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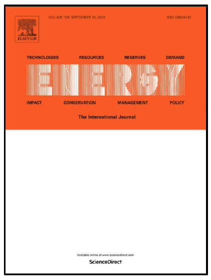

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Z. Yahia, A. Pradhan

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Optimal load scheduling of household appliances considering consumer preferences: an experimental analysis

Z. Yahia[a,b,*], A. Pradhan[a]

[a] Department of Quality and Operations Management, University of Johannesburg, Johannesburg, South Africa

[b] Department of Mechanical Engineering, Fayoum University, Fayoum, Egypt

* Corresponding author.

E-mail addresses: zakariay @uj.ac.za, zakaria.yahia@fayoum.edu.eg (Z . Yahia), anupp@uj.ac.za (A. Pradhan).

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ABSTRACT

This paper discusses an experimental study of the home appliances scheduling problem that incorporates realistic aspects. The residential load scheduling problem is solved while considering consumer's preferences. The objective function minimizes the weighted sum of electricity cost by earning relevant incentives, and the scheduling inconvenience. The objective of this study is five-fold. First, it sought to develop and solve a binary integer linear programming optimization model for the problem. Second, it examined the factors that might affect the obtained schedule of residential loads. Third, it aimed to test the performance of a developed optimization model under different experimental scenarios. Fourth, it proposes a conceptual definition of a new parameter in the problem, the so-called "flexibility ratio". Finally, it adds a data set for use in the literature on the home appliance scheduling problem, which can be used to test the performance of newly-developed approaches to the solution of this problem. This paper presents the results of experimental analysis using four factors: problem size, flexibility ratio, time slot length and the objective function weighting factor. The experimental results show the main and interaction effects, where these exist, on three performance measures: the electricity cost, inconvenience and the optimization model computation time.

Keywords:

Household appliances · Residential load scheduling · Inconvenience · Consumer preferences and flexibility · Binary integer linear programming · Experimental analysis

1. Introduction

Over the last decades, the energy crisis has attracted great attention, particularly regarding energy utilization efficiency and energy saving. Residential or domestic customers contribute significantly to total electricity consumption, as well as seasonal and daily peak demand [1]. The residential sector accounts for around 30~40% of total energy use all over the world [2]. The U.S. Department of Energy and European Union Energy Commission released statistics that suggest the energy consumption from residential and commercial buildings might increase by 20%–40% of the total yearly consumption [3]. The European Commission reports that the residential and services sectors are responsible for the growth in electricity consumption in the EU. The consumption of electricity by selected sectors shows that electricity consumption in the residential sector increased by 31 % during the period from 1990 to 2015 [4]. Furthermore, an analysis of the final end use of energy in the EU in 2015 shows three dominant categories: households came second with around 25.4 % of total energy consumption [5].

There are a limited number of solutions to meet this dramatic expansion of electricity demand. Most contemporary solutions are based on the conventional idea of increasing supply to match demand. Instead of supply side management, Demand Side Management (DSM) is considered an effective tool to curtail electricity demand. Furthermore, Demand Response (DR) aims to support this idea by managing the demand to match the available energy [6]. DR targets an effective cooperation between utilities and consumers to adjust load profiles resulting in benefits to all stakeholders [7].

One of the major goals of a DR program is to reduce consumption during peak hours and shift demand to off-peak hours. DR is defined by the U.S. Department of Energy (2006) [8] and the Federal Energy Regulatory Commission (2012) [9] as "*changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized*".

The electrical load scheduling problem has attracted significant interest on the part of researchers during the last decades; however, more effort is needed to tackle the issues that continue to arise. In their review paper, Benetti et al. [10] recommend that the trend in research on Electric Load Management (ELM) points to the extension of optimization methods to include more and more features and expanded modeling details. This is necessary in order to enhance the accuracy of results through the optimization of more complete models. However, a trade-off between computational complexity and scalability must be investigated. The high computational cost associated with solving optimization models may lead to scalability issues. Benetti et al. [10] conclude that large-scale systems have not been investigated in depth so far, and they recommend that research needs to address this issue in the future. Furthermore, they draw attention to the lack of a benchmarking framework, which makes the comparison between different ELM methods more difficult. They recommend the development of benchmark data sets that can facilitate testing of new methods and allow for comparison of different solutions.

The advent of Smart Grids (SG) has diversified the techniques and methods of DSM. Meyabadi and Deihimi [11] developed a novel theoretical framework by aggregating the methodologies of DSM used in the literature and presenting explicit definitions of the relevant concepts. They aimed to unify the terminology, concepts, and modalities presented in the literature. They concluded that the evolution of DSM concepts and methods as well as the lack of explicit definitions of some concepts in the literature, imply the necessity of developing a theoretical framework for this branch of energy management. Furthermore, Bari et al. [12] list many challenges associated with SG applications that must be tackled. All of these issues establish a need for decision-theoretic tools such as optimization to properly model and analyze various DR situations.

1.1. Literature survey

Many review papers have discussed DR and the load scheduling problem. Benetti et al. [10] presented a systematic review of the scientific literature on ELM. Furthermore, given the multi-disciplinary nature of the problem, they described and summarized the most relevant terminology adopted in various scientific papers. They also identified synonyms and delineated the relations among the different terms used. Gelazanskas and Gamage [13] focused on DSM and DR, including the drivers and benefits thereof, shiftable load scheduling methods, peak shaving techniques, and DSM techniques found in the literature. Haider et al. [14] presented an overview of the literature on Residential DR systems (RDR), load scheduling techniques, and the latest information and communication technologies that support RDR applications. Most recently, Wang et al. [15] presented a state-of-the-art of ‘‘Integrated DR” with the integration of “Multi-Energy Systems” and incorporation of sustainable energy. They introduced and analyzed the basic concept and value of the issues under consideration. Furthermore, they summarized the relevant research and explored the key issues and potential research topics on ‘‘Integrated DR” with the integration of “Multi-Energy Systems”.

