SCHEDULING SMART HOME APPLIANCES USING GOAL PROGRAMMING WITH PRIORITY

A Thesis
Submitted to the Graduate Faculty
of the
North Dakota State University
of Agriculture and Applied Science

By

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In Partial Fulfillment of the Requirements
for the Degree of
MASTER OF SCIENCE

Major Department:
Computer Science

April 2016

Fargo, North Dakota

North Dakota State University
Graduate School

Title

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The Supervisory Committee certifies that this ***disquisition*** complies with North Dakota State University's regulations and meets the accepted standards for the degree of

MASTER OF SCIENCE

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ABSTRACT

Driven by the advancement of smart electrical grid technologies, automated home energy management systems are being increasingly and extensively studied, developed, and widely accepted. A system like this is indispensable for and symbolic of a smart home. Mixed integer linear programming (MILP) together with dynamic electricity tariff and smart home appliances is a common way to developing energy management systems capable of automatically scheduling appliance operation and greatly saving monetary cost. This study transformed an existing plain MILP model to a goal programming model with priority to better address the conflict among each single appliance cost saving objective and user time preference objective. Constraints regarding the delays between pairs of closely related appliances are either extended or newly introduced. Numerical experiments on five appliances under different situations justify the validness of the proposed framework. Besides, the influences of key parameters on model performance are also investigated.

ACKNOWLEDGMENTS

I would like to express my sincere appreciation to Dr. Kendall Nygard, my advisor and supervisory committee chair, for his wise guidance, helpful suggestion, and kind encouragement during the whole process of this study and thesis writing.

I am particularly grateful for Dr. David Franzen, one of my committee members and my Soil Science master program advisor, for his indispensable spiritual and financial support.

I would also like to thank Dr. Juan Li and Dr. Kong Jun, my other two supervisory committee members, for their invaluable time and outstanding expertise in guiding me through this exciting journey.

My heartfelt gratitude is owed to all my family members for their deepest love and persistent support.

TABLE OF CONTENTS

LIST OF TABLES

Table Page

LIST OF FIGURES

Figure | Page

LIST OF EQUATIONS

Equation Page

LIST OF ABBREVIATIONS

MILP ....Mixed Integer Linear Programming

PHEV ....Plug-in Hybrid Electric Vehicle

UTP ....User Time Preference

RETC ....Relative Extra Time Cost

ROE..Relative Objective Error

DW...Dishwasher

WMD ....Washing Machine and Dryer

EO ....Electric Oven

RETEC...Relative Extra Total Electricity Cost

1. INTRODUCTION

1.1. Smart Grid

The grid, or in other words, the electric grid, is a network composed of transmission lines, substations, transformers and more that deliver electricity from the power plant to commercial or residential customers. The current electric grids in use today in all developed countries were designed or built more than 50 years ago (Gelazanskas and Gamage, 2014); for example, the U.S. electric grids were built in 1890s (U.S. Department of Energy, 2014). Smart grid technologies are increasingly employed to improve and upgrade the old grid to increase its availability, reliability, efficiency, security, and resilience, and thus to automate and more effectively manage the increasing complexity and needs of electricity. Smart grid benefits from the integration of advanced sensing, information, and communication technologies, having the ability to do real-time optimal and adaptive coordination of information from generation supply resources, demand resources, and distributed energy resources. One of the interesting and essential features of the smart grid is its capability of two-way communication between the utility and its customers (El-Hawary, 2014) via smart meters, which means the smart grid is useful to the utility, but allows consumers to make choices about their energy use. The smart meter provides information and tools that customers can use to increase their energy efficiency. Smart metering infrastructure is necessary to enable two-way communication between the smart grid utility and the consumer. It includes meters that measure and record electricity usage at a minimum of hourly intervals and provide data to both the utility and the utility customer at least once daily. A smart meter can therefore dynamically interact with the smart grid system and to enable automation of home energy management (Zipperer et al., 2013). An example of the smart meter is illustrated in Figure 1.1.

Figure 1.1. A smart meter. Photo sourced from National Renewable Energy Laboratory (NREL) database, PIX 21394, http://www.osti.gov/bridge.

Demand side management within smart grid is receiving more recent attention because both the supply side (utility) and the demand side (consumer) can benefit from customer engagement. Demand side management is realized through a demand response program, which is an electricity tariff or a program that motivates end-users to decrease or shift their power consumption at times of load peak (for which utilities charge higher power rates) or when grid reliability is jeopardized (U.S. Department of Energy, 2015). Reduced peak demand lowers costs for utilities and ultimately lowers power costs for consumers. Small shifts in peak demand can result in substantial savings for both sides (Spees and Lave, 2008). It was estimated that more than 5% of total peak US national demand can be reduced under existing demand response programs in which customer participation is involved (Cappers et al., 2009). Another study showed that even a 5% reduction in US demand during the top 1% of the hours of the years would yield a present value of $35 billion in benefits (Faruqui and Sergici, 2010).

1.2. Energy Consumption Facts

According to the U.S. Energy Information Administration (2015), the U.S. residential sector used 36% share of the total U.S. electricity in 2013 and accounts for a larger share of peak demand.

In 2013, U.S. electric utilities had 51,924,502 advanced (*smart*) metering infrastructure (AMI) installations. About 89% were residential customer installations (U.S. Energy Information Administration, 2014b)

An investigation of energy use in North Dakota in February 2013 indicated that 49% of North Dakota households with families having annual income less than $50,000, spent an estimated average of 19% of their after-tax income on energy (ACCCE, 2013). Involving average residential users in smart grid energy management might decrease their energy expenses while reducing peak demand.

Increasingly, smart home appliances are being used by families that consume a large share of the total household energy consumption from utilities. According to the U.S. Energy Information Administration (2014a), within an average U.S. resident family, the energy consumed by appliances (including lighting, but excluding water heating, space heating and air conditioning) represented approximately 63% of the total home electricity consumption in 2012. A survey (U.S. Energy Information Administration, 2013) recently indicated that rapidly increased electricity use due to ever-growing numbers of household devices powered by electricity have a disproportionate effect on the amount of total primary energy needed to meet residential electricity demand.

1.3. Dynamic Pricing

Electricity tariffs are price incentive programs that encourage consumers to change their energy usage to avoid the load peak period by using less electricity during load peak or shift the electricity loads to off-peak periods through scheduling of appliance use. The tariff is usually an hourly-based dynamic pricing program with peak load hour price carrying the greatest cost. Figure 1.2 illustrates a typical 24-hour tariff, which shows the contrast between the lowest price and the highest price within the same day. The 24-hour ahead hourly electricity tariff data of November 3. 2013, for Long Island of New York State used in this paper was taken from NYISO (New York Independent System Operator) (www.nyiso.com). The highest price (57.86 USD/MWh) was 2.56 times the lowest cost (22.57 USD/MWh). A tariff can be real-time pricing or day-ahead market pricing. In case of real-time pricing, the next day's hourly costs have to be predicted as a reference in order for consumers to optimize the use of household appliances.

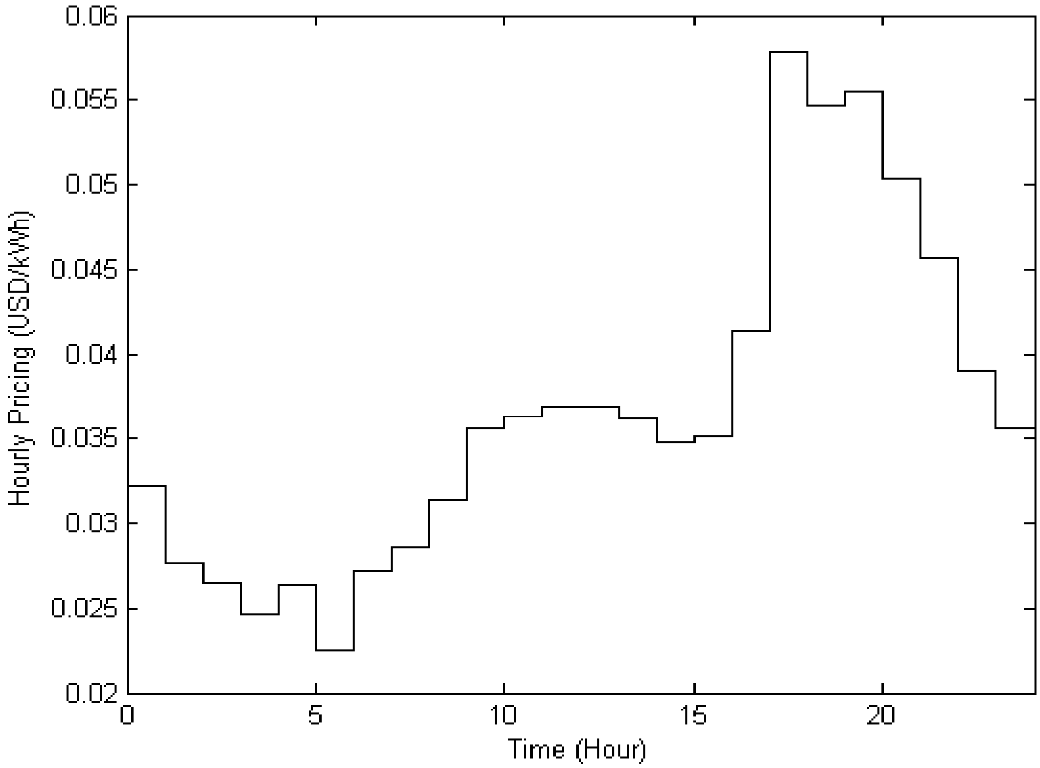

Figure 1.2. Hourly pricing data of one day, November 3, 2013, Long Island, NY. (NYISO)

1.4. Smart Home Appliances Scheduling Overview

Dynamic electricity costs are driving consumers to take advantage of more economical energy management by scheduling home appliances at times of lowest daily cost. However, most residential energy consumers have been accustomed to fixed-rate electricity and are not willing or able to conduct appliance scheduling, because of the time and mathematical calculations required. Time restrictions, knowledge of utility rate dynamics and math skills are impediments to average household users to correctly respond to dynamic energy costs (Mohsenian-Rad and Leon-Garcia, 2010). Easy to use home appliance automation systems and energy decision support systems are highly desirable and they may be the keys to greater residential energy consumer use of more efficient energy scheduling.

A smart appliance is an appliance that can communicate directly with the utility operator for efficient use of electricity over an internet connection. Web-enabled smart appliances under the expanded addressing space of Internet Protocol version 6 (IPv6) are becoming common, and older appliances can be IP control enabled through devices such as smart power bars. Many recently produced smart appliances allow users to view their operation status and control the operations through a smartphone or tablet. With the application of mathematical programming, multiple appliances can be optimally controlled or scheduled simultaneously. Mathematical programming for smart appliance operation is developed to minimize or maximize an objective or multiple objectives subjected to a group of constraints.

Smart appliances and mathematical programming have the potential to optimize appliance scheduling automatically. The schedule developed using smart appliances with scheduling programming can be used by the household users or the appliances themselves. With the rapid development of smart grid, smart home and smart appliances, programming to increase energy efficiency of residential appliances has attracted the attention of more researchers. Solutions to this optimal appliance scheduling problem based on mixed integer linear programming (MILP) represents a major research direction for many of these researches. The programming protocol of MILP is a widely used subset of mathematical programming in which the objective function is a linear function of decision variables which can be integer or non-integer. Each constraint is formed from a linear combination of the decision variables (Smith and Taskin, 2007). Published research involves single home or multiple homes, may involve renewable energy or not, may involve single-goal or multiple goals, may involve deterministic linear programming or probability programming, may involve using external solvers or applying customized heuristic algorithms. A detailed literature review can be found in the next chapter.

1.5. Methodology Used in and Contributions of This Study

The object of this study is to provide an improved programming basis for scheduling smart home appliances using MILP, based on previous work (Sou et al., 2011: Bu and Nygard, 2014) but which incorporates fuzzy goal programming technique (Ignizio and Romero, 2003) and introduces new practical constraints.

Compared to our previous work, this study is more comprehensive and versatile in that it includes a more complete literature review, modifies and generalizes formulas for the new introduced constraints restricting the delay between two closely related or repeatedly used electric appliances, simplifies the worst deviation level constraints, and validates the model with more appliances and more details.

The contributions of this study are the following:

a. The proposed new model supports priority distinctions for different appliances;
b. rigid time preference constraints are transformed into soft ones and included in the fuzzy goal programming framework with priorities;
c. two types of devising constraints are introduced that are capable of more practically modeling the relationship of processing delay between closely related or repeatedly used appliances.

1.6. Thesis Organization

The literature review is given in the second chapter, where the research question statement of this study is also included. The proposed model's theory and formulation are presented in Chapter 3. Numerical experiment setup is given in Chapter 4. Experimental results and discussion are conducted in Chapter 5. Conclusions are drawn in the final chapter.

2. BACKGROUND AND LITERATURE REVIEW

2.1. Overview

2.1.1. Common Optimization Elements

Smart home appliances scheduling is a mathematical optimization problem, and thus shares many common elements such as objective(s), constraints, mathematical programing type, software or algorithm used to find solutions, global optimal solution or local optimal solution, with many other mathematical optimization problems.

The objective is one of the most important elements that measures the cost or the benefit of the solution. It involves the questions of: is it a single-objective or multiple-objective problem, are these objectives correlated or irrelevant or conflicting with each other, what these objectives are, and how these objectives are integrated to address the general purpose. For multiple-objective problem, objectives are conflict more or less with each other, therefore, creating a general objective by assigning a weight or coefficient to each single objective is an effective practice that is commonly employed by programmers. Another way of dealing with multiple and conflicted objectives is using goal programming. Reducing or minimizing economic cost of electricity use by all appliances is the indispensable objective, because it is the primary incentive for residential energy users to more easily respond to dynamic pricing. Additional objectives will be discussed later in this chapter.

