savings obtained after the implementation of the optimization model for Cases 1 and 2. Notice that Case 2, where energy and peak-demand costs are minimized simultaneously, results in the best chiller operation. Case 1 performs the savings better for energy cost reduction, but the total savings are negative, whereas total savings for Case 2 are almost 5% of the actual electricity costs. The latter are mainly due to the reduction of the total peak demand of the water cooling system.

The total peak demand profiles and energy consumption for May 2013, for the base case and Cases 1 and 2, are shown in Figures 4.10 and 4.11, respectively. The four highest peak demand days for Case 1 are a consequence of negative HOEP, which increases the final electricity bill. On the other hand, observe that the peak demand is maintained as low as possible in Case 2, due to the minimization of peak-demand costs. In fact, the peak demand profile for this case is less than the base peak demand of the water cooling system for most days. Additionally, energy consumption is slightly increased for both cases, with Case 2 having a smaller value than Case 1.

The chiller scheduling is performed considering the monthly maximum switching operations allowed. This constraint is enforced by (4.13), and the final results are presented in Figure 4.12. Note that in both cases, the final switching operations are maintained below the limit set by the customer; in fact, the chiller operations are significantly reduced. The main reason for this reduction is that Chillers 2 and 4 operate more frequently than Chillers 1 and 3, as shown in Figure 4.13. In addition, the time interval ΔT of the optimization model is 1 hour, and hence turn-on or turn-off decisions take place during that time period, thus limiting the number of possible switching operations.

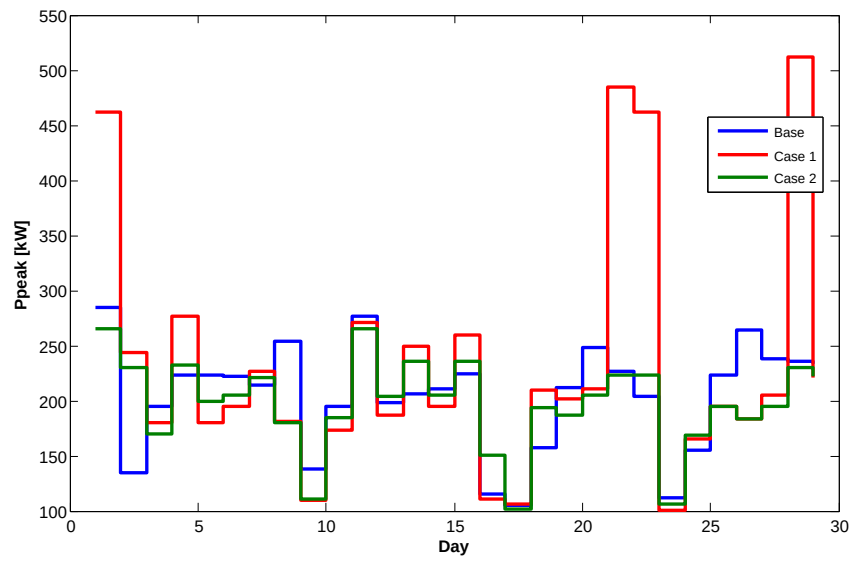


Figure 4.10: Total peak demand profile of chiller operation for May 2013.

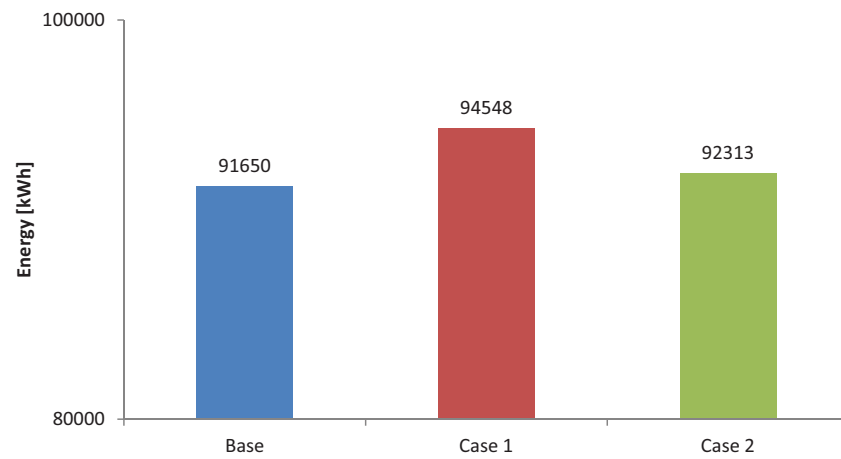


Figure 4.11: Total energy consumption of chiller operation for May 2013.