In this study, only the literature of the general ELM problem and the Residential appliances/Load Scheduling Problem (RLSP) is considered. Consumer preference and convenience is an important aspect to be considered in the RLSP. On one hand, many authors guarantee consumer convenience and preference in their models through the use of constraints. Sou et al. [16] developed a Mixed Integer Linear Programming (MILP) model for the RLSP in order to minimize the electricity charge/bill while satisfying technical operation constraints and consumer preferences. Baldauf [17] introduced a scheduling algorithm and an intelligent residential DSM system aiming to reduce costs of the customer and power losses on the grid. Meanwhile, he tried to avoid the consumer's inconvenience by considering historical data of the consumer's habits. Yao et al. [18] developed a home energy management system using an MILP technique for a smart home consisting of renewable energy source, energy storage system, a set of schedulable home appliances, and dynamic electricity tariff. They aimed to minimize the energy cost required to satisfy the scheduled load demands without violating the operating constraints of smart home and the convenience level of consumers. İzmitligil and Özkan [19] proposed an MILP model and a home power management system to minimize electricity cost and reduce high peak demand while maintaining user comfort. Rasheed et al. [20] applied an optimization algorithm to solve the RLSP in a typical household setting. They aimed to minimize electricity bill as well as peaks reduction. Moreover, to facilitate the user in terms of comfort, time scheduling flexibility is introduced so that users can adopt any appliance based on their preferences.

Recently, Özkan [21] developed a real-time appliance scheduling system with the aim of reducing electricity cost while maintaining user comfort. He developed a new appliance control algorithm, using Petri nets, that interacts with appliances in a priority order based on user comfort. Simulation results demonstrated that the proposed algorithm provided improvements in terms of the energy consumption reduction, cost reduction and peak reduction at high demand periods. Most recently, Shirazi and Jadid [22] addressed the RLSP using an MILP model that considers both energy consumption and generation simultaneously. The objective was to minimize the overall energy cost as well as peak demand from main grid while considering the so-called Discomfort Index (DI). They defined the DI as the deviation from the most desired temperature and load shifting from the preferred running period. The latest, Mohseni et al. [23] considered the household appliances scheduling problem while including photovoltaic systems, battery energy storages and electric vehicles. They developed an MILP model with the objective function of minimizing the costs of supplying the residential microgrid power demand while considering the consumer's time preferences.

On the other hand, few authors have solved the RLSP with consumer convenience-related objective functions. Setlhaolo et al. [24] proposed a Mixed Integer Non-Linear Programming (MINLP) optimization model for the RLSP with the objective function that minimizes electricity costs while considering the trade-off between incentive and inconvenience. The inconvenience is calculated as the squared difference between the consumer preference schedule and the optimal schedule. Using the same objective function and formulation, Setlhaolo and Xia [25] applied genetic algorithm to solve the MINLP model. Thereafter, Setlhaolo and Xia [26] extended the MINLP formulation to include battery scheduling based on the same objective function. Lastly, Setlhaolo and Xia [27] extended their formulation to include multiple households with photovoltaic and storage system and aiming of minimizing the consumer's cost, inconvenience and CO_2 emissions. However, the proposed model formulation is nonlinear which raises the issue of complexity and obtaining an optimal solution in a reasonable time.

The lack of experimental studies in the RLSP literature is one of the obstacles to solving the problem. Where studies have been done, authors have attempted to analyze the effect of control factors on the problem solution and the performance of the solution approach. The most common experimental factors considered in the RLSP literature are: problem size and considering different case studies, weighting factor in the problem objective function, electricity price, time sampling/slot length, and the amount of money that consumers are willing to pay.

Few authors have conducted scalability tests by attempting to solve different, large-scale case studies. The main target of their experiments was to test and evaluate the performance and usefulness of their proposed approach. Sou et al. [16] demonstrated the effectiveness of their proposed approach by testing it on three different areas of a SG, each with different types of customers, namely residential, commercial and industrial customers. To test the limit of computation time and memory requirements for solving the developed model, a scalability test was conducted by hypothesis scenarios with increasing numbers of appliances from 1 to 20. They found that CPLEX runs out of memory for solving the scenario with 10 appliances. Furthermore, the method for finding the first feasible solution failed with 20 appliances. They also concluded that, for the scenarios with less than 9 appliances, the computation time to optimality increased rapidly as the number of appliances increased. Logenthiran et al. [28] presented a DSM strategy based on a load shifting technique that has been mathematically formulated as a minimization problem of the peak load demand of the SG. Simulations were carried out on a SG which contains a variety of loads in three service areas, one with residential customers, another with commercial customers, and the third one with industrial customers. The simulation results showed that the proposed DSM strategy achieved cost savings, while reducing the peak load demand on the SG.

Furthermore, Kinhekar et al. [29] presented multi-objective DSM solutions based on integer genetic algorithms to benefit both utilities and consumers. To illustrate the usefulness of their proposed technique, simulations were carried out on an Indian practical distribution system which contains a variety of loads in two service areas: large commercial and industrial areas. The simulation results showed that the presented DSM technique comprehended reasonable savings to both utility and consumers simultaneously, while reducing the system peak. Similarly, Yalcintas et al. [30] tackled the load shifting and scheduling problem and applied their approach to both commercial and industrial buildings. Setlhaolo and Xia [27] developed an MINLP mathematical model for the RLSP while considering photovoltaic, storage and CO_2 emissions issues. They tested their model under different five case studies (households) in South Africa. They demonstrated that consumer preferences on the cost sub-functions of energy, inconvenience and carbon emissions affected consumption patterns. Also, they found that consideration of carbon emissions could give customers an environmental motivation to shift loads during peak hours, as this can enable co-optimization of electricity consumption cost and carbon emission reduction.

Many contradictions and trade-offs in the RLSP encourage multi-objective function formulations. For examples, the trade-off between the benefits for consumers, utilities, and society and environment raises the need for multi-objective problem formulation. Also, it is necessary to compromise between minimizing electricity cost and satisfying consumer convenience expectations. However, some consumers may favor a schedule that cuts down on electricity costs over their individual convenience. Formulating consumer preference and convenience as an objective function enables consumers to take control of how they favor scheduling inconvenience over cost. Because adjusting the relative weighting for multi-objective functions is a critical issue, the authors analyze the obtained schedules at different relative weighting values.

Setlhaolo et al. [24] studied RDR through the scheduling of typical home appliances in order to minimize electricity cost and the inconvenience levels associated with the new schedule. An MINLP optimization model is built under a TOU electricity tariff. They tested the solution of the daily cost and the inconvenience at different values of the weighting factor. Their result showed that, at different values of the weighting factor, the obtained schedule gives varying costs. From this, the consumer is able to know the inconvenience level that comes with the new schedule and is able to adjust it according to his preferences in regard to the cost and the inconvenience. Kinhekar et al. [29] presented multi-objective DSM solutions based on integer genetic algorithms to benefit both utilities and consumers. They tested the developed algorithm with different weightings given to individual objective curves. Their simulation results showed that the developed DSM technique accrued reasonable savings to both the utility and consumers simultaneously, while also reducing the system peak. Similarly, Setlhaolo and Xia [27] proposed an energy management system that combines DSM strategies to illustrate the optimal decisions in the presence of trade-offs between multiple (three) objectives. The first was to minimize the consumer's cost incorporating the consumer's preferences and electricity consumption as well. The second and third terms were to minimize inconvenience and carbon emissions respectively. They conducted experimental analysis on the weighting factor values for each of the three objectives and demonstrate that consumers' preferences on the cost sub-functions of energy, inconvenience and carbon emissions affect consumption patterns.