Constraints are a series of equalities or inequalities which are necessary for restricting solutions to a feasible domain. For example, total electricity used by all appliances during a given period cannot exceed the allowed peak value, each appliance has its own electric specification, some appliances are closely related to each other in terms of the interval or time delay, and every user has his own appliance use preferences.

An optimization problem can formulated or deduced to a certain type of mathematical programming such as linear programming, nonlinear programming, deterministic programming, stochastic programming, integer programming (include mixed integer linear programming and binary integer linear programming) or continuous programming. In the case of a linear programming, all the constraints and the objective function are linear. Unlike deterministic programming, stochastic programming involves uncertainty in some parameters. Integer programming is characterized by some or all of its variables are restricted to be integers, while continuous programming variables are continuous in specified ranges.

Mathematical programming can be solved using different algorithms and/or software. For integer linear programming, exact algorithms such as cutting plane methods, branch and bound, branch and cut, and branch and price are widely used (Lima and Grossmann, 2011). Heuristic algorithms (Fong et al., 2009; Ha et al., 2006; Giorgio, 2012; Chavali et al., 2014; Ogwumike et al., 2015) were developed to solve certain problems. Heuristic algorithms prove more efficient in some large-scale problems, but each designed algorithm can only be effectively applied to limited types of problem and the solution may not be globally optimal. IBM ILOG CPLEX (IBM, 2013) is one of the most famous integer linear programming formulation commercial solvers or optimizers that exploits both exact algorithms such as branch and cut algorithm and heuristic methods. The programs AMPL, MATLAB, and SAS are effective programming tools to solve mathematical optimization problems, too. The CPLEX program provides Application Program Interfaces or Application Programming Interfaces (APIs) to C++, Java, and MATLAB. A free toolbox called YALMIP for modelling and optimization within the program MATLAB has become popular as a support for most mainstream optimizer and enable rapid algorithm development (Löfberg, 2004). Use of a combination of MATLAB, YALMIP, and CPLEX MILP Solver can expedite the verification of the ideas associated with mathematical programming.

2.1.2. Special Optimization Elements

Optimal smart home appliance scheduling can be made either for a single home or for a neighborhood with multiple homes. Where multiple homes are considered, trade-offs of electricity use by appliances within each home and among all homes have to be included in the calculations..

User preferences for appliance use is another concern. Are the preferences imposed for time convenience or for temperature comfort if thermal or air-conditioning devices are used? How these preferences are measured and modeled? Are the preferences included in the objective function or listed as constraints? Are the preference constraints rigid (broken is absolutely prohibited) or soft (more flexible)? Is the priority of different appliances considered and how is it modeled?

Type of dynamic pricing referred to in the existing literatures also varies. Is the price tariff day-ahead, real time, or based on prediction? What is the price tariff time interval between price changing? Hourly-based tariff is most considered in the literature, but, other options include 15-minute-based tariff and peak-off-peak-based tariff that use flat rate during off-peak time and much higher prices during peak time.

The type and number of appliances involved are the real objects in the optimization and their types are so diverse that mathematical formulation and solution are substantially influenced by their consideration and properties. Thermal appliances are often scheduled and optimized separately. Other appliances can be divided into several categories (Lee and Lee, 2011) based on whether they are elastic, interruptible, and with or without storage. Elastic means the appliance's energy consumption can be flexibly adjusted at each sub-interval; interruptible means the appliance can be intermittently turned on and off without any performance degradation; and with storage means the appliance's performance only relies on the total energy consumption, while without storage means the appliance's performance depends only on the current energy consumption level in the current sub-interval. Air conditioners, heaters, and light bulbs with controllable brightness are examples of appliances with elastic energy consumption without storage. Battery chargers with controllable charging rates can be classified as appliances with elastic energy consumption with storage. Battery chargers without controllable charging rates are considered as appliances with non-elastic and interruptible energy consumption. Light bulbs without controllable brightness and televisions are appliances with non-elastic and non-interruptible energy consumption. Some appliances are not absolutely interruptible, but rather are interruptible only between its energy phases, such as a clothes washing machine that can be interrupted between its first rinse and second rinse cycles. Each energy phase is treated as uninterruptible. Not all existing research in the literature used the concept of energy phase. Most of the research studies considered an appliance working as a single or uniform process. A more general criterion for appliances classification is whether the load is shiftable or not. An appliance is classified as shiftable or deferrable if some or all of its energy phases' energy consumption can be shifted from a time period to another period. A special electrical load is the plug-in hybrid electric vehicles (PHEVs) that are becoming more popular and therefore are receiving more attention from home appliances scheduling researchers. A PHEV consumes so much electricity that including it in the optimization can greatly reduce the end user economic cost as well as the overall peak load. Recharging PHEVs are shiftable electric loads.

A common technique applied to home appliance scheduling is using time slots. A planning time horizon is usually divided into multiple uniform time slots, for example 5 minutes or 10 minutes or 1 hour. The smaller the time slot is, the less the cost will be, and the more computational complexity the problem will involve. The optimal solution will determine what appliances are going to run at what power level during each time slot. Distributed energy resources such as storage and those based on advanced renewable technologies are being integrated into optimization programs in the most recent literature.

2.2. Categorical Literature Review

2.2.1. Objective Type Review

2.2.1.1. Single-objective

Usually, if the model has a single-objective, then the objective must be the total economic cost of electricity consumption during a fixed study period. Xiong et al. (2011) proposed a simple home appliance scheduling model where the only constraint was the total power demand. Another simple home appliance MILP scheduling model that relied only on the peak hour load constraints was reported to have the capability to save electricity cost up to 35% (Yu et al., 2013). Sou et al. (2011) proposed a single-objective MILP formulation for the home appliance scheduling problem where the length of time slot is 5 minutes and the electricity price tariff is one-day ahead. Three shiftable appliances, dishwasher, washing machine, and dryer, were numerically evaluated with the proposed method based on IBM ILOG CPLEX solver and Yalmip MATLAB interface. Ogwumike et al. (2015) proposed a similar model as that of Sou et al. (2011), but solved it using a heuristic greedy algorithm. Giorgio (2012) developed a similar single-objective MILP formulation as that proposed by Sou et al. (2011), but included two more energy sources in addition to the utility power grid: domestic renewable energy and batteries.

The polishing technique and a heuristic greedy searching strategy were used to find the optimal solution. Tushar et al. (2014) also included renewable energy sources in their MILP model to jointly minimize the total cost of appliances and electrical vehicles. Du and Lu (2011) presented a commitment algorithm for optimally scheduling thermostatically controlled household loads. Only one appliance, an electrical water heater, was involved in this single-objective optimization study based on dynamic electricity price and consumption predictions. Lee and Lee (2011) divided appliances into 4 classes and developed a separate characterization model for each class so that the total electricity cost of appliances was minimized. Lee et al. (2011) classified the operations of household appliances into preemptive and non-preemptive operations when setting up constraints. The scheduling of preemptive operations is based on the schedule of non-preemptive operations. Liu et al. (2012) proposed a single-objective real-time household loads scheduling algorithm based on the classification of appliances into three energy consumption categories and the prediction of renewable source availability to maximize the benefits of renewable sources for consumers. Instead of using linear programming, Carli and Dotoli (2014) developed a mixed integer quadratic programming model for minimizing single-home total electricity cost.

In a multi-home appliances scheduling study where the objective was to minimize the total electricity cost of all neighbor homes (Bakr and Cranefield, 2013), shiftable loads including PHEVs were scheduled. The time slot length was one hour and only three electric costs were considered: off-peak, mid-peak, and on-peak. Another single-objective and multiple-home appliances scheduling study using MILP involved the use of wind generation and electrical storage (zhang et al., 2011). Barbato et al. (2011) proposed a single-home appliance scheduling model and a multi-home scheduling model, both of which were single-objective type. A dynamic-programming-based game theoretic algorithm instead of integer linear programming was developed to schedule multi-home appliances and estimated that the users would save an average of 29% monetary cost from its use (Liu et al., 2014).

2.2.1.2. Multiple-objective

Numerous studies that address multiple-objective smart home appliance scheduling are available. One of the common strategies for converting multiple objectives to a single general objective is to combine them to a single objective using the weighted sum method.

Environmental cost minimization is receiving more attention in recent years. Inspired by the model developed by Sou et al. (2011), the CO_2-footprint cost was included into the objective function by giving it a weight for environmental concerns (Wu, 2012; Sou et al., 2013; Paridari et al., 2014). A dynamic programming strategy was proposed by Sou et al. (2014a; 2014b) to solve the MILP problem addressed in the study of Sou et al. (2013) where both the energy cost and the CO_2-footprint cost are optimized.

Total appliances shift time or user waiting time minimization is another widely-used objective. Bapat et al. (2011) developed a household appliance scheduling system called "Yupik" that takes both the energy costs and self-defined time-related inconvenience costs as the objectives. Day-ahead hourly prices were used in this system, where three devices (TV, music system, and power strip) were involved using a one hour time slot. An advantage of this system is that it can generate multiple schedules simultaneously with costs close to optimal so that a user can select the option most suitable. An appliance load scheduling model was reported to optimize the trade-off between minimizing electricity costs and minimizing the waiting time for each appliance in a household (Mohsenian-Rad and Leon-Garcia, 2010). The model predicted real-time electricity prices and included a PHEV as one of the loads. Yi et al. (2013) developed a real-time opportunistic scheduling model for home appliance load management based on the theory of optimal stopping rules in order to minimize both the total electricity cost and total user waiting time. Lin and Tsai (2015) applied a genetic algorithm to solve the home appliance scheduling problem minimizing both total electricity cost and total appliances shift time. In the multi-home appliance scheduling study made by Chavali et al. (2014), besides the minimization of monetary cost of energy consumption, optimization of optimal start time of each appliance was a sub-objective and a greedy iterative algorithm was used to find a sub-optimal solution. In another multi-home appliance scheduling study (Liu et al., 2014) where a distributed algorithm was used to find the optimal solution, the general objective was a weighted sum up of three sub-objectives: total energy cost, total appliances shift time, and total power gap.

Climate comfort maximization is one of the most common objectives in thermal appliance scheduling. A MILP model for home appliances scheduling that integrated climate comfort factor into the objective function due to the inclusion of air conditioner was proposed (Agnetis et al., 2011). Battery and renewable energy resource were also included in this model. The model did not further divid each appliance operation into more detailed phase stages, meaning that each appliance must run continuously until its cycle was completed. Lu and Du (2011) in their thermal appliances scheduling formulation also tried to maximize users' temperature comfort while minimizing cost based on dynamic electricity price and user preferred comfort settings.

Minimization of peak-to-average ratio in terms of total energy use in each unit time period can reduce peak load and balance the electricity use, and thus is also used extensively as an objective. Caron and Kesidis (2010) proposed a dynamic pricing scheme incentivizing consumers to achieve an aggregate load profile suitable for utilities. Based on the degree of information sharing, distributed scheduling algorithms were designed to reduce the total cost and peak-to-average ratio, and improve the overall load profile of the system. Peak-to-average ratio as an objective was also considered in other studies (Mohsenian-Rad et al., 2010; Chaouch and Ben.Hadj.Slama 2014; Zhou and Li, 2014).

Other types of sub-objectives may also be considered in the general objective. Significant energy savings were reported by a multiple-home appliance MILP scheduling study (Zhang et al., 2013) involving the use of electricity generated by wind turbine and minimization of total electricity cost and related equipment' operation and maintenance cost (e.g., electrical storage maintenance cost). Real-time half-hourly time slot grid electricity prices were used and peak demand costs were included. Yang et al. (2015) defined a user dissatisfaction cost formula and included minimization of dissatisfaction as a sub-objective of the general objective by giving it a weight when scheduling home appliance operation and battery charging. The dissatisfaction cost is essentially a reflection of total deviation from target energy consumption during a time slot. A third sub-objective in this study was the minimization of battery loss. A mixed integer nonlinear formula was developed and the solution used a distributed mixed optimization approach.

Attaching a weight to each sub-objective is the most popular and simplest way to handle multiple conflict objectives optimization. Another theoretically improved method is to utilize goal programming. Dehnad and Shakouri (2013) applied goal programming theory to solve two conflicting goals, minimizing electricity cost and reducing the load peak (similar to minimizing peak-to-average ratio), in a single-home appliance scheduling. Unfortunately, the authors only referred to goal programming as their solution, but did not provide any details of how it was used, not even a description of the type of goal programming or formula they employed. Our previous research work on smart home appliances adaptive scheduling framework (Bu and

Nygard, 2014) was also featured in this publication, with integrated goal programming methodology that helps handle the optimization of multiple-and-conflicting-objective, one of which is the self-defined user preference time cost. Our previous work made the initial and rough trial of employing goal programming in smart home appliance scheduling problem and was briefly tested with three same home appliances as those used by Sou et al. (2011).

2.2.2. Non-deterministic Mathematical Programming Review

Techniques based on Markov model and process were found to be widely used to deal with uncertainties in various situations. Using Markov chain and reinforcement learning techniques to model both energy prices and residential device usage, O'Neill et al. (2010) proposed an energy management system called CAES for residential demand response applications to reduce residential energy costs and smooth energy usage. Chang et al. (2013) developed a home appliance energy management algorithm that can handle end users' random behavior in making requests to use an appliance based on Markov decision process theory. In another stochastic home appliance scheduling study, uncertainty of distributed wind power generation was dealt with the Markov Chain Monte Carlo method, and both shiftable and unshiftable appliances were scheduled (Chen et al., 2013).