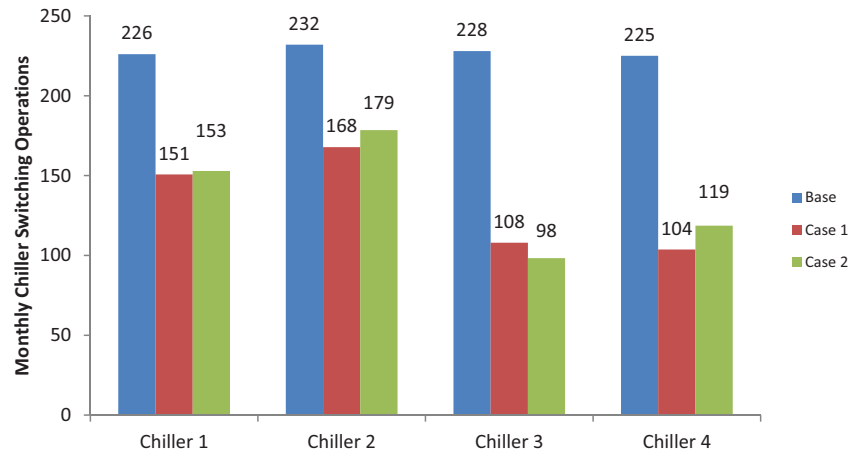


Figure 4.12: Total chiller switching operations for May 2013.

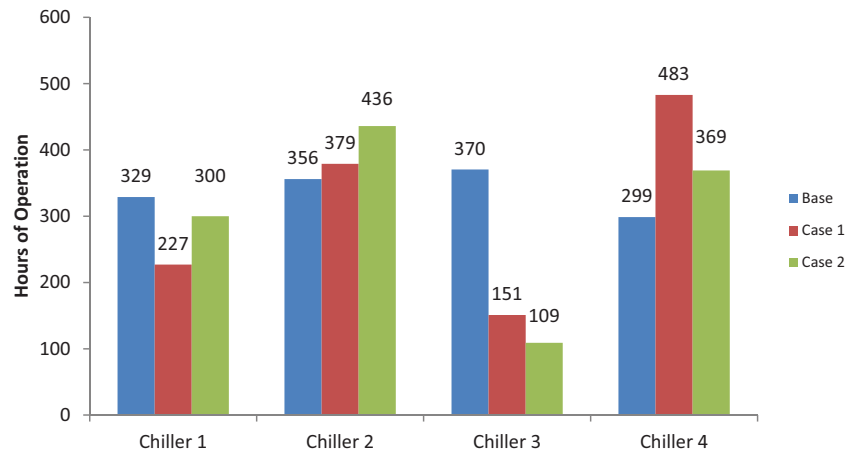


Figure 4.13: Total chiller operating hours for May 2013.

The active power required for every chiller for May 30, 2013, is shown in Figures 4.14 to 4.17. Note that Chillers 2 and 4 are used more frequently in the optimized operation, and have a smaller peak demand in Case 2, whereas Case 1 shows higher peak demands associated with negative HOEP values.

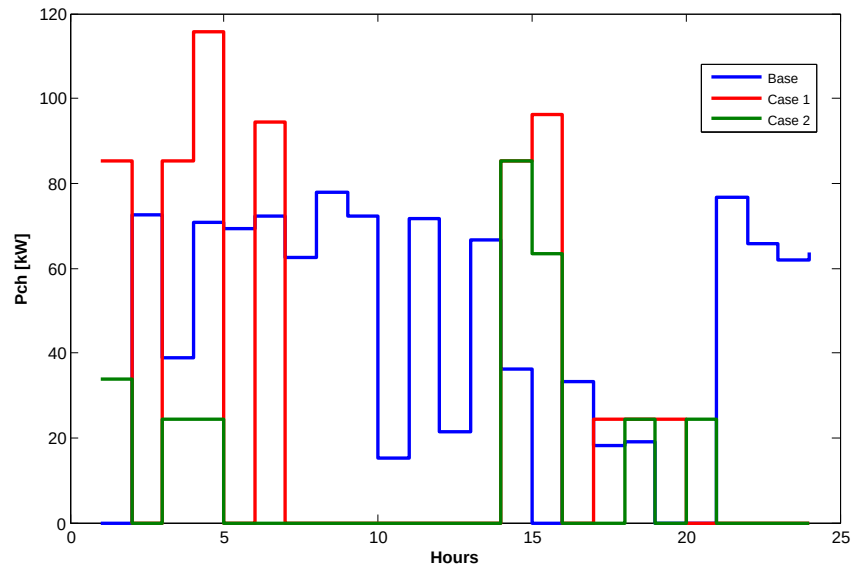


Figure 4.14: Active power demand of Chiller 1 for May 30, 2013.