Electricity tariffs are a key driver in the RLSP, and changing tariffs to encourage consumer involvement and commitment is a base concept in DR. Few studies have addressed the extent to which tariff fluctuations motivate changes in power consumption behavior.

To analyze the effect of changing price schemes on the obtained schedule, two case studies based on tariffs in Sweden and the USA were considered. In the first case, the electricity tariff was taken to be the spot price on Feb 15th, 2011 in Sweden. The tariff in the second case was the spot price in New York City on Feb 15th, 2011. The results confirmed the intuition that tariff fluctuation needs to be large enough to motivate changes in power consumption behavior. Cortés-Arcos et al. [31] presented a multi-objective problem that includes DR to real-time prices. Two objectives were considered to minimize both the daily cost of electricity and consumer dissatisfaction. Hourly prices corresponding to a tariff currently existing in Spain have been used to evaluate the daily cost of the consumed electricity. In their experiments, they used two cases of hourly prices; a weekday case and a weekend day case. For each case, the Pareto Fronts obtained for each of the two cases showed how the two objectives changed depending on the pricing schemes.

To the end of real-time household appliances scheduling, approaches should be tested to provide optimal power profiles with shorter time slots within reasonable computation time. Sou et al. [16] concluded that the tuning parameter which is responsible for the trade-off between computation time and model fidelity is the length of the time slot. They solve the problem with three different time slot lengths (3, 5, 10 minutes). Their results suggested that while the time slot length has a significant impact on computation time, its effect on the optimal cost is not very obvious.

To encourage customer commitment and satisfaction, attempts to find the best way to schedule appliances based on the desired budget or the amount consumers are willing to pay are increasingly necessary. Setlhaolo & Xia [26] conducted a sensitivity analysis and reveal that energy cost saving is sensitive to the amount consumers are willing to pay. When this increases, the energy cost also increases and the inconvenience cost decreases. This is in line with practical expectations in that if the consumer has a higher budget he is likely to have less tolerance for inconvenience and higher energy consumption costs.

1.2. Limitations of previous work

Based on the above literature review, there are five crucial issues outlined which this paper attempts to fill.

First, only a few publications have formulated consumer preference and convenience as an objective function. The majority of publications consider this issue as a set of constraints, in which the resulting appliance schedule does not guarantee minimal electricity charge. However, some consumers may favor a schedule that cuts down electricity bills over their individual convenience. Based on the literature survey, only Setlhaolo et al. [24] and Setlhaolo and Xia [25-27] have tackled the RLSP with an objective function that minimizes electricity costs and consumer inconvenience, simultaneously. However, they model the RLSP with a nonlinear formulation [24-27]. The nonlinearity issue is raised by the quadratic formulation of the inconvenience term as the squared difference between the consumer preference schedule and the optimal schedule. Furthermore, they formulated the 'uninterruptible operation' set of constraints in a nonlinear form as well. However, such a nonlinear model formulation may raise issues of complexity and obtaining an optimal solution in a reasonable time. The general case of nonlinear optimization problems is the most difficult to be solved. To sum up, and as indicated by Vaziri et al. [32], linearization is one of the most efficient approaches to solving nonlinear programming problems. Furthermore, achieving such efficiency should be the focus of upcoming research.

Second, few publications have included experimental analysis. A majority of experimental studies are based on 'one-factor-at-a-time' experiments that examine the effect of only a single factor or variable. There is thus a need for conducting a full factorial experiment by considering all possible combinations of all considered factors. Such an experiment allows for study of the effect of each factor on the response variable, as well as the effects of interactions between factors on the response variable.

Third, there is a lack of explicit definition of some concepts in the literature. This gap is seen in the RLSP literature and is indicated by Meyabadi and Deihimi [11], who argued for the development of novel terms and explicit definitions regarding SG and DSM concepts and methods.

Fourth, there is a lack of data sets and a benchmarking framework in the ELM, as explicitly concluded by Benetti et al. [10]. This makes comparison between different ELM methods more difficult. Developing benchmark data sets will facilitate testing of new methods and allows for comparison of different solutions.

Fifth, the trade-off between computational complexity and scalability has not been investigated soundly in the literature. Benetti et al. [10] concluded that large-scale systems have not been investigated in depth so far; they recommend that future research address this issue.

1.3. Study contributions

This study attempts to fill the aforementioned gaps in previous RLSP-related work. The contributions of this paper with respect to previous research in the area can be summarized as follows.

First, a Binary Integer Linear Programming (BILP) optimization model is presented for the RLSP, with the objective function of minimizing electricity costs and the inconvenience level, simultaneously. The objective function minimizes the weighted sum of a cost-incentive term and the associated schedule inconvenience level. This enables consumers to take control of how they favor scheduling inconvenience over cost. The inconvenience level is a measure of the disparity between the preferred and optimal schedules. The BILP model determines the optimal scheduling of home appliances under Time-Of-Use (TOU) electricity prices.

Second, based on the developed BILP optimization model, this paper seeks to conduct an experimental analysis with two aims. The first aim is to analyze the effect of a set of experimental factors on the obtained appliance schedules. The second aim is to test the performance of the developed BILP optimization model under different scenarios for a set of experimental factors, especially from a computation time perspective.

Third, the new concept of "flexibility ratio" is presented to the RLSP. The effect of flexibility ratio on the BILP model performance and the obtained schedules is investigated. Setlhaolo et al. [24] presented a case study involving 10 appliances with high flexibility ratio. This paper extends their case study by adding a new configuration for the low flexibility ratio case. Furthermore, the new case study involves 20 appliances with both low and high flexibility ratio scenarios.

Fourth, this paper provides a data set and benchmarking framework for the RLSP, including all scenarios of the experimental study.

Fifth, a new artificial large-scale smart home case study is presented along with the case study presented in the reference [24]. In the large-scale case study, more appliances are considered to consider most of the appliances operated in normal consumer houses. The large-scale case study tests the performance and scalability of the developed BILP optimization model, especially regarding how computation time is affected.

The remainder of this paper is organized as follows: Section 2 focuses on defining the problem and the BILP optimization model. Section 3 presents the small and large-scale case studies, a complete data set, and the experimental factors and levels of each used in this paper. Comparisons and experimental analysis are presented and discussed in Section 4 before conclusions are drawn in Section 5.