Many other techniques have also been used by research programmers. To handle the load uncertainty in developing a real-time residential load scheduling model, a series of energy phase concepts, including sleep, awake, active, finished, inactive were introduced (Samadi et al., 2013). These energy phases are different from the commonly considered functional energy phases. Chen et al. (2013) developed a stochastic home appliance scheduling model that considered uncertainties in household appliance operation time and intermittent renewable generation. The technique first used linear programming to efficiently compute a deterministic scheduling solution without considering uncertainties, and then combine the stochastic parameters in the model. Similar to Chen et al. (2013), Adika and Wang (2014) designed a time-of-use probability profile for each home appliance and incorporated them into the appliance scheduling system with renewable energy sources considered. Jacomino and Le (2012) classified the uncertainty parameters as either external (such as a weather forecast) or internal (such as random use of an appliance) and set up a stochastic-based robust linear programming formulation for home electric load scheduling. Vivekananthan et al. (2015) took into consideration uncertainties in real-time pricing and residential appliance power consumption pattern during appliances scheduling. To handle the uncertainties of the electricity price, outdoor temperature, and other factors, a conditional value-at-risk strategy was applied (Wu et al., 2014). A worst-case-uncertainty approach was adopted to study the impact of load demands uncertainties in a multiple-home load management system (Kim et al., 2013). To minimize the expected energy payment of the user with respect to demand uncertainties in house load management, an approximate dynamic programming approach was developed (Samadi et al., 2013).

2.2.3. User Preferences Review

There are two ways user preferences can be incorporated into a mathematical formulation model. The most common method is to model them as constraints, and the other is to model them as one of the objectives that minimizes violation cost.

Time-related user preference is one the most common preference types seen in smart home appliances scheduling formulation. Users may prefer to use or prohibit from use some appliances in some fixed time periods during a day. In the models proposed by Sou et al. (2011), Wu (2012), and Giorgio (2012), user time preferences can be found in the constraints, while in the model proposed by Bapat et al. (2011), time-related user preferences were modeled as inconvenience costs and used as one of the minimizing objectives. The inconvenience costs were calculated based on a user's characteristic energy use patterns. A user cannot specify the preferred usage profile for a particular day. Instead, the system-generated schedule is considered which uses previously used and fixed use patterns considered when the scheduling program was formulated. Saha (2013) categorized users based on how sensitive they were to the price of the electricity. Each group of users were then assigned a specific user time preference. Three types of constraints: power, appliance operation time, and user time preferences were then established to define the feasible solutions. Temperature-related user preferences were often modeled as objective function (Agnetis et al., 2011; Lu and Du, 2011; Jacomino and Le, 2012). Agnetis et al. (2013) incorporated both thermal comfort and user time preferences into the objective function.

2.3. Summary and Conclusion

Automating the scheduling of smart home appliance benefits both the end users and the utility companies, and therefore is receiving increasing attention from industry and academia. Because of the complexity and inconsistency of appliance characteristic and type classification, uncertainties of user behaviors and real-time electricity prices, possible inclusion of renewable energy sources, having to consider trade-off between single home and neighborhood, and design of effective and efficient algorithm for practical use by residential electricity users, most of the current published research is focused on theoretical modelling, with use of numerical experiments or simulation tests. Researchers have used sophisticated advanced and novel programming methods in appliance scheduling; however, the science is till in development. For example, priorities of different appliances are often not considered, the relationships between or among closely related appliances have not been included in constraints, and the user preferences were usually addressed in rigid and unrealistic ways.

3. MATHEMATICAL FORMULATION

3.1. Mixed Integer Linear Programming

Mixed integer linear programming is a widely used subset of mathematical optimization method. In a MILP problem, the objective function is a linear function of the decision variables, some of which must be restricted to integer (discrete values). Also, each constraint requires that a linear combination of the decision variables is equal to, or more than, or less than, or no more than, or no less than a scalar value. No nonlinear constraints are included in MILP. Detailed introduction to MILP can be found in Castillo (2002) and Smith and Taskin (2007). The following is a typical mathematical formulation of MILP:

$$\begin{aligned}
\text{Minimize:}\quad & c^T x \\
\text{Subject to:}\quad & A \cdot x \leq b \\
& Aeq \cdot x = beq \\
& lb \leq x \leq ub \\
& x^i \in \mathbb{Z}, \forall i \in I
\end{aligned} \tag{3.1}$$

In Equation 3.1, c is a column vector of constants, x is the column vector of decision variables, A and Aeq are constraint matrices, and b, beq, lb, ub are vectors of constraint bound. The last constraints are integrality constraints ensuring some or all decision variables must take integer values, and I is a collection of indices whose corresponding decision variables must be integer. In this study, all the integer decision variables are restricted to 0 or 1, and they are called binary variable. Other forms of MILP can be transformed to this standard form (3.1). The MILP problems can be solved using total unimodularity, or exact algorithms such as cutting plane methods and branch and bound methods, or various heuristic algorithms. Representative commercial solvers for MILP include Matlab optimization tool box, SAS/OR, CPLEX, Gurobi, Lingo, and SNOPT. Common open-source solvers include GLPK, LP_Solve, CBC (Wikipedia, 2015).

3.2. Goal Programming and Fuzzy Goal Programming

3.2.1. Goal Programming

A mathematical optimization problem can include multiple objectives, called sub-objectives, which are usually conflicting which means that full optimization of a single one will degrade the performance of others. A balance must be found between or among these sub-objectives. In practice, reducing the multiple-objective problem to a single-objective problem is the common method, which can be implemented by two classic strategies. One strategy is to optimize one objective and transform other objectives into constraints. The alternate strategy is to optimize the general objective formulation using a weighted sum of each objective. There are two disadvantages of the first strategy (Oliveira et al., 2003): first, representing the objectives by means of constraints often lead to infeasibility of the solution particularly in large optimization problems, making it very hard to find the constraints that cause the infeasibility; second, it is difficult or subjective to make a decision on which objective among multiple objectives should be selected as the single objective. The second strategy also has shortcomings: it attempts to achieve an absolute or ideal optimal solution rather than a practical optimal solution; each objective value range can be significantly different from others and thus make the general weighted-sum-objective unreliable.

Most real-world decision problems are more data-massive and complex than those encountered in the classroom and require special models and approaches than conventional models that idealistically and unrealistically make presumption on the objective and constraints. Goal programming was introduced by Charnes and Cooper (1961; 1977) as a more powerful and effective way of handling multiple and conflicting objectives in an optimization problem. It performs better than conventional linear programming models in handling relatively large numbers of variables, constraints and objectives (Tamiz et al., 1998). The two major differences of goal programming from conventional linear programming models are the incorporation of flexibility into the constraint functions to replace rigid constraints, and the satisficing principle that seeks a more balanced, implementable, and practical solution rather than an absolute optimal one (Ignizio and Romero, 2003). Satisficing principle in goal programming evaluates the goodness of any solution not by objective function, but by an achievement function, which defines the degree of nonachievement of the original goals. Forms of the nonachievement function determine the sub-types of goal programming. There are numerous forms of goal programming, of which the three most common forms are Archimedean (also known as weighted) goal programming, non-Archimedean (also known as Lexicographic) goal programming, and Chebyshev (also known as fuzzy) goal programming.

3.2.2. Fuzzy Goal Programming

Introduced by Flavell (1976), fuzzy goal programming seeks to minimize the normalized maximum unwanted deviation from any single optimized goal value. This applies the Chebyshev distance metric that emphasizes justice and balance rather than brutal and extreme optimization. Normalization is necessary in order to overcome the problem of incommensurability due to the fact that different goals are usually measured in different units (Tamiz, 1998). Based on the degree of importance of each goal, priorities can be added to these deviations to reflect different penalties applied to different failures to meet the optimal goals (Hu et al., 2007). A new general goal based on the weighted sum of the maximum unwanted deviations can therefore be formed, and transformed to a standard linear programming form, and finally solved. A better understanding of fuzzy goal programming can be achieved through the detailed mathematical formulation for smart home appliances scheduling given in the next section.

3.3. Mathematical Formulation for Smart Home Appliances Scheduling

3.3.1. General Description

As previously explained in Chapter 1, the mathematical programming we propose for smart home appliances scheduling is an expansion and improvement of that conducted by Sou et al. (2011) through introduction of soft user time preference constraints and transformation of existing framework to a fuzzy goal programming framework with priority. In addition, novel constraints are developed to make the solution more relevant to real situations. Previous goal programming research in appliance scheduling (Dehnad and Shakouri, 2013) lacked any detail regarding the form of goal programming used and how it was used. Also, in their study, user time preferences were modeled as ordinary constraints rather than incorporated into the goal programming framework.

3.3.2. Assumptions and Parameters

Only time-shiftable or deferrable appliances (clothes washing machine, dishwasher, etc.) in a single-home are considered in our research. Time-slot-based mathematical formulation instead of energy-phase-based mathematical formulation are developed for modelling the smart home appliance scheduling problem as the former was a more refined optimization and experimentally shown to have greater ability to save energy bill cost (Wu, 2012). A time slot is a short time period (for example, 5 minutes) obtained by uniformly discretizing an appliances execution cycle. An energy phase is used to denote an uninterruptible sub-process of the whole operation process of an appliance. Energy phases are appliance-specific and each appliance has a single or multiple energy phases that must be operated in sequence with each using a prespecified amount of electric energy. For example, a dishwasher may include energy phases such as pre-wash, wash, first rinse, drain, second rinse, and drain & dry, and they are operated in sequence, for instance, wash will not begin until pre-wash is done.

The appliances execution time cycle used in our MILP fuzzy goal programming formulation is exactly one day (24 hours). Suppose each hour is uniformly discretized into h time slots, then the number of total time slots of a day is

$$m = 24 \times h \tag{3.2}$$

Denote N as the number of appliances involved in the formulation, and denote n_i for $i = 1,2, \dots, N$ as the number of uninterruptible energy phases for each appliance.

The technical specifications of appliances defined by the manufacturers of appliances must meet. One typical type of technical specifications or manufacturer-defined constraints are upper and lower limits of the instantaneous power consumed, which are equivalent to upper and lower limits of the energy consumed during a time slot. The upper and lower instantaneous power are the maximum operating power and idle power, respectively. Another technical specification is related to the nominal operating time for a specific energy phase.

Additional constraints must be used to ensure the sequential operations of some appliances, the delay between two energy phases of a same appliance, the delay between two closely related appliances, and the total energy consumed within a certain period not exceeding the peak energy allowed, etc.

The ultimate goal of this study is to search for the best combination of energy profiles that balances the objective of saving the end consumer's energy cost and satisfying the consumer's appliance using time preferences. Here an energy profile refers to the time-dependent energy assignment to an energy phase of an appliance during the execution period. So a final solution specifies how much energy should be assigned during each different time slot for each different appliance.

Parameters $\lambda_g(0 < \lambda_g < 1, g = 1,2, \dots, N + 1)$, satisfying

$$\sum_{g=1}^{N+1} \lambda_g = 1 \tag{3.3}$$

are introduced to indicate the priorities assigned to each single deviation goal in the fuzzy goal programming. Here $\lambda_g(g = 1,2, \dots, N)$ is for the deviation goals related to each corresponding appliance energy cost, and λ_{N+1} is the priority for the user time preference penalty deviation goal. $\lambda_g(0 < \lambda_g < 1, g = 1,2, \dots, N + 1)$ is specified by the user according to his preference or priority feeling for different appliances.

T_{ij} $(i = 1,2, \dots, N, j = 1,2, \dots, n_i)$ is introduced to represent the nominal processing time for energy phase j in appliance i in minutes, $\underline{\gamma}$ and $\overline{\gamma}$ $(0.5 < \underline{\gamma} < 1 < \overline{\gamma} < 1.5)$ are the lower and upper processing time limits factor for energy phase j in appliance i. To denote the lower and upper limits of power (not energy) assignment, respectively, to the corresponding energy phase in each time slot, $\underline{P}_{ij}^k$ and $\overline{P}_{ij}^k$ are introduced. The delay between two energy phases of an appliance is restricted by $\underline{D}_{ij}$ and $\overline{D}_{ij}$, the appliance technical specifications defining the lower and upper delay time, respectively, in minutes. E_{ij} is used to denote the total energy an energy phase should use according to the technical specification.

3.3.3. Decision Variables

Continuous decision variables p_{ij}^k $(k = 1,2, \dots, m; i = 1,2, \dots, N; j = 1,2, \dots, n_i)$ are introduced to indicate the energy assigned to energy phase j of appliance i during the whole period of time slot k. The unit of p_{ij}^k used in this study is kWh.

To indicate during time slot k whether a particular energy phase j of appliance i is being processed, a series of binary decision variables $x_{ij}^{k} \in \{0,1\}$ are introduced, with $x_{ij}^{k} = 1$ indicating energy phase being processed and otherwise not being processed.

Binary variables $s_{ij}^{k} \in \{0,1\}$ are introduced to indicate whether the processing of a particular energy phase is already finished by a particular time slot. If and only if $s_{ij}^{k} = 1$, energy phase j of appliance i is done by time slot k. For example, assume k_0 is the first time slot after the last energy phase of appliance i is finished, or in other words, $k_0 - 1$ is the last time slot that the last energy phase of appliance i is being processed, then $s_{ij}^{l} = 1$ is true for any $l \geq k_0$. For all other time slots, this binary variable is 0.

To indicate whether appliance i is making a transition between energy phase $j - 1$ to j at time slot k, binary variables t_{ij}^{k} $(j = 2, \dots, n_i)$ are introduced. $t_{ij}^{k} = 1$ if and only if during time slot k, the appliance i has finished energy phase $j - 1$ in some earlier time slot, but the energy phase j has not started yet. These variables are useful for restricting the delay between energy phases of an appliance.

For the purpose of fuzzy goal programming formulation, parameters $\delta_g (\delta_g > 0, g = 1,2, \dots, N + 1)$ are introduced to denote the normalized maximum unwanted deviation from the optimized value of each single objective function. Specifically, $\delta_g (g = 1,2, \dots, N)$ are for the corresponding appliances, and δ_{N+1} is for the user time preference. The final or general objective is to find solutions that minimize the weighted sum of these maximum deviation.