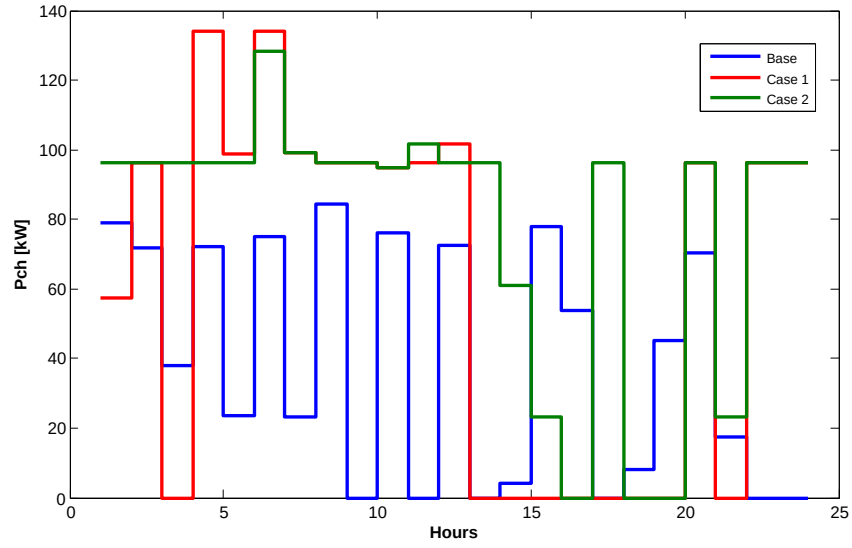


Figure 4.15: Active power demand of Chiller 2 for May 30, 2013.

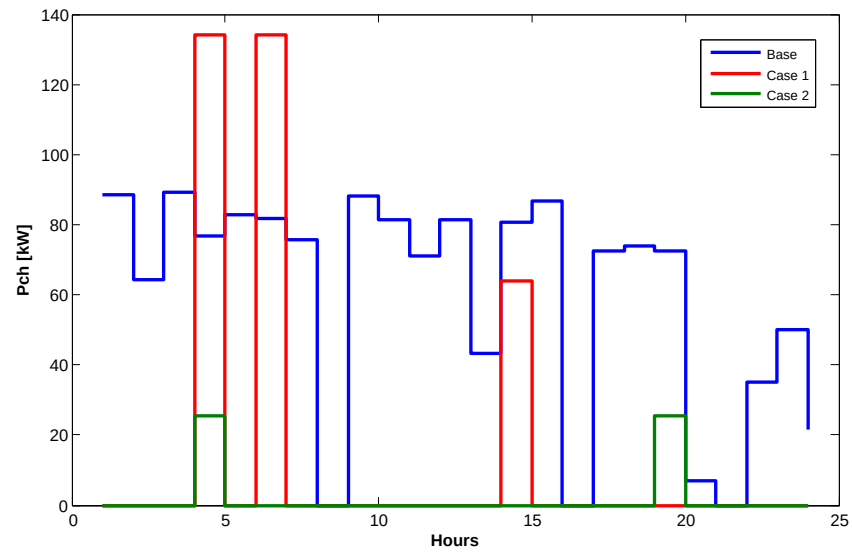


Figure 4.16: Active power demand of Chiller 3 for May 30, 2013.

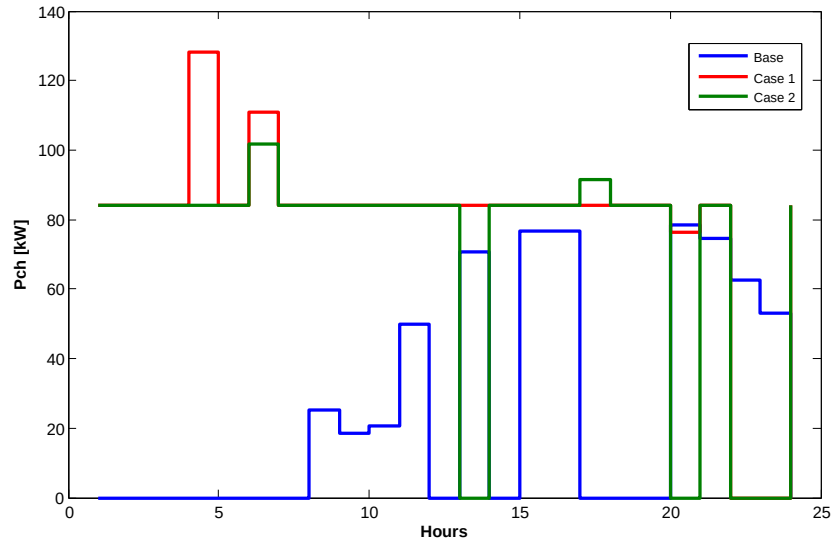


Figure 4.17: Active power demand of Chiller 4 for May 30, 2013.