2. The proposed mathematical model

The load scheduling problem is concerned with the selection of an optimal on/off status of each home appliances over the course of a day. In this study, the RLSP is considered as including consumer's preferences. The main objectives of an electricity-consuming household are to minimize its electricity cost and the inconveniences that may arise from an optimal appliance schedule. To achieve these objectives, a weighted objective function is considered. It minimizes the relatively weighted sum of both the electricity cost, including incentives offered, (EC) and scheduling inconveniences (IC). The IC term seeks to minimize the disparity between the preferred and optimal schedules. In this research, postponement and advancement of the schedule are both regarded as an inconvenience. A BILP mathematical model is presented to tackle this problem. Considering a sampling time (Δt) and a study period (T), the BILP mathematical formulation for the problem is presented below. The indices, parameters and decision variables used in this paper are summarized in Table 1.

Table 1: Notation summary

Notation	Description
Indices:	
$i \in I$	Index of home appliance, I is the total number of appliances.
$t \in T$	Index of time/ time slot, $t = 1, \ldots T$, where T is the horizon, which is 24 h.
Parameters:	
P_i	The rated power of appliance i.
N_i	The required number of time slots to complete the normal operation of appliance i.
D_i	The time duration (in terms of minutes) required to complete the normal operation of appliance i.
S_i	The start of the time interval in which the appliance i is to be scheduled.
E_i	The end of the time interval in which the appliance i is to be scheduled.
C_t	The electricity price at time t.
V_t	The incentive offered at time t.
Δt	The sampling time or the time slot length.
α	The weighting factor, which represents the relative importance of scheduling convenience ($1 \geq \alpha \geq 0$). Where ($1-\alpha$) is the weight for the EC term.
Q	The maximum cost that the consumer is willing to incur in one day.
$X_{i,t}$	A binary parameter represents consumer's preferred/baseline on/off status of appliance i at time t, which equals 1 if the consumer would like to turn appliance i ON at time t and zero otherwise.
Main decision variables:	
$x_{i,t}$	A binary variable represents the optimal ON/OFF status of appliance i at time t, which equals 1 if appliance i is to be turned ON at time t and zero otherwise.
Auxiliary decision variables (derived from main decision variables):	
$z_{i,t}$	A binary indicator function for inconvenience, which equals 1 if there is a miss-match between the preferred schedule and the optimal schedule for appliance i at time t and zero otherwise.
$y_{i,t}$	A binary indicator function for incentives, which equals 1 if consumers may earn incentives because they switched off appliance i at time t, against their preference, and zero otherwise.
$u_{i,t}$	A binary indicator function to guarantee uninterrupted operation, which equals 1 if the operation of appliance i is already completed during time slot t and zero otherwise.

To consider consumer preferences, customers can set an operating time window (i.e. preferred start and end hours) for each appliance. The load can be turned on at any time during the operating time window. This paper presents the new term "flexibility ratio" which represents the average degree of flexibility in shifting an appliance within the appliance operating time window. The wider the appliance operating time window, the greater the flexibility ratio.

The home appliance load scheduling problem including consideration of incentives and consumer preferences is formulated as a BILP model as follows.

$$Minimize \left[(1-\alpha)\cdot\sum_{t=1}^{T}\sum_{i=1}^{I}P_i\cdot\left[C_t\cdot x_{i,t}-V_t\cdot y_{i,t}\right].\Delta t+\alpha\cdot\sum_{t=1}^{T}\sum_{i=1}^{I}z_{i,t}\right] \quad (1)$$

$Subject\ to$

$$X_{i,t}-x_{i,t}\le y_{i,t} \qquad \forall i\in I,\forall t\in T \quad (2)$$

$$X_{i,t}-x_{i,t}\le z_{i,t} \qquad \forall i\in I,\forall t\in T$$
$$x_{i,t}-X_{i,t}\le z_{i,t} \qquad \forall i\in I,\forall t\in T \quad (3)$$

$$\sum_{t=1}^{T}\sum_{i=1}^{I}P_i.\left[C_t\cdot x_{i,t}-V_t.y_{i,t}\right].\Delta t\le Q \quad (4)$$

$$\sum_{S_i}^{E_i}x_{i,t}\ge N_i \qquad \forall i\in I \quad (5)$$

$$x_{i,t}\le 1-u_{i,t} \qquad \forall i\in I,\forall t\in T$$
$$x_{i,t-1}-x_{i,t}\le u_{i,t} \qquad \forall i\in I,\forall t\ge 2 \quad (6)$$
$$u_{i,t-1}\le u_{i,t} \qquad \forall i\in I,\forall t\ge 2$$

$$x_{i,t}\le u_{\tilde{i},t} \qquad \forall\, t \quad (7)$$

$$x_{i,t}\in\{0,1\}$$
$$y_{i,t}\in\{0,1\}$$
$$z_{i,t}\in\{0,1\} \qquad \forall i\in I,\forall t\in T \quad (8)$$
$$u_{i,t}\in\{0,1\}$$

The objective function (1) minimizes the electricity cost considering incentives (EC) and the scheduling inconveniences (IC), which can be expressed in short as (1- α) EC+ α IC. $x_{i,t}$ is a binary decision variable that configures the optimal/new ON/OFF status of appliance i at time t.

$X_{i,t}$ is a binary input parameter that defines the consumer's preferred/ baseline ON/OFF status of appliance i at time t. $y_{i,t}$ is a binary indicator function that allows consumers to earn an incentive only when they switch off their appliances during peak times. This function is formulated linearly in constraint set (2).

$$y_{i,t} = \begin{cases} 1, \text{ if } \left(X_{i,t} - x_{i,t}\right) > 0 \\ 0, \text{ if } \left(X_{i,t} - x_{i,t}\right) \leq 0 \end{cases}$$

The second term (IC) seeks to minimize the disparity between the preferred and optimal schedules. $z_{i,t}$ is a binary indicator function that causes the obtained schedule to suffer a penalty if it does not match the preferred schedule. Thus, $z_{i,t}$ can be modeled using the absolute value of the difference between the preferred and optimal schedules. The formulation of $z_{i,t}$ is linearized using the equivalent linear constraint set (3).

$$z_{i,t} = \left|X_{i,t} - x_{i,t}\right| = \begin{cases} 1, \text{ if } X_{i,t} \neq x_{i,t} \\ 0, \text{ if } X_{i,t} = x_{i,t} \end{cases}$$

Constraint (4) guarantees that the cost associated with the optimal appliance schedule does not exceed the amount that the consumer is willing to incur in one day (Q). Constraint (5) ensures that the scheduled-ON time slots for appliance i are within the preferred operating time window [S_i, E_i] and are equal to the required number of time slots to execute the appliance operation i in terms of slots (N_i). The constraint set (6) ensures continuous, uninterrupted operation of the appliances and that the assigned time slots for each appliance are successive. For appliances that may be operated more than one time per day (i.e., oven operation for lunch and dinner), the appliance can be treated as two separate appliances. A new auxiliary binary decision variable $u_{i,t}$ is used to state that the operation of appliance i is already completed during time slot t and, if $u_{i,t} = 1$, the operation of appliance i is already completed during time slot t. Hence, the corresponding $x_{i,t}$ must be zero. Furthermore, $u_{i,t} = 1$ when $x_{i,t}$ switches from 1 to zero (i.e., the operation of the appliance is just finished), as in the reference [16].