The introduction of objective functions and constraints in the next section will enable the understanding of the meaning of these decision variables as well as those parameters introduced in section 3.3.2 clearer.

3.3.4. Constraints

All constraints are generally divided into four categories. The first category includes those that are directly related to goal programming, specifically speaking, those involved with the normalized maximum unwanted deviation from the optimized value of each single objective function; the second category includes those that are used to directly restrict appliances but do not directly involve any energy phase; the third category includes those that are used to directly restrict each appliance' energy phase; the last category covers those that are used to define the range of each basic decision variable.

3.3.4.1. Constraints directly related to fuzzy goal programming

Since these constraints involve the single objective functions from which the unwanted deviations can be deducted, each single objective function has to be constructed first. Basically, there are two types of single objective function: the objective function for a specific single appliance energy monetary cost, and the objective function for user time preference violation penalty. The second type of objective function is used in order to substitute soft user time preference constraints for rigid user time preference constraints. Sou et al. (2011) used the rigid constraints to ensure that not even one minute is allowed be used during the prohibited time. Instead of strictly prohibiting an appliance from being used during the non-preferred time through rigid constraints, a violation penalty is imposed and corresponding cost is calculated if the non-preferred time is used by the appliance. The more non-preferred time an appliance uses, the greater the penalty cost will be.

A single appliance energy monetary cost objective function is denoted by $Z_i (i = 1,2,\dots,N)$ and reflects the total electricity cost for appliance i during the entire execution period, and is given below:

$$\sum_{k=1}^{m} \sum_{j=1}^{n_i} c^k p_{ij}^k \tag{3.4}$$

where c^k denote the electricity tariff for time slot k.

To construct the objective function for user time preference violation penalty, we consider a simple user time preference situation in which a whole day (a whole execution period) is divided into two parts: one that appliances can be and are preferred to run during which and the other one cannot or non-preferred. Let $TP_i^k \in \{0,1\}$ denote the user time preference interval, and $TP_i^k = 0$ if and only if none of the energy phase of appliance i can be run during time slot k. Assume k_{start}^i, k_{mid}^i, and k_{end}^i is the first, middle, and the last slot number of the whole user prohibited time period (which is continuous) for appliance i, respectively, then the penalty for using prohibited time is defined as

$$\sum_{i=1}^{N} \sum_{j=1}^{n_i} \sum_{k=k_{start}^i}^{k_{end}^i} x_{ij}^k \alpha^{-\left|k-k_{mid}^i\right|} \tag{3.5}$$

where $\alpha > 1$ is a constant and called base parameter, and

$$k_{mid}^i = \left[(k_{start}^i + k_{end}^i)/2\right] \tag{3.6}$$

is the round integer of $(k_{start}^i + k_{end}^i)/2$. Formula (3.5) is the objective function for violation penalty of user time preference and is denoted as Z_{N+1}. Note that this function is a weighted penalty in that the closer to the middle of the prohibited time zone, the higher penalty that results.

With all single objective functions have been defined, now it is able to develop the constraints that are directly related to fuzzy goal programming. Simply put, these constraints are to demand that the normalized deviation of each single objective from its best objective value should no worse than the worst deviation level for the corresponding single objective. The worst deviation level will eventually be minimized.

Let U_i and L_i be the best possible and worst possible values, respectively, for the k^{th} single objective, then we have the following constraints:

$$(U_i - Z_i)/(U_i - L_i) \leq \delta_i, i = 1,2, \dots, N+1 \tag{3.7}$$

$$\delta_i \geq 0 \in \mathbb{R}, i = 1,2, \dots, N+1 \tag{3.8}$$

Each $\delta_i(i = 1,2, \dots, N+1)$ represents the worst deviation level for the k^{th} objective. Each U_i and L_i are obtained by optimizing (minimizing) corresponding Z_i and $-Z_i$ alone, respectively, without regard to other objectives and under all necessary constraints including the hard user time preference constraints. The expression $(U_i - L_i)$ in constraint (3.7) helps normalize the objective deviation level and thus adjust different levels to similar fluctuation range. With the normalized deviation levels, applying desired priorities to different objectives will become easier.

3.3.4.2. Constraints directly related to appliances

3.3.4.2.1. Sequential operation between appliances

Sequential operation between appliances means that a specific appliance must not start operation until an associated appliance has finished all its tasks. A typical example is the dryer can start only after the washing machine is done, and another example is in the case of the only dishwasher in a home is going to be used twice or more times a day, each time the dishwasher is treated as a different appliance, and thus sequential operation requirement must be satisfied.

Suppose the appliance $\tilde{\imath}$ must be finished before the appliance i starts, then the following constraint restricting the relationship between the last energy phase of the appliance $\tilde{\imath}$ and the first energy phase of appliance i must be satisfied:

$$s_{\tilde{\imath} n_{\tilde{\imath}}}^{k} \geq x_{i1}^{k}, \forall k \tag{3.9}$$

Equation (3.9) allows the start of an appliance immediately after another is done and is the one adopted by Sou et al. (2001). For two appliances that are not closely related, this will work well in reality, but for appliances such as the washing machine and the dryer that are closely related, Equation (3.9) is not enough because time is needed to transfer clothes from the washing machine to the dryer. Another example is when the same appliance such as the dishwasher is used twice a day, the immediate sequential processing restriction will not give the user any time to remove washed dishes from the dishwasher and load dirty dishes into be unit. A more practical sequential processing constraint for these appliances should therefore be developed. Assuming that no less than v time slots between two sequentially processed appliances are required, then we have the following constraint:

$$\sum_{j=k-v}^{k} s_{\tilde{\imath}n_{\tilde{\imath}}}^{j} \geq \sum_{l=k}^{k+v} x_{i1}^{l}, \forall i, \forall k = 2,3, \dots, m-1 \tag{3.10}$$

This constraint is an extension of Equation (3.9).

If $v = 0$, then Equation (3.10) is equivalent to Equation (3.9). In our study, we will use the case of $v = 1$ which results in the following equation based on Equation (3.10):

$$s_{\tilde{\imath}n_{\tilde{\imath}}}^{k-1} + s_{\tilde{\imath}n_{\tilde{\imath}}}^{k} \geq x_{i1}^{k} + x_{i1}^{k+1}, \forall i, \forall k = 2,3, \dots, m \tag{3.11}$$

In conclusion, when two appliances are closely related, Equation (3.11) should be imposed, otherwise Equation (3.9) will be applied.

3.3.4.2.2. Between-appliance delay

In practice, two closely related appliances should follow not only the sequential processing restriction, but also the no-very-large-delay-in-between restriction. For example, the delay between the running of washing machine and that of the dryer should not be very large in real life. Assume the appliance i must start working within $u \geq 1$ time slots after the appliance $\tilde{\imath}$ is done, then all the following $(m - u)$ constraints hold:

$$s_{\tilde{\imath}n_{\tilde{\imath}}}^{k} - s_{\tilde{\imath}n_{\tilde{\imath}}}^{k-1} \leq \sum_{l=k}^{k+u-1} x_{i1}^{l}, k = 2,3, \dots, m+1-u \tag{3.12}$$

To prove the correctness of these constraints. Assume k_0 is the first time slot after the last energy phase of appliance $\tilde{\imath}$ is finished, then $k_0 - 1$ is the last slot when the last energy phase of appliance $\tilde{\imath}$ is being processed. When $k = k_0$, we have $s_{\tilde{\imath}n_{\tilde{\imath}}}^{k} = 1$, $s_{\tilde{\imath}n_{\tilde{\imath}}}^{k-1} = 0$, in this case, the appliance i must start at a time slot within the range of k to $k + u - 1$, indicating that Equation (3.12) is correct in this case. When $k < k_0$, we have $s_{\tilde{\imath}n_{\tilde{\imath}}}^{k} = 0$, $s_{\tilde{\imath}n_{\tilde{\imath}}}^{k-1} = 0$, in this case, each $x_{i1}^{l}(k \leq l \leq k + u - 1)$ must be 0 due to the sequential processing restriction, so Equation (3.12) holds. When $k > k_0$, we have $s_{\tilde{\imath}n_{\tilde{\imath}}}^{k} = 1$, $s_{\tilde{\imath}n_{\tilde{\imath}}}^{k-1} = 1$, in this case, because of the uninterruptible restrictions imposed on an energy phase (which will be presented later in this chapter), an $x_{i1}^{l}(k \leq l \leq k + u - 1)$ can be 0 or 1 depending on whether the first energy phase of the appliance i starting in the first case, where $k = k_0$, is done or not. In this case, Equation (3.12) holds too. So theoretically Equation (3.12) is valid and hence can ensure the delay between two closely related appliances not be too large.

In this study, the case of $u = 3$ is explored, and the corresponding constraints can be obtained based on Equation (3.12):

$$s_{\tilde{\imath}n_{\tilde{\imath}}}^{k} - s_{\tilde{\imath}n_{\tilde{\imath}}}^{k-1} \leq x_{i1}^{k} + x_{i1}^{k+1} + x_{i1}^{k+2}, \forall k = 2,3, \dots, m-2 \tag{3.13}$$

3.3.4.3. Constraints directly related to energy phases

3.3.4.3.1. Sequential processing between energy phases

Sequential processing between energy phases applies only to a same appliance and means that only after its preceding phase has finished can an energy phase starts. The following constraints guarantee this requirement:

$$s_{i(j-1)}^{k} \geq x_{ij}^{k}, \forall i, k, \forall j = 2,3, \dots, n_i \tag{3.14}$$

3.3.4.3.2. Between-phase delay

The delay between two energy phases of an appliance is restricted to a specific range. Suppose $\underline{D}_{ij}$ and $\overline{D}_{ij}$ are the appliance technical specifications defining the lower and upper delay, respectively, in minutes, then the following constraints must be satisfied:

$$\left\lceil \frac{\underline{D}_{ij}}{60} h \right\rceil \leq \sum_{k=1}^{m} t_{ij}^{k} \leq \left\lfloor \frac{\overline{D}_{ij}}{60} h \right\rfloor, \forall i, \forall j = 2,3, \dots, n_i \tag{3.15}$$

Here h is the number of time slot in one hour, and t_{ij}^{k} is the binary variable satisfying $t_{ij}^{k} = 1$ if and only if during any time slot k, the appliance i has finished energy phase $j-1$ in some earlier time slot, but the energy phase j has not started yet. The above-constraints restrict the total number of transition time slots between two phases.

Transition binary variable t_{ij}^{k} is not isolated from other decision variables and must meet the following requirement:

$$t_{ij}^{k} = s_{i(j-1)}^{k} - x_{ij}^{k} - s_{ij}^{k}, \forall i, k, \forall j = 2,3, \dots, n_i \tag{3.16}$$

To prove the validity of Equation (3.16), all possible situation have to be considered. In fact, there are only four possible combinations of variables t_{ij}^{k}, $s_{i(j-1)}^{k}$, x_{ij}^{k}, and s_{ij}^{k}. When $t_{ij}^{k} = 1$, we have $s_{i(j-1)}^{k}$=1, $x_{ij}^{k} = 0$, and $s_{ij}^{k} = 0$; When $t_{ij}^{k} = 0$, and $s_{i(j-1)}^{k}$=0, we have $x_{ij}^{k} = 0$, and $s_{ij}^{k} = 0$; When $t_{ij}^{k} = 0$, $s_{i(j-1)}^{k}$=1, and $s_{ij}^{k} = 0$, we have $x_{ij}^{k} = 1$; When $t_{ij}^{k} = 0$, $s_{i(j-1)}^{k}$=1, and $s_{ij}^{k} = 1$, we have $x_{ij}^{k} = 0$. The above discussions indicate that in all cases, equation (3.16) is valid.

3.3.4.3.3. Uninterruptible operation of an energy phase

Each energy phase of an appliance is characteristic of uninterruptible operation, meaning that once it starts it must continuously run until the finish. This requirement ensures the integrity and continuity of an energy phase. The following constraints are established for this purpose:

$$x_{ij}^{k} \leq 1 - s_{ij}^{k}, \forall i, j, k \tag{3.17}$$

$$x_{ij}^{k-1} - x_{ij}^{k} \leq s_{ij}^{k}, \forall i, j, \forall k = 2,3, \dots, m \tag{3.18}$$

$$s_{ij}^{k-1} \leq s_{ij}^{k}, \forall i, j, \forall k = 2,3, \dots, m \tag{3.19}$$

Equation (3.17) ensures that during any time slot, a phase cannot be processed and finished simultaneously; Equation (3.18) ensures that in any time slot, once transition of an energy phase from being-processed to not-being-processed happens, this energy phase is supposed to have finished; Equation (3.19) ensures that if an energy phase has finished in a time slot, then in all time slots thereafter this energy phase is seen to be done.

3.3.4.3.4. Energy phase process time limits

Each energy phase j in appliance i has its nominal processing time T_{ij} (in minutes) specified by the manufacturer, and in reality this processing time is allowed to have fluctuations to some extent. Let $\underline{\gamma}$ and $\overline{\gamma}$ ($0.5 < \underline{\gamma} \leq 1 \leq \overline{\gamma} < 1.5$) be the lower and upper processing time limits constant factor for energy phase j in appliance i, then we have the following constraint:

$$\left\lceil \frac{T_{ij}h}{60} \underline{\gamma} \right\rceil \leq \sum_{k=1}^{m} x_{ij}^{k} \leq \left\lfloor \frac{T_{ij}h}{60} \overline{\gamma} \right\rfloor, \forall i, j \tag{3.20}$$

where $\lceil \quad \rceil$ and $\lfloor \quad \rfloor$ are ceiling and floor functions, respectively.