The water flow rate for every chiller is shown in Figures 4.18 to 4.21, for May 30, 2013. Again, it is shown that Chillers 2 and 4 are frequently scheduled for the optimization model to supply the cooling load of the system. Note also that the water flow rate of these chillers is not affected by the negative HOEP values in Case 2, unlike Chillers 1 and 3, as these are less efficient.

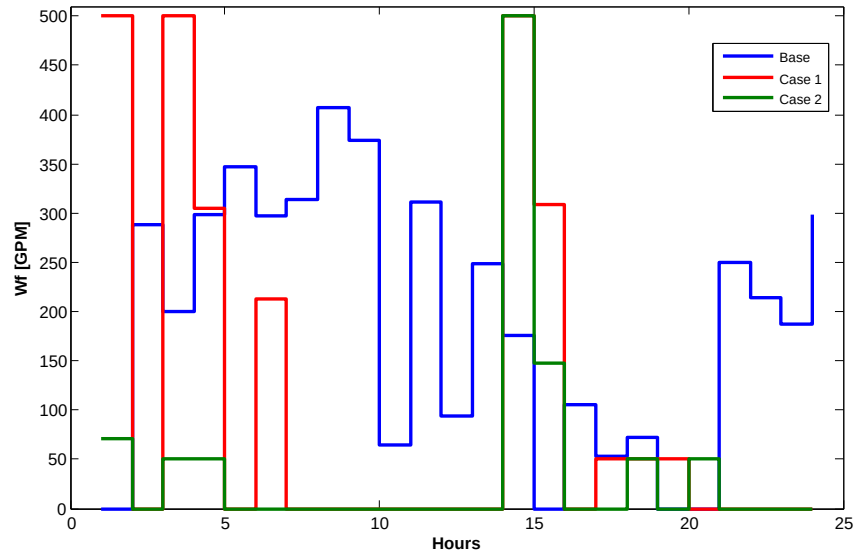


Figure 4.18: Water flow rate of Chiller 1 for May 30, 2013.

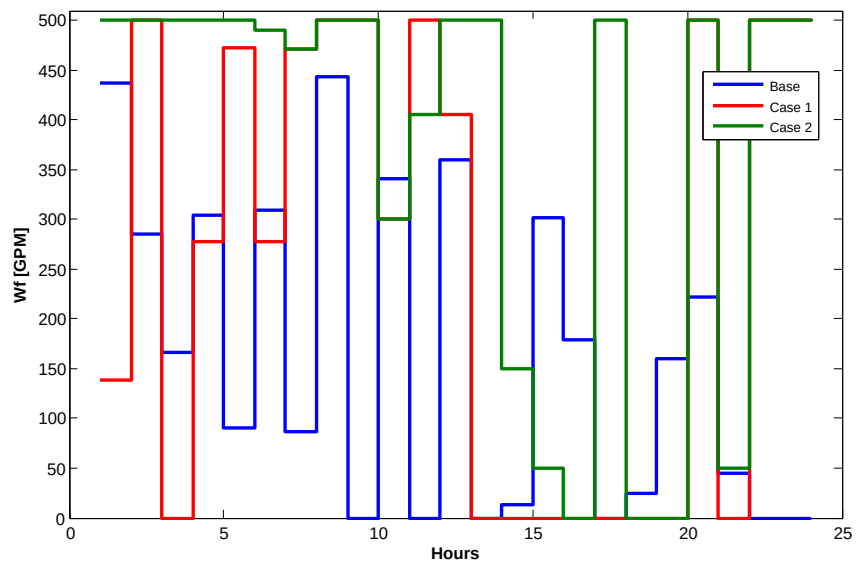


Figure 4.19: Water flow rate of Chiller 2 for May 30, 2013.