Of course, the start of appliance operation should respect a logical sequence between any two sequential operations of appliances. Sequential operation between appliances means that an appliance operation cannot be processed unless its preceding appliance operation has finished. For example, the operation of a clothes dryer follows the operation of a washing machine. This condition can be represented as $x_{i\,=\,\text{clothes dryer},t} \leq u_{i\,=\,\text{washing machine},t}$. Similarly, there is a logical sequence between the cooker hood and the Stove. The general form of this constraint is presented in constraint (7), where $\tilde{i}$ is the index of the appliance which must be finished before i can start. Finally, the set of constraints (8) reflects the binary nature of the main and auxiliary decision variables.

3. Experimental design

To illustrate the usefulness of the proposed BILP scheduling optimization model and to capture the effect of experimental factors on the obtained appliance schedule, an experimental design is developed based on four main factors. The four experimental factors considered in the design are presented in this section. Table 2 provides details about the levels used for each factor and how these levels are realized in the optimization model.

3.1. Problem size

Problem size (Size) reflects the number of appliances considered in the case study. Two case studies are used to assess the performance of the BILP scheduling optimization model. The first case study is based on real data from one urban household in South Africa [24]. The second one is an artificial and enormous case study, and is used to test the proposed model under large-scale problem conditions. In the large-scale case study, an additional 10 appliances are considered along with the 10 appliances considered in the small-scale case study. The upper half of Table 3 represents the small-scale case study (L) and the whole table represents the large-scale case study (H). Furthermore, all parameters for each appliance are summarized in Table 3.

Generally, the tariff used is based on South Africa's TOU tariff for residential consumers. The TOU tariff peak and off-peak data are: C_t (peak) = R1.4452 and C_t (off-peak) = R0.4554. Eskom's peak times are 07:00 – 10:00 and 18:00–20:00 [33]. The hourly charge is discretized based on the sampling time (the applied time-slot Δt), and the optimization is over a 24-h period. An assumed incentive of V_t = R0.2/kWh is used, guided by the reference [24]. The scheduling is achieved by deciding whether to turn on the appliance at the beginning of each time-slot.

Table 3 shows the values of the model input parameters such as: the power rating P_i, average operation time/duration D_i, the equivalent number of time slots N_i, and the operation range [S_i, E_i]. Practically, there some appliances which are continuously on/off, such as: the EWH, laptop and ceiling fan. Those appliances are exempted from the uninterruptible operation constraint. The optimal appliance schedule is bounded by the maximum cost that the consumer is willing to incur in one day (Q), which is not more than R25 (R denotes the South Africa currency, ZAR or rand) for the small-scale case study and R70 for the large-scale case study. The consumer's preferred schedule is included in Table 3.

3.2. Flexibility ratio

Flexibility ratio (FR) represents the average degree of flexibility in scheduling an appliance within the appliance operation range [S_i, E_i]. The wider the appliance operation range, the greater the flexibility ratio. First, the FR is calculated for each appliance as the number of time slots in the operation range for an appliance [S_i, E_i] divided by the required number of time slots to complete the normal operation of that appliance N_i. Then, the average FR for all appliances is calculated. In this paper, the FR factor is proposed and introduced to the knowledge area of the ELM problem and the RLSP. As shown in Table 2, there are two levels for the FR factor: low flexibility ratio (L) and high flexibility ratio (H). Table 3 shows the values of the operation ranges [S_i, E_i] based on the flexibility ratio level. For example, appliance 1 (Stove) is scheduled twice in a day for at least 30 and 50 minutes in the morning and evening, respectively. For the high FR case, it is to be switched on at any time from 5:00 to 7:00 and from 16:00 to 20:00, respectively. On the other hand, the operation range is tightened for the low flexibility case which eliminates the flexibility of the appliance load shifting. The low FR case is less flexible compared to the former. It proposes to commit stove usage any time from 6:00 to 7:00 and from 17:30 to 19:00 for the morning and evening, respectively. As another example, Appliance 2 (Microwave) is scheduled once a day for at least 10 min any time from 16:00 to 19:00 and from 17:40 to 18:10 for high and low FR, respectively. This implies a FR of (180/10 = 18) and (30/10=3) for the high FR and low FR, respectively. One of the practical reasons for this measure is that household with non-working family members may be willing to have a less strict operation range while working families or families with school-going children, may have to cook and use other appliances within more rigidly specified times.

3.3. Time slot

This study explores the full modeling power of the BILP mathematical model. Thus, this paper conducts a numerical study and demonstrates a typical scheduling scenario with three different values of time slot lengths. Time slot (Δt) represents the length of each time slot t. In this paper, one day is discretized into a prescribed number T of uniform time slots, so that the total number of time slots in a day depends on the value of Δt. As shown in Table 2, the three different values of time slot lengths (L, M and H) are 1, 5 and 10 minutes yielding 1440, 288 and 144 number of time slots in a day, respectively. Table 3 shows the number of the time slots N_i required for each appliance operation based on the value of Δt. For example, the operation duration D_i for Appliance 2 (Microwave) is at least 10 minutes, resulting in a requirement of 10, 2 and 1 time slots based on time slot length, respectively.

3.4. Weighting factor

The weighting factor (α) represents the relative importance of scheduling convenience (IC) within the objective function, where (1-α) is the weight for the EC term. The purpose of this experimental design is to allow the consumer to adjust the weighting of each term based on his own preferences. The effect of different combinations of weighting factors on cost and inconvenience are explored. Table 2 shows the five values for α that are used in this study.