3.3.4.3.5 Technical specifications on energy phase energy assignment

Each energy phase uses a fixed amount of energy E_{ij} specified by the manufacturer:

$$\sum_{k=1}^{m} p_{ij}^{k} = E_{ij}, \forall i, j \tag{3.21}$$

Besides, the energy assignment in any time slot for each energy phase of each appliance should satisfy the following constraint:

$$\frac{\underline{P}_{ij}^{k}}{h} x_{ij}^{k} \leq p_{ij}^{k} \leq \frac{\overline{P}_{ij}^{k}}{h} x_{ij}^{k}, \forall i, j, k \tag{3.22}$$

where $\underline{P}_{ij}^{k}$ and $\overline{P}_{ij}^{k}$ are the lower and upper limits of power (not energy) assignment in unit kW, respectively, to the corresponding energy phase. These limits are also specified by the appliance manufacturer.

3.3.4.3.6. Power safety requirement

To ensure power safety, the total energy assigned during any time slot for all appliances and all energy phases is not allowed to exceed the peak signal, or in other words, the total slot energy upper bound:

$$\sum_{i=1}^{N}\sum_{j=1}^{n_i} p_{ij}^{k} \leq PEAK^{k}, \forall \mathrm{k} \tag{3.23}$$

In most cases, $PEAK^{k}$ is constant for all time slots, and in this study a constant peak value for every time slot will be adopted.

3.3.4.4. Constraints used to restrict basic decision variables

$$p_{ij}^{k} \geq 0 \in \mathbb{R}, \forall i, j, k \tag{3.24}$$

$$x_{ij}^{k} \in \{0,1\}, \forall i, j, k \tag{3.25}$$

$$s_{ij}^{k} \in \{0,1\}, \forall i, j, k \tag{3.26}$$

$$t_{ij}^{k} \in \{0,1\}, \forall i, k\ \forall j = 2, \dots, n_i \tag{3.27}$$

3.3.5. Cost Function

The final total cost function representing the weighted sum of the maximum unwanted deviation from each corresponding single goal is given below:

$$\sum_{i=1}^{N+1} \lambda_i \delta_i \tag{3.28}$$

3.3.6. General Formulation for the Proposed Framework

The general formulation of the proposed framework is summarized as follows:

$$
\begin{aligned}
&\underset{p,x,s,t,\delta}{\text{minimize}} && \text{Cost function (3.28)} \\
&\text{subject to} && \text{Constraints of (3.7), (3.8), either (3.9) or (3.11)} \\
& && \text{depending on associated appliances type, and (3.13)} \\
& && \text{- (3.27)}
\end{aligned}
\tag{3.29}
$$

This is a MILP formulation transformed from the fuzzy goal programming formulation, and it can be solved using either classical search methods or heuristic algorithms.

3.3.7. General Formulation for Optimizing Single Objectives

Since in solving problem described in Equation (3.29), both the minimum and maximum values of each single objective Z_i $(i = 1,2, \dots, N, N + 1)$ given in Equation (3.4) and (3.5) must be acquired first, the following optimization problem should be solved ahead of solving of problem (3.29).

$$
\begin{aligned}
&\underset{p,x,s,t}{\text{minimize}} && \text{Each } Z_i \text{ and each } -Z_i \; (i = 1,2, \dots, N, N + 1) \\
&\text{subject to} && \text{Constraints of either (3.9) or (3.11) depending on} \\
& && \text{associated appliances type, and (3.13) - (3.27)}
\end{aligned}
\tag{3.30}
$$

3.3.8. General Optimization Process

The overall process for achieving an optimized smart home appliances operation schedule is as follows:

(1) Determine or specify the values of all necessary parameters including electricity tariff, number of time slots in one hour, appliance type and technical specifications, and priority for each single objective that involved in the optimization;

(2) Solve each optimization problem described in Equation (3.30) to obtain the best and worst objective values of each single objective;

(3) Based on step (1) and step (2) solve problem (3.29) to obtain the value of each p_{ij}^{k} $(\forall i, j, k)$, which determines how much energy should be assigned to a specific energy phase of a specific appliance during a specific time slot;

(4) Repeat the previous three steps if using different parameter values.

4. NUMERICAL EXPERIMENTS SETUP

4.1. Platform and Algorithm

Numerical or simulation experiments instead of practical experiments were carried out in this study to validate the effectiveness of the proposed smart home appliance scheduling optimization framework. All experiments were conducted on a desktop computer with an Intel^{R} Core^{TM} 3.40GHz CPU and 16GB RAM. The optimization problem was solved using MATLAB (The Mathworks, Inc., 2012) interface of YALMIP (Löfberg, 2004) and IBM ILOG CPLEX 12.5 solver for MILP (IBM, 2013).

YALMIP, implemented as a free toolbox for MATLAB, provides the extremely easy-to-use modelling language supports for a large number of optimization classes by implementing numerous modeling tricks and keeping it consistent with the standard MATLAB syntax (Löfberg, 2012), making it possible for users to focus mainly on the language and the higher level algorithms and hence can test ideas and develop programs rapidly. Basically, YALMIP relies on external solvers such as CPLEX solvers for the actual computations.

A new algorithm called "Dynamic Search" was implemented by CPLEX MILP Solver that basically uses a branch and cut algorithm to find the optimal solution (Lima and Grossmann, 2011). Branch and cut algorithm is a modification of branch and bound algorithm by incorporating the technique of cutting planes to solve a series of relaxed linear programming sub-problems more effectively, and it can be used in conjunction with heuristics to speed up the feasible solutions searching process (Mitchell, 2000). CPLEX Mixed Integer Optimizer did use heuristics and a sophisticated mixed integer preprocessing system to help find initial good solutions. It guarantees the ability to solve large and difficult integer problems quickly and efficiently. Currently, the Dynamic Search algorithm is still treated as proprietary and there is no way of looking into its details. But two things for sure about it are branch-and-cut-based and heuristics-employed. With the CPLEX Mixed Integer Optimizer C++ or Java API, user can also develop relevant executable applications that can solve MILP problems faster.

4.2. Fixed Parameter Values

Some of the parameters involved in this study will be fixed at a corresponding level or value in various optimization modeling situations. These parameters include one-day-ahead hourly electricity tariff, smart home appliances and their technical specifications, user time preferences, relationships between appliances, and the base parameter appearing in the definition of the penalty for using prohibited time period (see Equation (3.5) for detail).

The 24-hour ahead hourly electricity tariff (parameter c) data was provided by New York Independent System Operator (NYISO, 2013). These predicted pricing data, starting from midnight to next midnight, describes the general daily electricity fluctuation trend of Nov. 3rd, 2013, for Island of New York State, United States. Figure 1.2 already illustrates this trend, and the specific data are given in Table 4.1.

Five controllable and time-shiftable smart home appliances, including a dishwasher (No. 1), a washing machine, a dryer, another dishwasher (No. 2), and an electric oven, are involved in this study. Note that in this study the same dishwasher is used twice a day, and the first time its identity is No. 1 and the second time No. 2. The technical specifications of the dishwasher, the washing machine, and the dryer are exactly the same as those used by Sou et al. (2011), and the specification of the electric oven is provided by http://users.tpg.com.au/users/robkemp/Power/ConsumptionTables.htm, and is running using an average power of 2400W at temperature 180℃. Table 4.2 through Table 4.5 list the detailed information about the technical specification of these appliances.

Table 4.1 One-day 24-hour ahead hourly electricity tariff data

Time	0am-1am	1am-2am	2am-3am	3am-4am	4am-5am	5am-6am
Price (USD†/MWh‡)	32.19	27.63	26.51	24.60	26.41	22.57
Time	6am-7am	7am-8am	8am-9am	9am-10am	10am-11am	11am-12pm
Price (USD/MWh)	27.21	28.60	31.45	35.64	36.35	36.86
Time	12pm-1pm	1pm-2pm	2pm-3pm	3pm-4pm	4pm-5pm	5pm-6pm
Price (USD/MWh)	36.87	36.21	34.82	35.17	41.37	57.86
Time	6pm-7pm	7pm-8pm	8pm-9pm	9pm-10pm	10pm-11pm	11pm-0am
Price (USD/MWh)	54.65	55.44	50.31	45.73	39.02	35.67

†USD is US dollar
‡MWh is Megawatt hour

Table 4.2. Dishwasher technical specifications

Energy phase	Energy required (Wh†)	Min power (W‡)	Max power (W)	Nominal operation time (minute)
pre-wash	16.0	6.47	140.0	14.9
Wash	751.2	140.26	2117.8	32.1
1st rinse	17.3	10.28	132.4	10.1
Drain	1.6	2.26	136.2	4.3
2nd rinse	572.3	187.30	2143.0	18.3
Drain & dry	1.7	0.20	2.3	52.4

†Wh is Watt hour
‡W is Watt

Table 4.3. Washing machine technical specifications

Energy phase	Energy required (Wh†)	Min power (W‡)	Max power (W)	Nominal operation time (minute)
movement	118.0	27.231	2100	26.0
pre-heating	5.5	5.000	300	6.6
Heating	2054.9	206.523	2200	59.7
Maintenance	36.6	11.035	200	19.9
Cooling	18.0	10.800	500	10.0
1st rinse	18.0	10.385	700	10.4
2nd rinse	17.0	9.903	700	10.3
3rd rinse	78.0	23.636	1170	19.8

†Wh is Watt hour
‡W is Watt

Table 4.4. Dryer technical specifications

Energy phase	Energy required (Wh†)	Min power (W‡)	Max power (W)	Nominal operation time (minute)
Drying	2426.3	120.51	1454	120.8

†Wh is Watt hours
‡W is Watts

Table 4.5. Electric oven technical specifications

Energy phase	Energy required (Wh†)	Min power (W‡)	Max power (W)	Nominal operation time (minute)
Warm up	800	1000	2700	20
Baking	200	50	600	40

†Wh is Watt hours
‡W is Watts

The energy phase energy requirements E_{ij} are listed in the "Energy required" column in these technical specification tables; $\underline{P}_{ij}^{k}$ and $\overline{P}_{ij}^{k}$, the lower and upper limits. Respectively, of power assignment for an energy phase of an appliance in one time slot, are listed in the "Min power" and "Max power" columns, respectively, in these tables; each column "Nominal operation time" in these tables corresponds to parameter T_{ij}.

The dishwasher, washing machine, dryer, and electric oven have 6, 8, 1, and 2 energy phases, respectively. The between-energy-phase-delay parameters $\underline{D}_{ij}$ for all cases is assumed to be 0, and $\overline{D}_{ij}$ for the dishwasher, washing machine, dryer, and electric oven are set to 5, 10, 0, and 3 minutes, respectively. The lower and upper energy phase processing time limit factors $\underline{\gamma}$ and $\overline{\gamma}$ for all phases are set to 0.8 and 1.2, respectively. The parameter α, which is the penalty term for using user prohibited time, was set to 1.1.

The dishwasher No. 1 is supposed to be used in the day between 7am-6pm and the dishwasher No. 2 to be used in the evening between 8pm to midnight. This condition automatically ensures that dishwasher No. 2 will have to start working until after dishwasher No. 1 has finished working for at least one time slot. The washing machine, the dryer, and the electric oven, are not supposed to be running during midnight to 6 o'clock in the morning. Due to the fact that the allowed working time for the washing machine and the dryer is overlapped and that these two appliances are closely related pairs, the dryer can only start working after the washing machine has finished for at least one time slot, and at the same time, the delay between them should be no more than 3 time slots.

4.3. Variable Parameter Values

Time slot length, peak signal for a specific length of time slot, and priorities assigned to single objectives are variable.

Three different time slot lengths, 20 minutes, 10 minutes, and 5 minutes, corresponding to the number of time slots (parameter h) of 3, 6, and 12 per hour, respectively, were investigated in this study. The total number of decision variables needed to be optimized for each length of time slot are 6264, 12528, and 25056, respectively. The corresponding peak signal (parameter $PEAK$) for each time slot length is 22000 Wh, 11000 Wh, and 5500 Wh, respectively. In the study conducted by Sou et al. (2011), an unreasonable fixed peak signal of 5500 Wh for all different tested time slot length was adopted.

Five representative priority combinations presented in Table 4.6 were investigated in this study. P1 has much higher user time preference (UTP) priority than that of any other priority combination; Both P1 and P2 have equal priority for each single appliance with each appliance priority in P2 being higher than that in P1; P3 assigns higher priorities to the dishwashers; P4 assigns higher priorities to the washing machine and the dryer; P5 assigns higher priority to the electric oven. Same priorities are assigned to the two dishwashers as they are actually one, and same priorities are also assigned to the washing machine and the dryer as they are closely related appliances. In reality, all the priority choices are made by the users and completely up to them with regard to their preferences. In the case of the user preferring strict appliances working time restrictions, the priority for UTP can be set to 1 and hence all others set to 0; In the case of the user being totally insensible to appliances working time, UTP priority can be set to 0 and hence all other priorities sums to 1; in the case of the user is not going to use a specific appliance the next day, simply set the priority for that appliance to 0.

Table 4.6. List of priority combinations

Priority choice	P1	P2	P3	P4	P5
Dishwasher (No. 1)	0.06	0.16	0.3	0.07	0.07
Washing machine	0.06	0.16	0.07	0.3	0.07
Dryer	0.06	0.16	0.07	0.3	0.07
Dishwasher (No. 2)	0.06	0.16	0.3	0.07	0.07
Electric oven	0.06	0.16	0.06	0.06	0.52
UTP	0.7	0.2	0.2	0.2	0.2

5. EXPERIMENTAL RESULTS AND DISCUSSION

5.1. Computational Strategy and General Objective Value

5.1.1. Influence of Computational Strategy

When using CPLEX MILP Solver to search for optimal solutions for scheduling problem, at least two computational strategies are available: one is using the default optimal solution terminating condition and the other is using the first feasible solution terminating condition to prematurely terminate the optimization process. The first strategy is actually based on the idea that searching for better and feasible solution using the first feasible solution as the start. Theoretically, considerable time saving is expected to occur when using the second strategy (Denoted as S2) instead of the first strategy (Denoted as S1). Table 5.1 summarizes the computation time in seconds for all possible combinations of time slot length and priority choice.