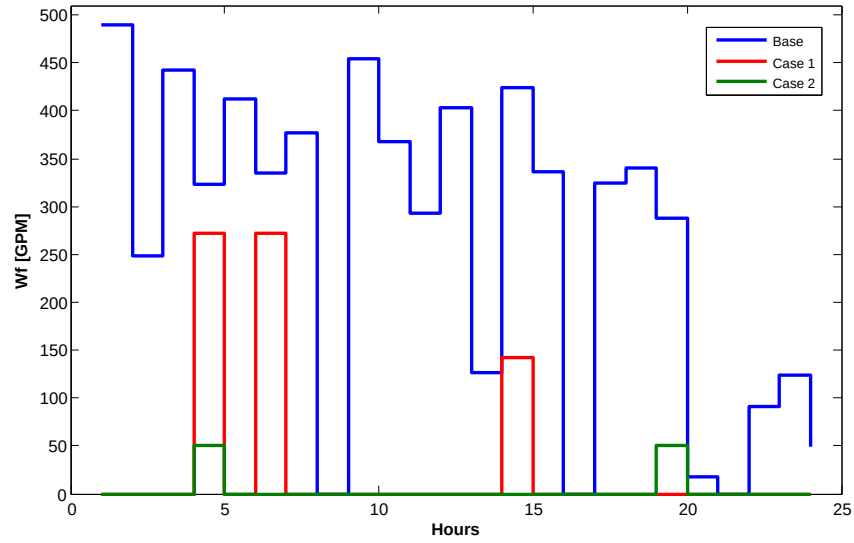


Figure 4.20: Water flow rate of Chiller 3 for May 30, 2013.

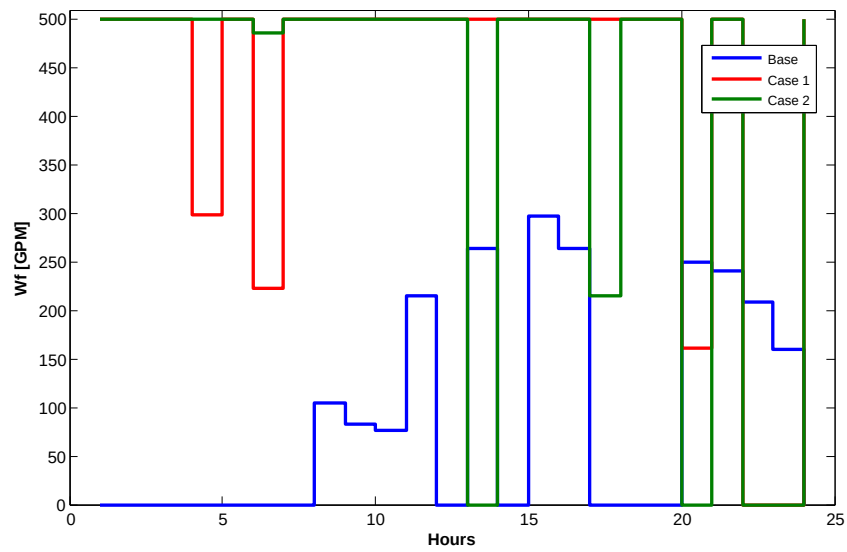


Figure 4.21: Water flow rate of Chiller 4 for May 30, 2013.

The inlet and outlet water temperature at the evaporator and the inlet water temperature at the condenser of every chiller for May 30, 2013, are shown in Figures 4.22 to 4.24. For Case 1, the effect of negative HOEP values, in particular at hours 4 and 6, is to increase the temperature as much as possible, so that the chiller power demand is maximized. This power demand increase reduces the final energy costs, as required in this case. Conversely, for Case 2, the OILM tries to reduce the water temperature, thus minimizing the active power required by the chillers.

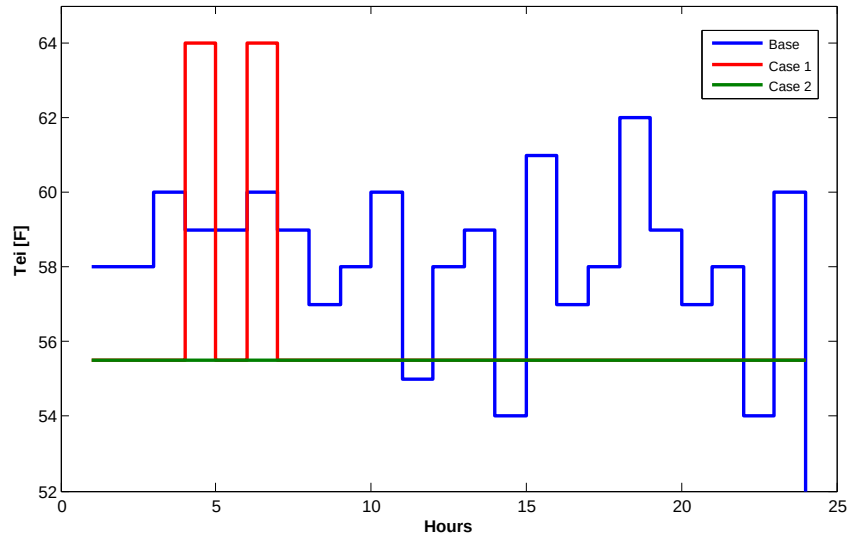


Figure 4.22: Inlet water temperature at the evaporator for May 30, 2013.