Table 2: Factors and values for each factor level

Factor	Levels					Realization method
	L	L+	M	H-	H	
Size: Problem size (Number of appliances)	10				20	Two problem sets are deployed. The first case involves 10 appliances, as in the reference [24], whereas in the second case, this is extended to 20 appliances.
FR: *Flexibility ratio*	2.0				5.7	Two problem sets are developed. The first is with low flexibility ratio (around 2.0), and the second is with high flexibility ratio (around 5.7).
Δt: Time slot (minutes)	1		5		10	The input parameters and the model are adapted based on the value of Δt.
α: Weighting factor	0	0.25	0.5	0.75	1	This controls the value of the weighting factor α in the objective function.

Table 3: Appliances data

No.	Appliance	Power rating, P_i (KW)	$X_{i,t}$	Duration, D_i (min)	Duration, N_i (time slot) based on Δt			*Operation range*			
								Low Flexibility		*High Flexibility*	
					L	M	H	ST_i	ET_i	ST_i	ET_i
1	Stove	3.000	6:00-6:30	30	30	6	3	6:00	7:00	5:00	7:00
			17:50-18:40	50	50	10	5	17:30	19:00	16:00	20:00
2	Microwave	1.230	17:50-18:00	10	10	2	1	17:40	18:10	16:00	19:00
3	Kettle	1.900	6:20-6:30	10	10	2	1	6:10	6:40	5:30	7:30
			18:00-18:10	10	10	2	1	18:00	18:30	17:40	20:00
4	Toaster	1.010	5:00-5:10	10	10	2	1	5:00	5:30	5:00	7:00
5	Steam iron	1.235	17:50-18:40	48	48	10	5	17:30	19:10	16:00	21:00
6	Vacuum cleaner	1.200	8:50-9:20	30	30	6	3	8:30	9:30	8:00	10:20
7	Electric Water Heater (EWH)	2.600	4:00-6:00	120	120	24	12	4:00	7:00	4:00	8:10
			17:20-19:20	120	120	24	12	17:00	21:00	16:00	22:00
8	Dishwasher	2.500	19:40-22:10	150	150	30	15	19:40	23:00	19:40	24:00
9	Washing machine	3.000	18:20-19:10	45	45	9	5	17:30	19:30	16:00	22:00
10	Tumble dryer	3.300	19:50-20:20	30	30	6	3	19:10	20:20	16:00	20:20
11	Cooker hood	0.2	18:00-19:00	60	60	12	6	17:30	19:30	16:00	20:50
12	Rice-Cooker	0.85	12:00-13:00	60	60	12	6	11:30	13:30	9:00	14:00
13	Blender	0.3	17:40-18:10	30	30	6	3	17:10	18:10	16:00	18:30
14	TV	0.3	17:00-22:00	300	300	60	30	17:00	23:00	17:00	24:00
15	Laptop	0.1	18:00-21:00	180	180	36	18	18:00	23:00	15:00	24:00
16	Desktop PC	0.3	18:00-23:00	300	300	60	30	17:00	23:00	14:00	24:00
17	Ceiling fan	0.1	11:00-13:00	120	120	24	12	9:00	14:00	7:00	20:00
18	Hairdryer	1.5	6:40-6:50	10	10	2	1	6:30	7:00	5:30	7:00
19	Phone charger	0.015	6:10-7:10	60	60	12	6	5:30	7:20	5:00	7:30
			17:30-18:30	60	60	12	6	17:00	19:00	16:00	19:30
			22:30-23:30	60	60	12	6	22:00	23:30	22:00	24:00
20	Car charger	5.2	1:00-4:00	180	180	36	18	1:00	5:00	1:00	7:00
			16:00-20:00	180	180	36	18	15:00	20:00	15:00	24:00

4. Experimental results

The experimental design consists of 60 different scenarios. The proposed BILP mathematical model describes the RLSP as solved optimally for each scenario with the commercial optimization solver LINGO 12.0 (LINDO Systems Inc.). All tests were run on an Intel Core i5 (2.6 GHz) with 4 GB of RAM, running under Windows 7. The comparisons in this experimental analysis are based on three performance measures, namely electricity cost and incentives (EC), inconvenience (IC) and computation time (CPU). The effect of each of the experimental factors is represented and analyzed for each of the three performance measures.

To illustrate the significance of the proposed model, a basic comparison is carried out between the consumer's preferred schedule, the schedule developed by Setlhaolo et al. [24] using their MINLP model, and the optimal schedule obtained from the proposed BILP model. This comparison is conducted for the high flexibility-small size case at the weighting factor (α) = 0.1 and time slot (Δt) of 10 minutes. Results showed that the proposed schedule could reduce the total EC by around 55% compared to the preferred schedule (from R23.5 to R10.5). Furthermore, it could reduce the total EC by around 31% compared to the schedule from Setlhaolo et al. [24] (from R15.1 to R10.5). In addition, and from the perspective of computation time, the proposed BILP model showed a significant superior performance. In order to conduct such a comparison, the authors formulated and solved their model using the same solver LINGO 12.0 (LINDO Systems Inc.) and on the same machine Intel Core i5 (2.6 GHz) with 4 GB of RAM, running under Windows 7. Based on Setlhaolo et al. [24] MINLP formulation, a solution (with optimality gap around 0.05%) required approximately 56:41 minutes (3401 seconds), while the proposed BILP model required only 2 seconds to provide the optimal solution, which means a reduction of 99.94% in computation time. Furthermore, the number of variables used in the MINLP model developed by Setlhaolo et al. [24] is about two thirds the number of variables in the BILP model proposed in this paper. Also, the number of constraints used in the proposed BILP model is about five times more than that of Setlhaolo et al. [24]. Actually, this matches the fact that the procedures for "linearizing" nonlinear integer problems typically involve a radical increase in the number of problem variables and constraints. Except that, the proposed BILP model could be solved optimally within few seconds.

Tables 4 and 5 present comparisons between the results obtained for all combinations based on four performance measures: the EC, the EC reduction percentage, the IC and the CPU. They summarize the results obtained for all combinations for the small-scale and large-scale scenarios, respectively. The value of the EC reduction percentage is defined as the difference between the EC for the consumer's preferred/baseline appliances schedule and the EC for the optimal schedule obtained by the BILP for the same problem setting divided by the former and multiplied by 100. The value of the EC for the consumer's preferred/baseline appliance schedule is R23.47 and R66.71 for the small-scale and large-scale case studies, respectively. Furthermore, the results of the low and high FR are represented for the small-scale and large-scale cases. Figure 1 illustrates the impact of the FR on the obtained appliances schedules. In order to study the effect of the four design factors on the three performance measures, the main effects plots are drawn in Figures 2 to 4.

4.1. The electricity cost related experimental results

The effect of the four experimental factors on the electricity cost were investigated, and the result for each factor are discussed in the following sub-sections.