Table 5.1. Computation time (unit: s)

Time slot length (minute)	20			10			5		
Strategy	S1	S2	RETC (%)	S1	S2	RETC (%)	S1	S2	RETC (%)
P1	5.76	3.61	60	249.26	64.94	284	7828.95	1985.23	294
P2	5.97	4.03	48	351.45	99.38	254	8546.69	2112.54	305
P3	5.55	3.41	63	222.36	57.26	288	7115.57	1668.27	327
P4	6.02	3.78	60	330.08	91.52	261	8092.31	2025.34	300
P5	5.72	3.57	60	245.66	62.65	292	8488.33	1969.91	331
Average	5.80	3.68	58	279.76	75.15	272	8014.37	1952.26	311

The relative extra time cost (RETC) of S1 compared to S2 in percent in each case is also presented in this table. RETC is calculated as follows:

$$RETC = (S1-S2) / S2 \times 100 \quad (5.1)$$

From the averaged RETC values for all priorities listed in the last row of Table 5.1, we can see that using strategy S1 will have to consume 58%, 272%, and 311% times more time than using strategy S2 for the time slot length of 20 minutes, 10 minutes, and 5 minutes. This does indicate that significant time can be saved if S2 is adopted.

While being highly superior in computation time saving to S1, S2 does not evidently degrade the final optimization results, as demonstrated by Table 5.2, a comparison of the optimized general objective results between using different computational strategies. Here the general objective refers to the one defined by Equation (3.28). And the ROE, relative objective error (in percent) is defined as follows:

$$\text{ROE} = (\text{S2}-\text{S1}) / \text{S1} \times 100 \quad (5.2)$$

Table 5.2. Optimized general objective results

Time slot length (minute)	20			10			5		
Strategy	S1	S2	ROE (%)	S1	S2	ROE (%)	S1	S2	ROE (%)
P1	0.0806	0.0824	2.23	0.0740	0.0765	3.36	0.0427	0.0446	4.55
P2	0.1087	0.1108	1.95	0.0736	0.0756	2.68	0.0490	0.0501	2.16
P3	0.0934	0.0973	4.15	0.0643	0.0652	1.46	0.0387	0.0401	3.67
P4	0.1167	0.1207	3.47	0.0947	0.0979	3.39	0.0705	0.0735	4.28
P5	0.0687	0.0705	2.66	0.0528	0.0549	3.94	0.0273	0.0280	2.49
Average	0.0936	0.0963	2.89	0.0719	0.0740	2.97	0.0457	0.0473	3.43

It can be seen from Table 5.2 that all ROEs are less than 5%, and the average ROE for time slot length of 20 minutes, 10 minutes, and 5 minutes are 2.89%, 2.97%, and 3.43%, respectively. The very small relative errors and the much less computational time of S2 compared to S1 confirm us to adopt S2 in this study to perform the optimization in all cases.

5.1.2. Influence of Time Slot Length and Priority Choice

Another result from Table 5.1 is that time slot length influences computational time. Regarding S2, the time cost of 10-minute slot length is about 20 times that of 20-minute slot, and the time cost of 5-minute slot length is approximately 26 times that of 10-minute slot length. This is because the smaller time slot length includes more parameters, decision variables, and constraints. Smaller time slot length also means consideration of more flexible arrangement of appliance operation, and as a result, better optimal results. Results from Table 5.2 show that the optimized general objective values of time slot length of 20-minute, 10-minute, and 5-minute are 0.0963, 0.0740, and 0.047, respectively. Significant decreasing (or better value) trend was observed from these results. No obvious influence from priority choice can be found for either computational time or the optimized general objective value.

5.2. Influence of Time Slot Length on Electricity Cost

In all cases, be it individual appliance electricity cost or total electricity cost, time slot length has a positive influence on electricity cost. The smaller the time slot length, the less the cost realized, as indicated by the total electricity cost summarized in Table 5.3. In Table 5.3, since each individual cost value from P2 to P5 under a specific time slot length is very similar, the last column of this table summarizes the average of all values from P2 to P5 within the same row. Also in Table 5.3, the resulted average values (0.2242, 0.2173, and 0.2148) in the last column are quite similar to each other, while the cost values (0.2681, 0.2577, and 0.2241) for different time slot under priority choice P1 are significantly different, indicating that time slot length has stronger influence on the total electricity cost when the UTP priority is relatively low. When UTP priority is relatively low, the appliances' priorities will be relatively high, meaning more cost-effective time slots will be available for appliances operation and hence better optimal results will be obtained. These better results, under a certain range of time slot length and a certain relatively low UTP priority, can be very similar to each other when in these situations the UTP priority dominates the optimization.

Time slot length impacts computational time, so when a smaller UTP priority is specified, a larger time slot length can be chosen in optimal solution search for the purpose of time saving because there will be no significant difference when using a smaller time slot length in this case.

Table 5.3. Total electricity cost

time slot length (minute)	P1	P2	P3	P4	P5	average of P2 to P5
20	0.2681	0.2281	0.2232	0.2177	0.2279	0.2242
10	0.2577	0.2157	0.2185	0.2166	0.2185	0.2173
5	0.2241	0.2145	0.2155	0.2142	0.2150	0.2148
average	0.2500	0.2194	0.2190	0.2162	0.2205	0.2188

5.3. Influence of Priority on Electricity Cost and on User Time Preference Violation

5.3.1. Influence of Priority on Electricity Cost

Discussion of the influence of priority on electricity cost is partially based on Table 5.3, from which it can be seen that UTP priority has much greater influence than does any other priority on total electricity cost. Higher UTP priority better satisfies the users need, but it will also lead to higher total electricity cost.

To investigate the influence of each priority on individual appliance’s electricity cost, Table 5.4, a summary of the grouped appliances total electricity cost in each case, has to be explored. By grouped alliances total electricity cost, we mean some appliances are grouped and studied together because of their close relationship and equal priorities. The electricity costs of the same dishwasher that has been used twice are summed up together, the washing machine and the dryer is grouped together, and the electric oven is the third group.

Table 5.4. Summary of appliances group electricity cost

time slot length (minute) and appliance group		P1	P2	P3	P4	P5
20	DW†	0.0817	0.0741	**0.0684**	0.0740	0.0740
	WMD‡	0.1592	0.1313	0.1313	**0.1201**	0.1313
	EO§	0.0272	0.0226	0.0235	0.0235	**0.0226**
10	DW	0.0860	0.0661	**0.0660**	0.0660	0.0669
	WMD	0.1482	0.1271	0.1290	**0.1271**	0.1289
	EO	0.0235	0.0226	0.0235	0.0235	**0.0226**
5	DW	0.0653	0.0649	<u>0.0653</u>	0.0644	0.0644
	WMD	0.1353	<u>0.1271</u>	0.1276	0.1272	0.1281
	EO	0.0235	0.0226	0.0226	0.0226	**0.0226**

†DW is the group of dishwasher used twice a day
‡WMD is the group of the washing machine and the dryer
§EO is the group of the electric oven.

For the dishwashers group, in the case of 20-minute and 10-minute time slot, the electricity cost using priority choice P3 is the minimum one among all DW costs within the corresponding time slot length restriction. The minimum values are highlighted with bold font. Both dishwashers have the highest priorities among all priority choices. So it is reasonable that with higher priority this group is assigned better operation time to save money. An exception occurs in the DW group in the case of 5-minute time slot length. Three reasons are possibly responsible for this: the optimization process is based on the first feasible solution and not the absolute optimal solution; when the time slot length is small enough, its influence will dominate other influences; unknown interactive effects of other factors.

The same conclusion can be drawn from the WMD group. As for the EO group, best values always appear under priority choice P5, which has the highest priority for this group. The advantage of higher priority for EO also becomes obscure when the time slot length decreases, meaning that again smaller time slot length is playing a greater role in final optimal results. This is demonstrated by the last row of Table 5.4, in which the EO cost values of all but the case of P1 are the same.

5.3.2. Influence of Priority on User Time Preference Violation

The overall total energy assignment illustrations are listed in Figure 5.1 through Figure 5.5, with each one representing a different priority choice and illustrating the optimal total energy assignment for all appliances in each time slot for the case of 10-minunte time slot length. In Figure 5.1 where the priority choice P1 was applied, since the UTP has the highest priority (0.7), less than one hour time period was violated from the UTP. Violations occurred because even though the UTP priority, it is still less than one, meaning a slight time violation is allowed. Figure 5.2 through Figure 5.5 display different results from Figure 5.1 in terms of major energy assignment time periods. Figure 5.2 through Figure 5.5 share the same feature: they are all based on the same UTC priority value 0.2. Lower UTC priority leaves higher appliances priorities, enabling them to take advantage of and occupy more cheap time slots.