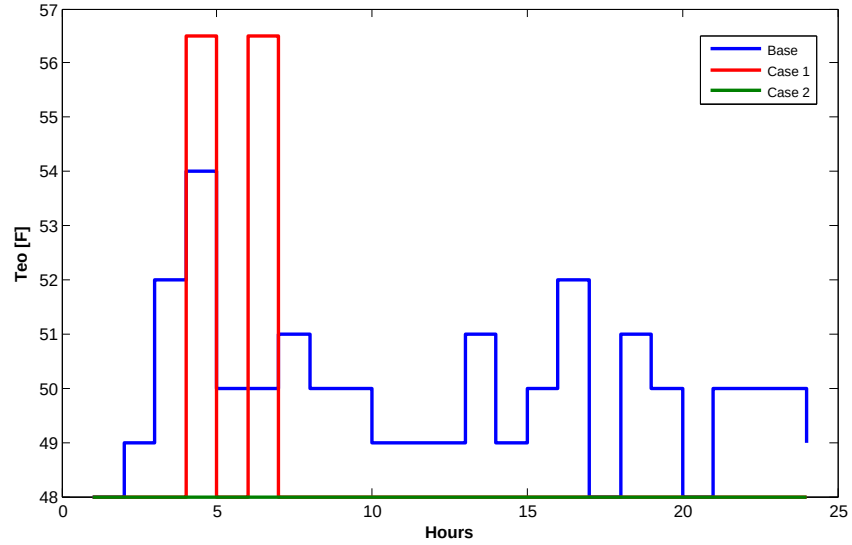


Figure 4.23: Outlet water temperature at the evaporator for May 30, 2013.

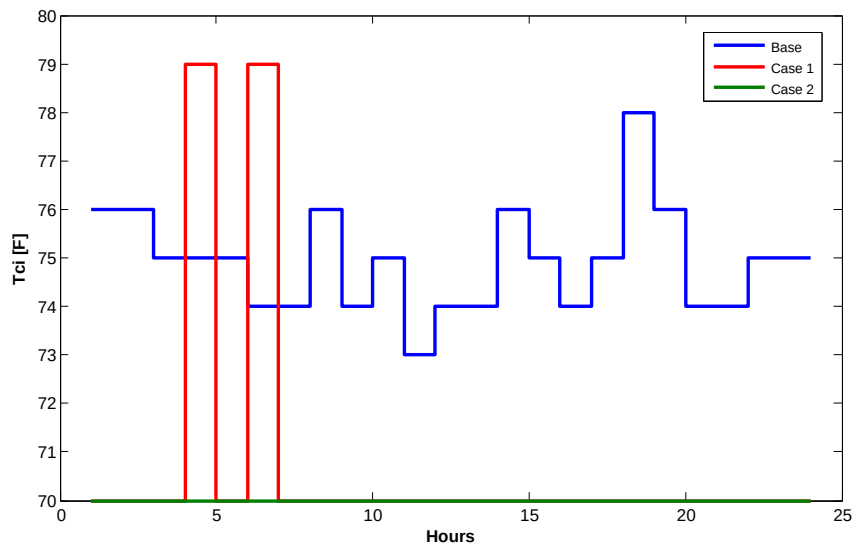


Figure 4.24: Inlet water temperature at the condenser for May 30, 2013.

4.3 Optimal Chiller Tank Storage Size

Another possible application of the proposed optimization model is to find the optimal size of the storage tank to minimize the total electricity costs of the water cooling system. In fact, [32] and [33] employ similar optimization models to size a CWS for the air conditioning system of an office building and pumps operating in a multilevel water pumping complex, respectively. Thus, the optimal sizing of the CWS is obtained here taking into account the current number of chillers available and the decommissioning of one of these chillers, as requested by the plant operators, considering the operating data for May 3, 2013, which corresponds to the highest daily cooling demand for that month. Additionally, a cooling load leveling sizing strategy is assumed [34], which consists on both the chillers and the CWS operating together all the time, based on the customer's current operating practice and to avoid oversizing the tank.

Figure 4.25 shows the final results of the optimal sizing of the CWS, considering both energy and peak-demand cost minimization. Observe that with 4 chillers operating optimally, a storage tank seven times the current capacity could result in maximum savings of around 21%, whereas a storage tank twice the current storage tank could achieve savings up to 7% with the decommissioning of one chiller.