4.1.1. The effect of problem size on the electricity cost

Problem size has a significant positive effect on the EC measure. The average electricity cost for the small-scale and large-scale case studies is R15.40 and R32.99, as shown in Table 4 and Table 5 respectively. Furthermore, Figure 2 illustrates the significant impact of problem size on the EC performance measure.

4.1.2. The effect of flexibility ratio on the electricity cost

Flexibility ratio has a moderate negative effect on the EC measure. For the small-scale case study, the electricity cost could be reduced on average by 29.9% with low flexibility ratio. However, it could be reduced on average by 40.8% with high flexibility ratio as shown in Table 4. This emphasizes the effect of flexibility ratio on the EC. For the large-scale case study, the effect of flexibility ratio on the electricity cost is less obvious. High flexibility could increase the average EC reduction from 48.9% to 53.4% as shown in Table 5. Figure 2 illustrates the impact of flexibility ratio on the EC performance measure. Figure 1 shows how the schedule of some appliances is affected by the FR. With higher FR (H), there is sufficient allowance for an appliance to be used outside of peak time, which reduces electricity cost. For example, the schedule of the stove in the low flexibility (L) scenario includes two time slots in the peak time. In the high flexibility (H) scenario, the stove schedule is moved completely off-peak which reduces EC.

4.1.3. The effect of time slot length on the electricity cost

Results show that the time slot length has no impact on the EC performance measure as depicted in Figure 2. This conclusion matches the results of the reference [16], where they concluded that the time slot length has minimal effect on the optimal cost.

4.1.4. The effect of weighting factor on the electricity cost

Weighting factor has a significant positive effect on the EC measure. The weighting factor (α) represents the relative importance of the IC term in the objective function. Consequently, less importance (1-α) is given to EC. This justifies the effect of the α on the EC. With higher values of α, the obtained schedule matches the preferred/baseline schedule more closely whatever the resulting cost. The results showed that there are no significant differences between the EC for α values between 0 and 0.5; however, there are significant differences above this range. Figure 2 shows that the average EC climbed sharply from around R20 to R35 over the earlier range of α.

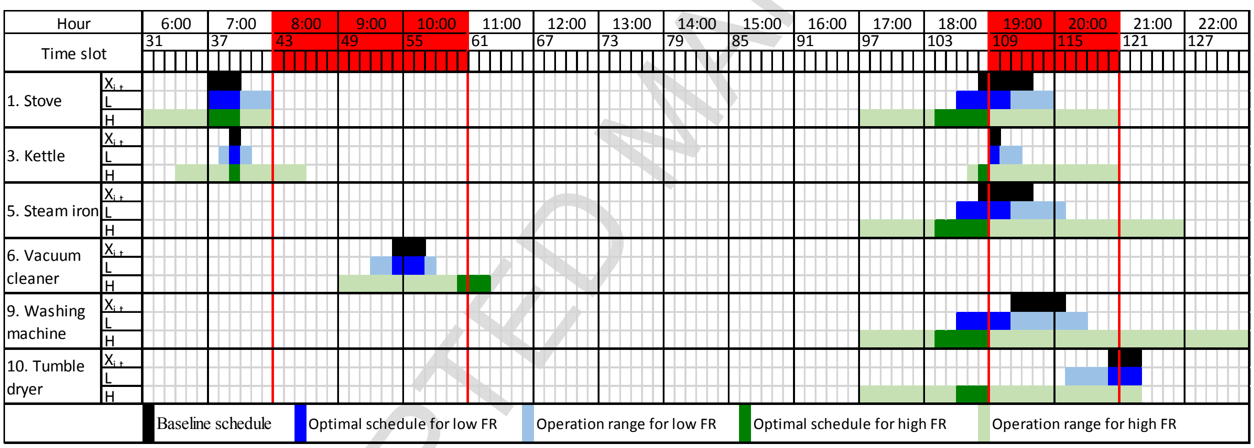

Fig. 1: Examples for the impact of the FR on appliance schedule

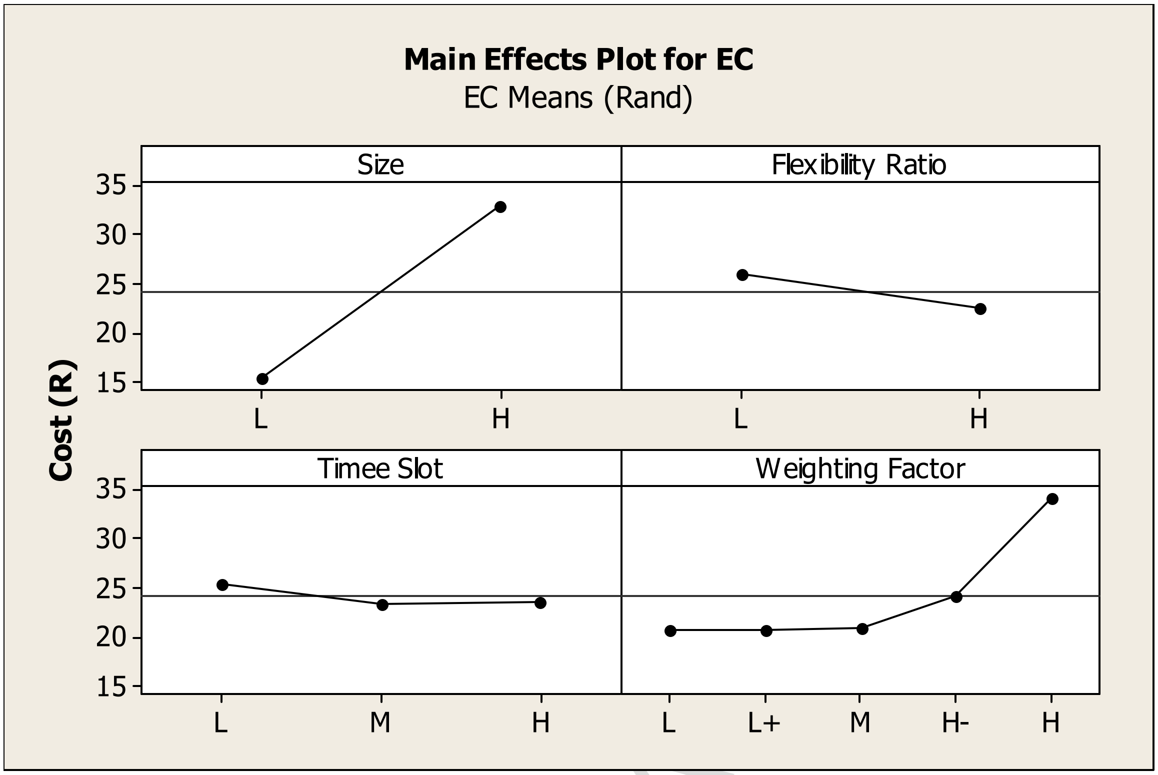

Fig. 2: Main effect plots for the EC

4.2. The inconvenience related experimental results

The effect of the four experimental factors on the inconvenience were investigated, and the result for each factor are discussed in the following sub-sections.