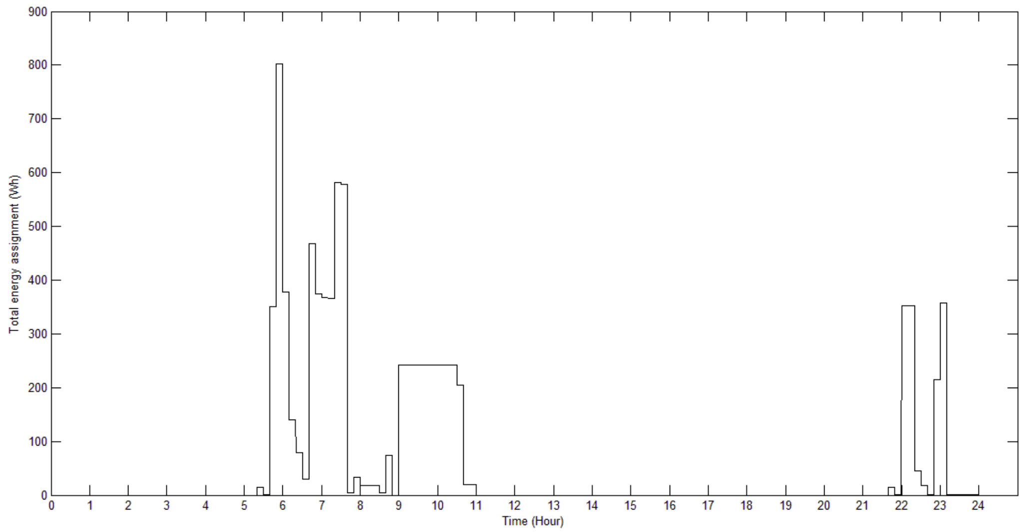

Figure 5.1. 10-minute-slot total energy assignment with priority choice P1

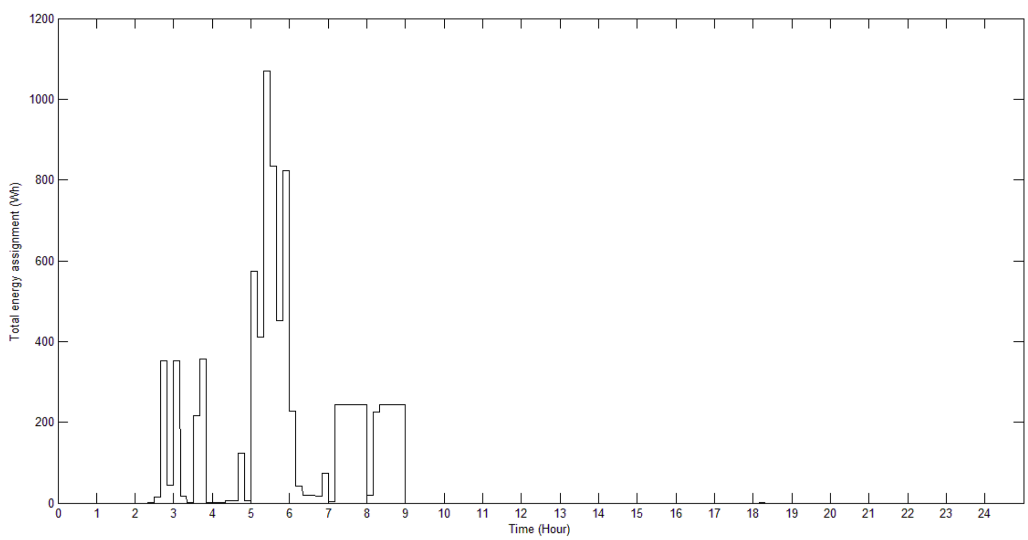

Figure 5.2. 10-minute-slot total energy assignment with priority choice P2

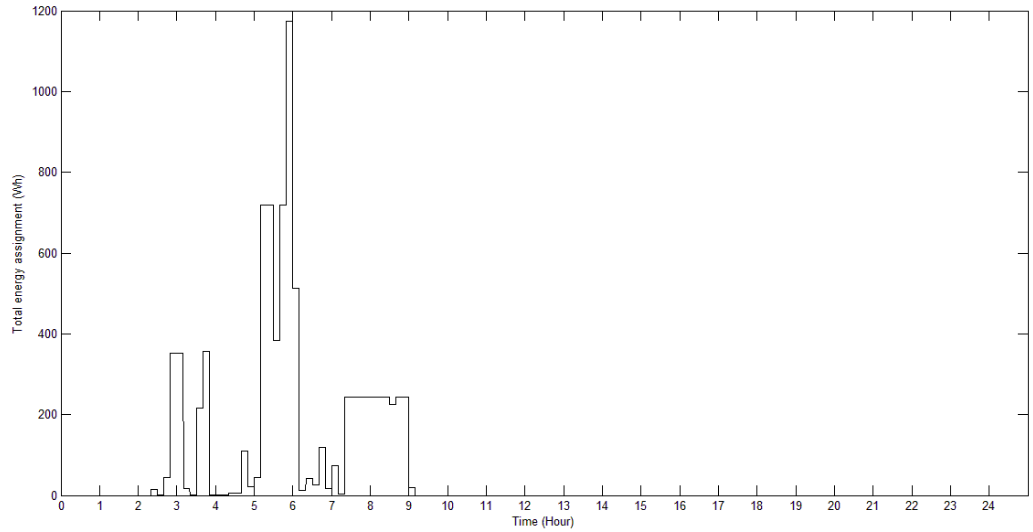

Figure 5.3. 10-minute-slot total energy assignment with priority choice P3

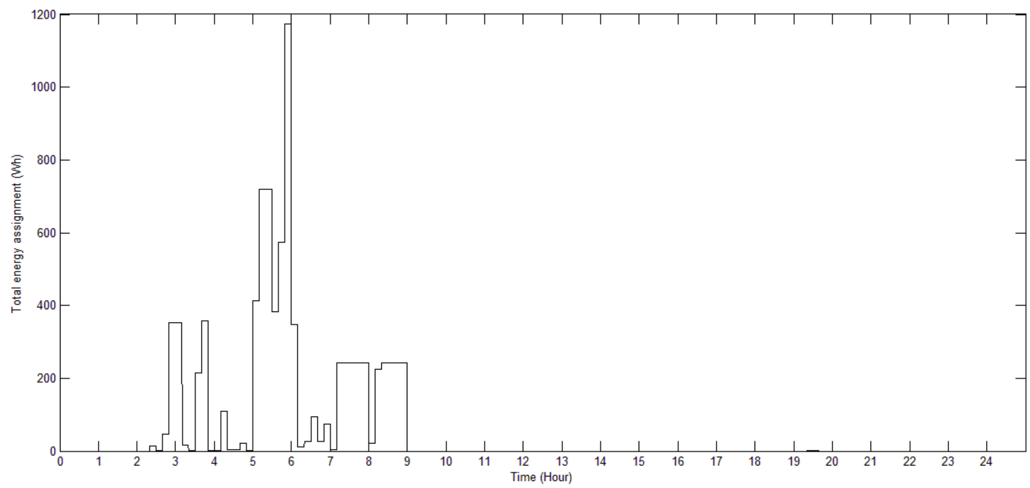

Figure 5.4. 10-minute-slot total energy assignment with priority choice P4

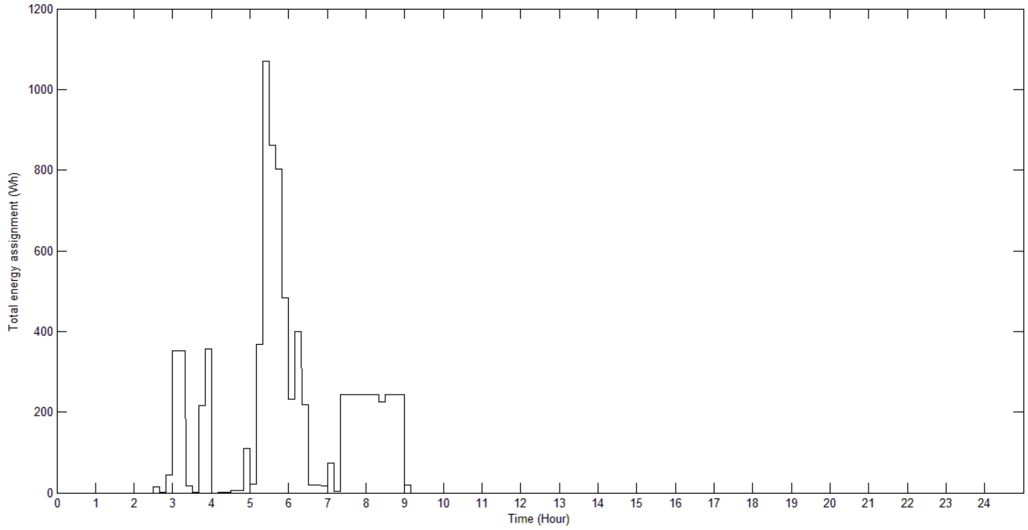

Figure 5.5. 10-minute-slot total energy assignment with priority choice P5

To examine of the influence of priority choice on time violation of UTP by making comparisons of the total energy assignment for each same appliance between lower and higher appliance priority. Figure 5.6 through Figure 5.10 illustrate the 10-minute time slot comparison differences for each appliance. Each comparison is made by using the priority choice in which the corresponding appliance has the highest priority to compare with the priority choice P1 who has the highest UTP priority and very low appliance priorities. These figures reveal that, except for the dryer (in Figure 5.9), a more severe UTP violation occurred for each appliance with higher priority than with lower priority. In some cases, very severe violations occurred, and the two dishwashers are representative examples. How to balance the energy cost saving and degree of the user time comfort is completely up to the user.

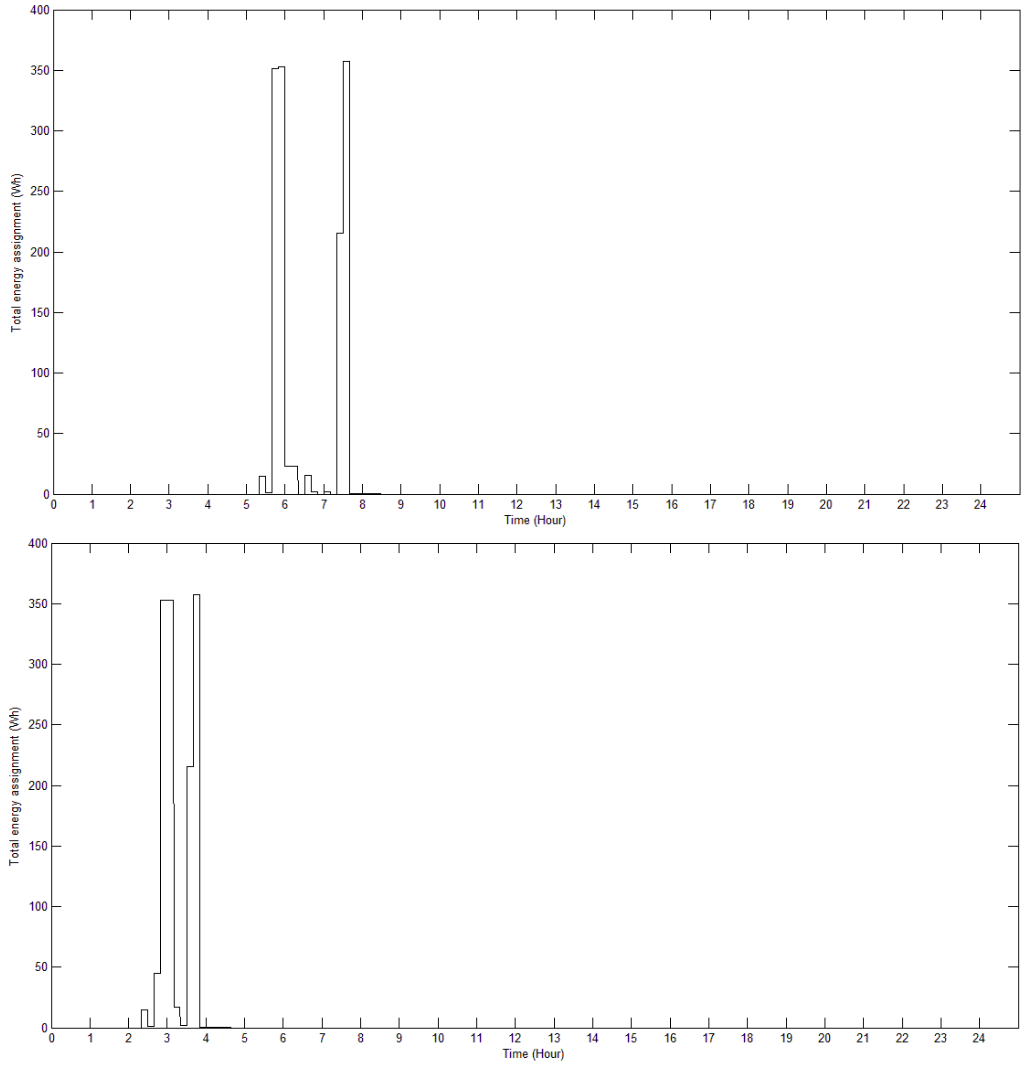

Figure 5.6. Comparison of 10-minute-slot total energy assignment for the dishwasher No. 1 between priority choices P1 and P3

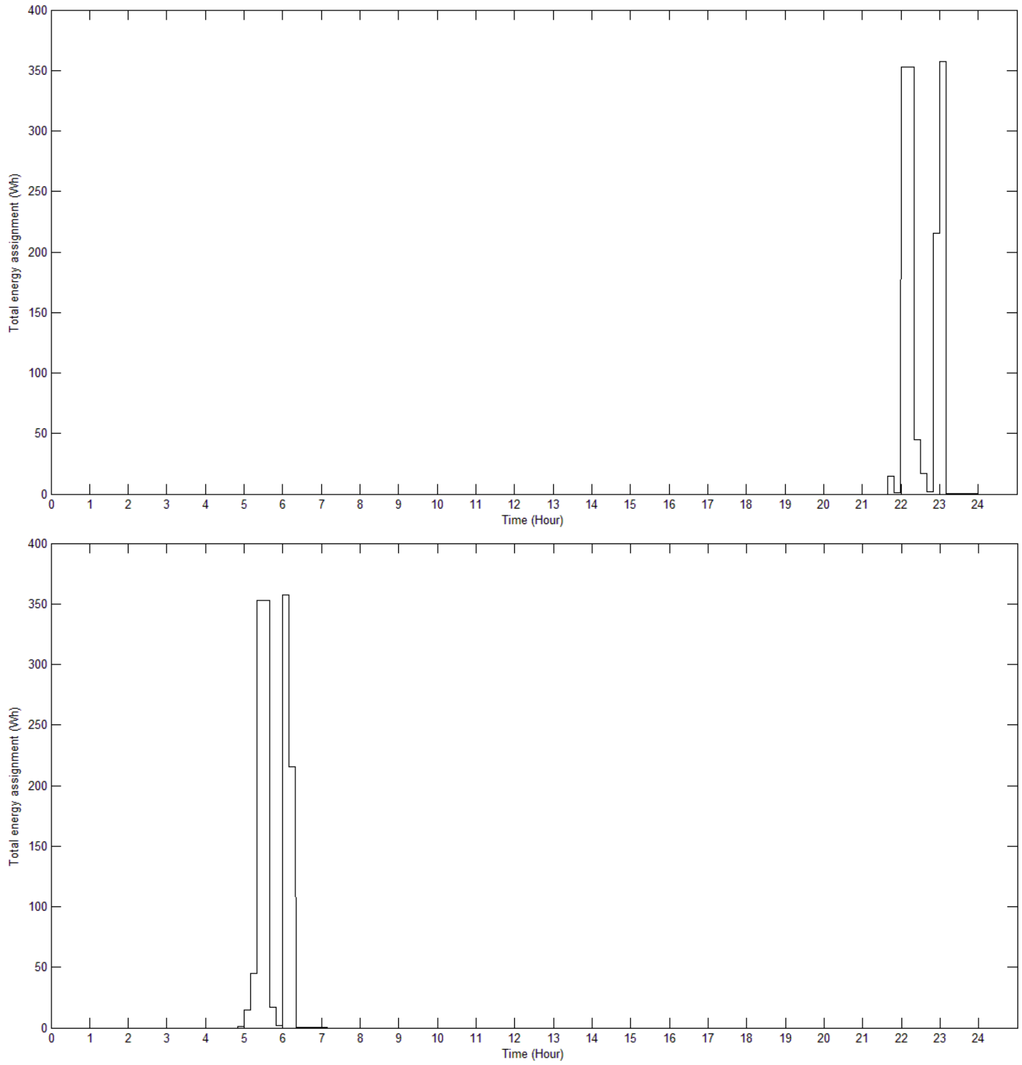

Figure 5.7. Comparison of 10-minute-slot total energy assignment for the dishwasher No. 2 between priority choices P1 and P3

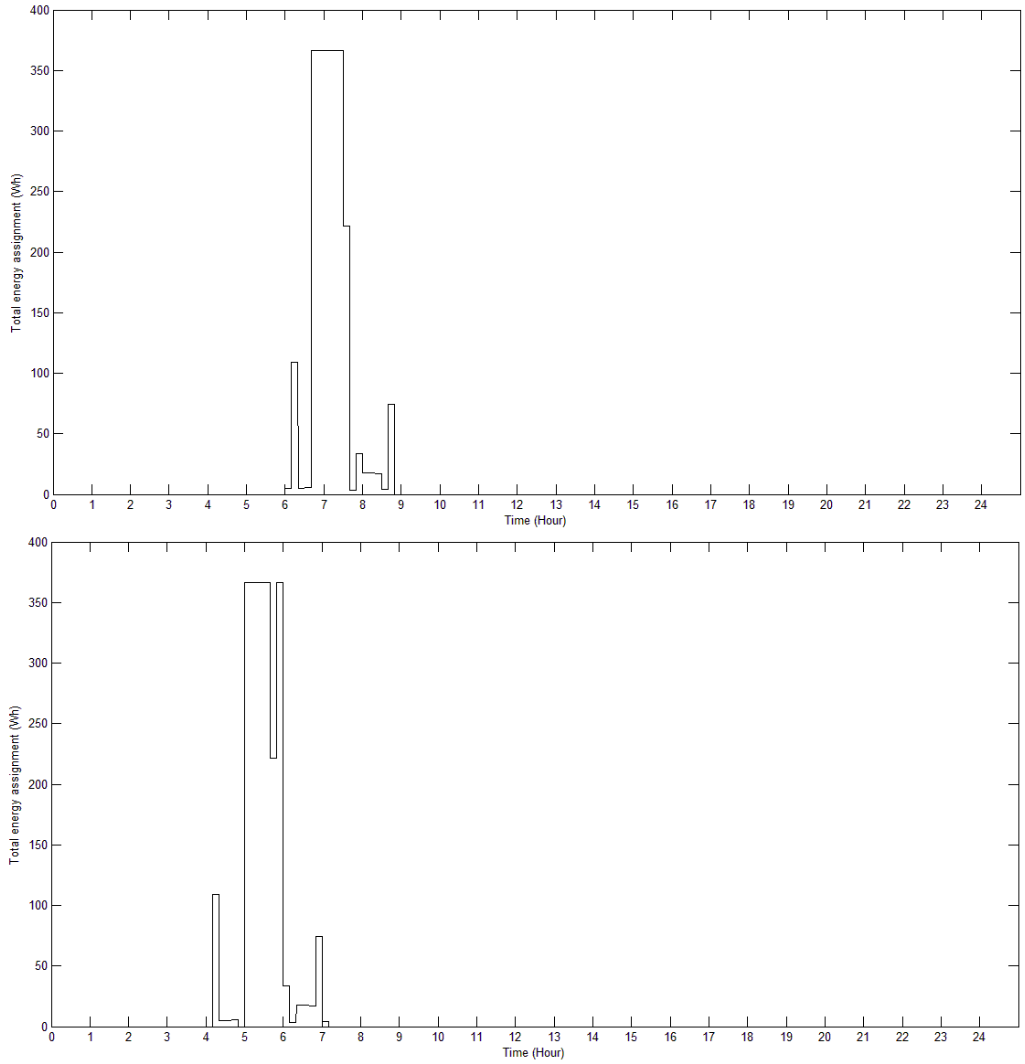

Figure 5.8. Comparison of 10-minute-slot total energy assignment for the washing machine between priority choices P1 and P4