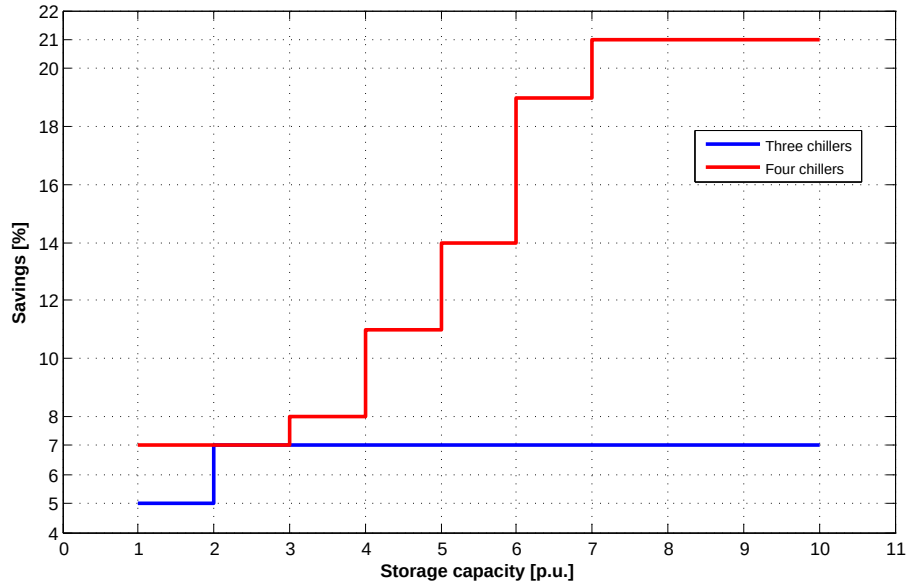


Figure 4.25: Optimal chiller storage capacity sizing.

4.4 Summary

This chapter presented the application of the optimization model discussed in Chapter 2 for the optimal scheduling of the chillers. A detailed description of the mathematical model to minimize the electricity costs of a water cooling system in industrial facilities was provided. This model was then applied to schedule four chillers in a water cooling system of an automotive manufacturing company, and two cases were evaluated, namely, energy cost minimization, and energy and peak-demand cost minimization, resulting in the latter yielding better electricity cost savings for the type of industrial facility studied. Indeed, savings of almost 7% were achieved for peak-demand cost minimization compared to the base case. In all cases, the total monthly number of chiller switching operations was maintained below the maximum allowed technically, with Chillers 2 and 4 operating more often than Chillers 1 and 3. These results demonstrate the significant advantages of the proposed optimization approach, which is shown to be feasible for supervisory control applications of real industrial processes.

Finally, the optimal size of an CWS, which is an essential component of a water cooling system, was determined considering all chillers and with a chiller out of service, with the former requiring seven times the current storage capacity to maximize potential electricity savings, whereas twice the current storage capacity is required to maximize possible savings with reduced cooling capacity due to the decommissioning of one chiller. Thus, the optimization model is shown to be not only capable of optimizing the current dispatch of the chillers, but also sizing the storage tank to maximize electricity cost savings.

Chapter 5

Conclusions

5.1 Summary and Conclusions

The present research focused on the optimal scheduling of industrial loads, based on the optimization model proposed in [21], so that electricity costs are minimized. To evaluate the effectiveness of this model, a chiller scheduling study was carried out in an automotive manufacturing company.

The work and main findings, presented in this thesis, are the following:

- The necessity of improving the efficiency of current operating practices in industrial processes to improve the electrical network operation and thus reduce the corresponding environmental impacts, were presented in Chapter 1 as the main motivation for the present work. Furthermore, a comprehensive literature review was also presented, covering general DSM programs and optimal approaches for process scheduling, and discussing the state of the art regarding process operation. Finally, the main objectives of the proposed research work were stated.
- DSM concepts and all the mathematical background required to develop optimization models for industrial load scheduling were introduced in Chapter 2. DSM programs, general and industrial, were described and then, due to the fact that a parametric regression model was used for active power estimation of the chillers under study, robust estimation, mainly focused on M estimators, was described in detail. Since the optimization model used to schedule the chillers in this work is an application of the general OILM presented in [21], this model was then briefly discussed. Finally,

the main optimization concepts and solvers associated with MINLP problems were presented.