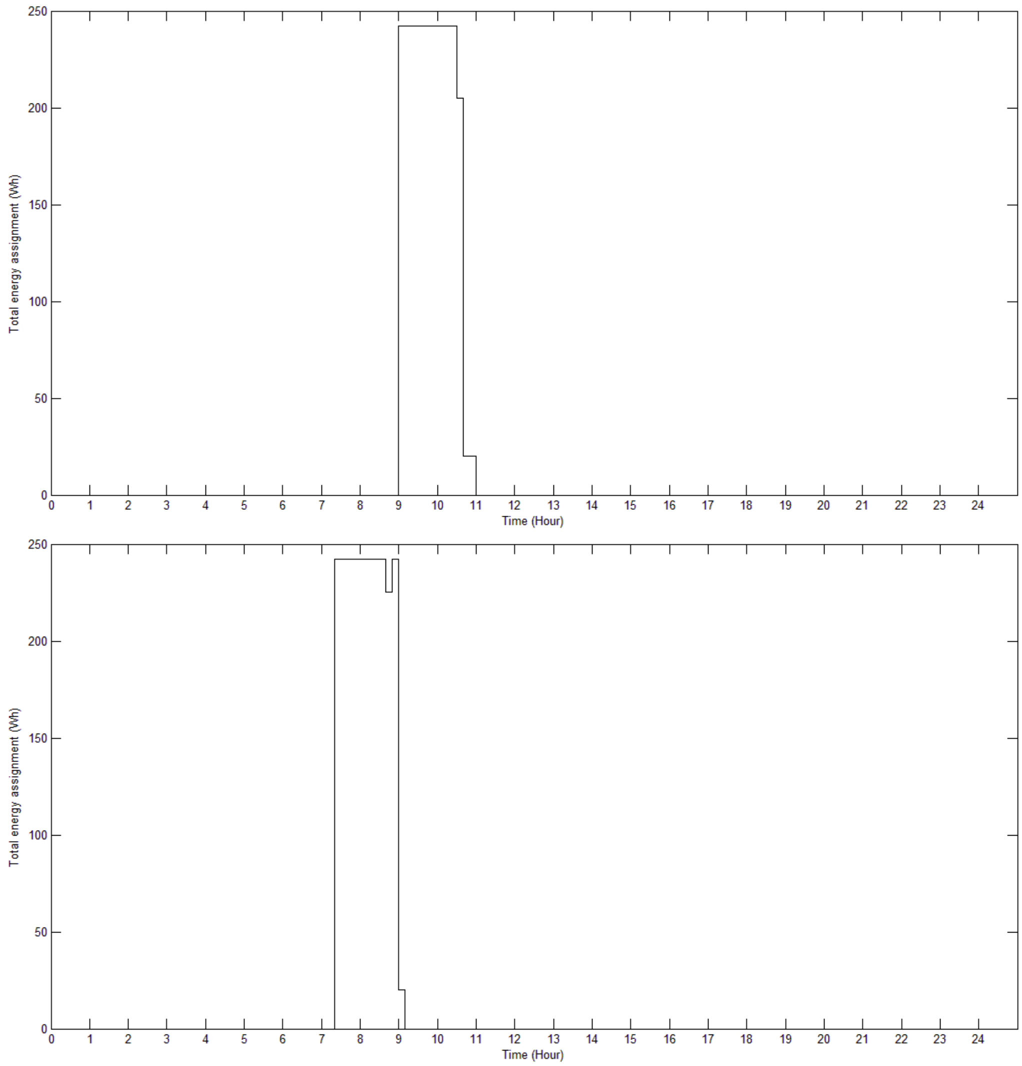

Figure 5.9. Comparison of 10-minute-slot total energy assignment for the dryer between priority choices P1 and P4

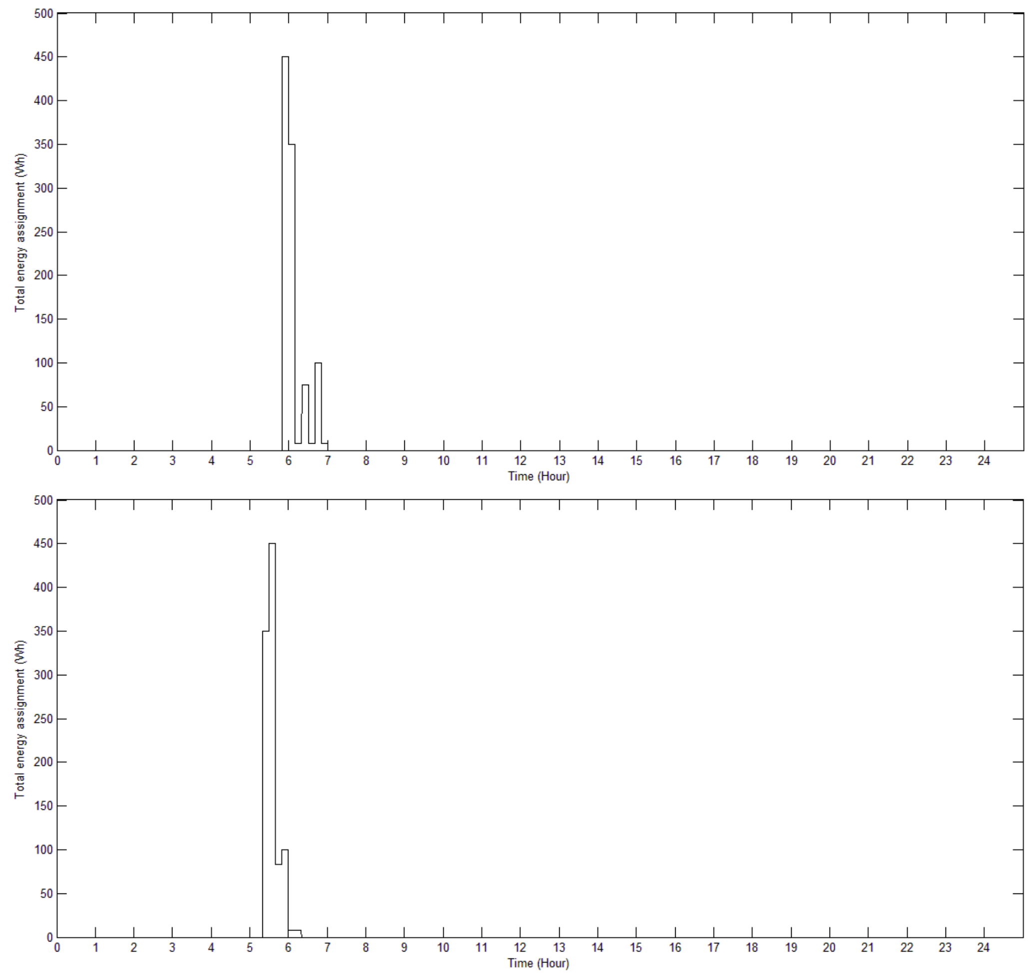

Figure 5.10. Comparison of 10-minute-slot total energy assignment for the electric oven between priority choices P1 and P5

5.4. Comparative Study

5.4.1. Relative Energy Cost Save

By maximizing the total energy cost of the plain MILP problem, the worst case total energy cost for each time slot length can be obtained, as shown in the second column of Table 5.5. A quick comparison between these worst values and those best values displayed in Table 5.3 indicates that a large percent of energy costs can be saved if using optimal scheduling method. The relative extra total electricity cost (RETEC) of the worst case compared to the corresponding best case in percent can be calculated as follows:

$$\text{RETEC} = (\text{worst - best}) / \text{best} \times 100 \tag{5.3}$$

The RETEC of P1 and the RETEC of the average of P2 to P5 are presented in the last two columns of Table 5.5, from which we can see that on average the worst case will cost the user 72% and 97% more money than will the best case.

Table 5.5. Relative extra total electricity cost

time slot length (minute)	worst case total energy cost	RETEC (%) of P1	RETEC (%) of the average of P2 to P5
20	0.4156	55	85
10	0.4400	71	102
5	0.4371	95	103
average	0.4309	72	97

5.4.2. Comparison with Similar Studies

The most similar study to this work was conducted by Sou et al. (2011), who used simple MILP with no fuzzy goal programming, did not use between-closely-related-appliance time slot number restrictions, and did not use a priority strategy. In addition, Sou et al. (2011) imposed rigid UTP on the appliance scheduling problem. Using exactly their proposed method to optimally scheduling the five appliances used in this study, the total electricity cost results for 20-minute, 10-minute, and 5-minute time slot length are 0.2824, 0.2720, and 0.2627, respectively. Compared to the corresponding values listed in Table 5.3 that are achieved using our proposed method, the method of Sou et al. (2011) results in greater electricity cost and are less realistic. The optimal results obtained using our method with priority choice P1 for 20-minute, 10-minute, and 5-minute time slot length are 0.2681, 0.2577, and 0.2241, respectively, which are less than the corresponding values using the Sou et al. (2011) methods. The differences between these methods is even greater when comparison is made with lower UTP priorities. There are two reasons for this: one is our method uses soft UTP instead of rigid UTP, and the other is the energy cost optimization is performed indirectly using fuzzy goal programming instead of directly using plain MILP.

Since our proposed method using fuzzy goal programming model involves more decision variables and constraints than does a plain MILP, the computation time is 13% more on average than that using Sou et al. (2011). The proposed model is designated to schedule appliance one day ahead, so the influence of the extra time cost will be marginal.

The study made by Saha (2013) employed semi-soft UTP constraints, however, the UTC constraint under each discrete sensitivity level was still rigid. Moreover, each appliance was treated as a unity that cannot be divided into different energy phases, and the number of constraints was very small, making the solution too ideal to be practically adopted.

One model employing goal programming technology for smart home appliance scheduling was made by Dehnad and Shakouri (2013). Our model is quite different from theirs in that they were trying to balance the objective of minimizing total electricity cost and the objective of minimizing peak-to-average ratio, while ours focuses on solving the conflict among each single appliance energy cost and user time preference violation penalty cost. Their study did not consider the energy phase concept and corresponding constraints.

6. CONCLUSION AND SUGGESTION FOR FUTURE WORK

The proposed fuzzy goal programming model for adaptive scheduling of smart home appliances based on the expansion and modification of an existing work (Sou et al., 2011) and improvement of our previous work (Bu and Nygard, 2014) has been thoroughly proven and validated, both theoretically and using simulation experiments. Our approach to residential energy scheduling is a more reasonable, realistic, flexible, and should realize greater energy cost savings due to the employment of fuzzy goal programming technique, using of soft user time preference, extension of the sequential processing constraint, introducing of new constraints that restrict the delay between two closely related appliances.

Instead of using the CPLEX MILP Solver default parameter settings to find the absolute optimal solution, the first feasible solution strategy was adopted as it can dramatically save implementation time and at the same time does not evidently degrade the final results or performance. We found that time slot length has a visible impact on total energy cost savings when the priority for UTP is high. For a better tradeoff between computational time and performance, an unreasonably small time slot length should be avoided in the application of this program. In addition, relatively high UTP priority should be used in the optimization practices to avoid the occurrence of the too-much-time violation. For other appliances priorities, users can freely make their own choices.

The MILP problem is known to be NP-hard (Smith and Taskin, 2007), meaning it is at least as hard as any NP (nondeterministic polynomial time) problem (Bovet and Crescenzi, 1994; Weisstein, 2015). Although IBM CPLEX MILP Solver employs advanced searching techniques, it is designed to fit the general and common requirements of all MILP problems and thus cannot guarantee the best implementation time for MILP problems belonging to a specific field or type.

Moreover, this solver has been shown to have a bottleneck in terms of algorithm space complexity (Sou et al., 2011) and thus cannot handle situations in which a large quantity of appliances is involved. To this end, developing custom heuristic algorithms to enable the real-time use of the proposed scheduling framework becomes necessary.

With the increasing demand of the public and governments for improved environmentally friendly practices, reducing CO_2 footprint should be considered as a single objective and included in the fuzzy goal programming framework. Finally, to make the proposed model even more realistic, more other common home appliances and reusable energy sources should be involved in the model by help of probability constrained techniques to deal with uncertainties.

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