- Chapter 3 discussed the modeling of chillers for optimal scheduling purposes, proposing a polynomial regression model. A detailed review of the vapor compression refrigeration cycle, which is the most commonly used, and how the chiller's components are related to it was first presented. Based on chiller operation theory, a second-degree polynomial model capable of estimating its active power demand was developed and validated, based on the bisquare method explained in Chapter 2 and measured chiller operation data at an automotive manufacturing plant; water flow rate and outlet temperature at the evaporator and inlet water temperature at the condenser were considered as predictor variables for this model. Six different models were evaluated for every chiller to determine the best polynomial model, based on fitting process statistics, showing that it was accurate enough for scheduling purposes using actual operation data.
- The optimal chiller scheduling for an automotive manufacturing plant was discussed in Chapter 4. Thus, the optimization model used for this task was first described in detail, with the main objective of minimizing electricity costs, which can basically be divided in energy and peak demand costs. Chiller and system constraints were considered in the model, based on equipment limitation and customer preferences. Two cost minimization cases were then considered and contrasted with the current chiller operation: energy cost minimization, and energy and peak-demand cost minimization. The final results showed that even though the energy cost was reduced for the first case, the total electricity cost was higher than the actual system operation, due to increased peak demand associated with negative electrical energy cost values. For the second case, conversely, the total cost was effectively reduced, with final savings of almost 5%, with respect to current operation. Peak-demand costs, were confirmed to be much more relevant for the industrial customer than energy costs; thus, peak-demand reduction should be the main goal for large industrial facilities. Finally, the optimal size of the system storage tank was also determined for the current number of chillers and with one chiller out of service, as requested by the industrial customer. Using a scenario-based approach, the final results showed that the water cooling system requires a storage tank seven times the actual capacity with the operation of four chillers to attain around 21% of maximum electricity cost savings, whereas the operation of a tank twice the actual capacity is enough to achieve total cost savings of up to 7% for the case of one chiller out of service. These results demonstrate the advantages of the proposed optimization approach, which is

shown to be feasible for supervisory control applications of real industrial processes, and for optimal equipment sizing purposes.

5.2 Contributions

The contributions of the present research are the following:

- The OILM model proposed in [21] is applied to a water cooling system of an automotive frame manufacturing plant. The final results demonstrate and validate the feasibility and benefits of the OILM approach.
- A novel second-order polynomial model, with water flow rate and outlet temperature at the evaporator and inlet water temperature at the condenser as predictor variables, is developed and validated for estimation of chiller active power demand. This model is shown to be suitable for optimal scheduling of chillers, and to accurately determine the active power requirements for actual operating conditions, based on actual plant measurements.
- A new model for optimal scheduling of chillers for an industrial water cooling system is proposed. The model is shown to minimize energy and peak-demand costs for chillers, considering relevant equipment and system constraints.
- The optimization model developed is tested for chiller scheduling to minimize energy cost, and energy and peak-demand costs in an actual industrial facility. Electricity savings are obtained for the latter, due to the type of industrial customer studied.
- The OILM is also applied to study enhancements to the water cooling system of the industrial facility. Thus, it is shown that the size of the CWS can influence maximum electricity savings due to optimal chiller scheduling.

The work presented here has been integrated into journal paper [35], and is expected to be submitted after approval from the research partners.

5.3 Future Work

The following ideas would expand the optimal load management of industrial facilities shown in this thesis:

- The current OILM model is able to handle the optimization of continuous production processes. Additional constraints should be included to consider batch production requirements.
- Industrial customers require the availability of on-site generation due to reliability concerns, and the optimal operation of these generators could help to achieve further electricity cost reductions. Thus, generation and electric storage constraints should be integrated into the current OILM model.
- Due to the fact that optimal scheduling of chillers has been obtained using fixed values of parameters such as cooling demand and energy price, methods to reduce the influence of uncertainty on these parameter values should be considered. A control method, such as MPC, could be applied to reduce the deviations of the forecasts against actual data.

APPENDICES

Appendix A

Water Cooling System Simulation Data

Relevant data to perform the optimal chiller scheduling simulation is provided next. Notice that the active power for every chiller, P_{ch} , is estimated using the polynomial coefficients given in Table 3.3.

$$\begin{aligned} \text{Set : } & j = 4; \quad t = 24; \quad v = 1 \\ \text{Parameter : } & K_{bt} = C_{pw}(60)/12000 \end{aligned}$$

Table A.1: Parameter data.	
Parameter	Value
ΔT	1 [hour]
β	16.01 [\$/kW]
C_{pw}	8.33 [Btu/(USgal°F)]
K_{pt}	0.284 [tons/kW]
n_{sw}	7

Table A.2: Process variable limits.

Variable	Max	Min
W_f [GPM]	500	50
T_{eo} [°F]	58	48
T_{ei} [F]	64	48
T_{ci} [°F]	79	70
s_{cap} [tons]	35	0

Table A.3: Energy price and total cooling system load for May 30, 2013.

Hour	α [\$ / kWh]	Q_t [tons]
1	0.01351	352.29
2	0.01282	305.86
3	0.00362	323.78
4	-0.00309	325.17
5	0.00165	338.95
6	-0.00182	307.82
7	0.01629	283.95
8	0.02357	296.97
9	0.02301	327.23
10	0.03273	270.33
11	0.03362	282.42
12	0.03488	279.60
13	0.03481	154.27
14	0.03702	391.82
15	0.03701	220.20
16	0.03704	153.64
17	0.03687	191.86
18	0.03488	173.66
19	0.03510	181.23
20	0.03546	190.15
21	0.03753	175.42
22	0.02753	153.77
23	0.02680	159.46
24	0.01460	277.21

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