4.2.1. The effect of problem size on the inconvenience

Problem size has a moderate positive effect on the IC measure. As shown in Tables 4 and 5, the average inconvenience almost doubled from around 1690 to 3370 for the small-scale and large-scale case studies, respectively. Furthermore, Figure 3 illustrates the moderate impact of problem size on the IC performance measure.

4.2.2. The effect of flexibility ratio on the inconvenience

While flexibility ratio has a moderate negative effect on the EC measure, it has no effect on the inconvenience as depicted in Figure 3. However based on Figure 1, Table 4 and Table 5, FR may have a slightly negative effect on inconvenience, though this is not obvious.

4.2.3. The effect of time slot length on the inconvenience

Although Figure 3 shows that time slot length has a negative impact on IC, it has no effect on the real schedule. This is a result of using shorter time slots which magnifies the number of time slots for the same time segment. For example, one 10-minute-time-slot mismatch results in an inconvenience value of 1; however, it results in an inconvenience value of 5 or 10 for the M and L time slot scenarios, respectively.

4.2.4. The effect of weighting factor on the inconvenience

Weighting factor has a significant negative effect on the IC performance measure. This is because the weighting factor (α) represents the relative importance of the IC term in the objective function, which justifies the effect of the α on the IC. With higher values of α, the obtained schedule more closely matches the preferred/baseline schedule, which significantly reduces the inconvenience. Results showed that there are significant differences between the IC values where α is in the range of 0-0.5 (L, L+ and M); however, there are no significant differences over this range (M, H- and H). Figure 3 shows that the average IC declined sharply over the former range of α.

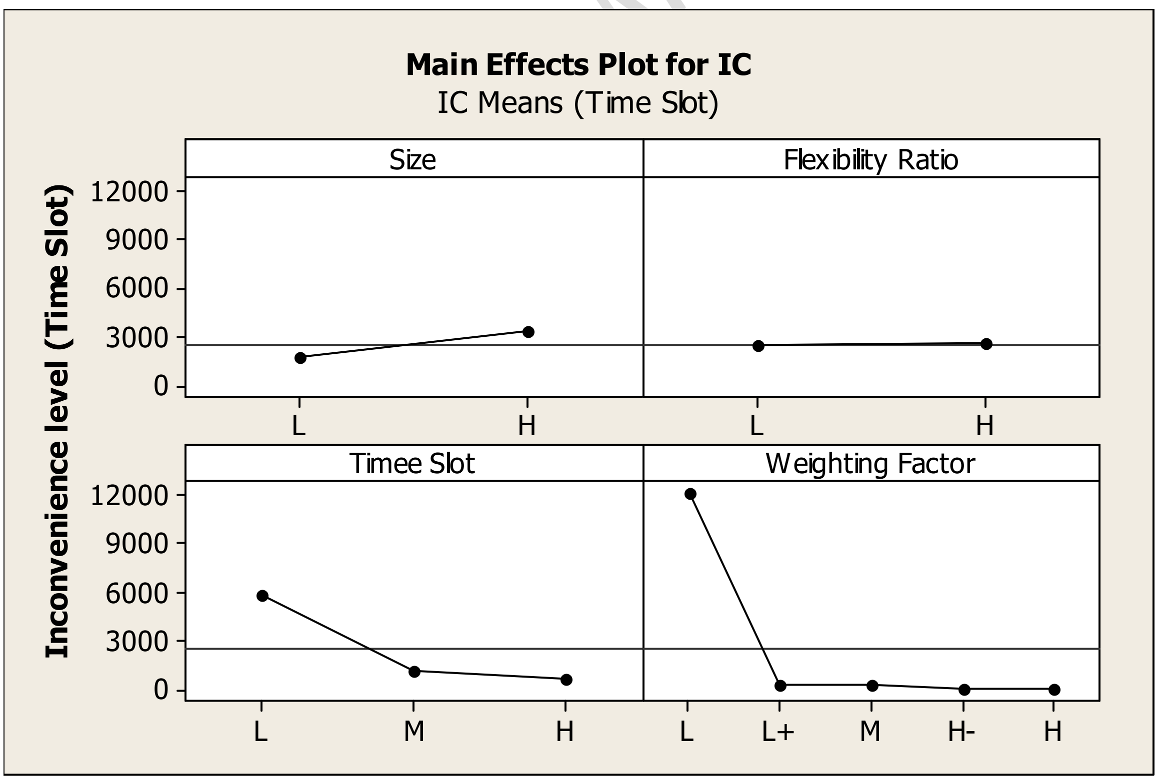

Fig. 3: Main effect plots for the IC

4.3. The computation time related experimental results

The effect of the four experimental factors on the computation time were investigated, and the result for each factor are discussed in the following sub-sections.

4.3.1. The effect of problem size on the computation time

Although the experimental results show that the developed BILP optimization model could guarantees an optimal solution for all combinations, problem size has a significant impact on the CPU measure. The average computation time over all combinations for the small-scale case is around 114 seconds. This computation time climbed sharply to 1215 seconds for the large-scale case, as shown in Tables 4 and 5 respectively. Furthermore, Figure 4 illustrates the significant impact of problem size on the CPU performance measure.

4.3.2. The effect of flexibility ratio on the computation time

Flexibility ratio has a significant positive effect on the CPU measure. For the low flexibility case, the average CPU over all combinations is around 89 seconds. However, it is around 10 times greater for high flexibility ratios (804 seconds) as depicted in Figure 4. This emphasizes the effect of flexibility ratio on CPU. High flexibility increases the search space of the RLSP, which makes the BILP optimization model consumes much more time searching for the optimal schedule.

4.3.3. The effect of time slot length on the computation time

Results showed that time slot length has a significant impact on the CPU performance measure as depicted in Figure 4. Using a shorter time slots increases the number of time slots which consequently enlarges the problem size. This conclusion matches the results of the reference [16], where they conclude that time slot length has a significant impact on computation time.

4.3.4. The effect of weighting factor on the computation time

Figure 4 shows that computation time increased sharply for the medium level of the weighting factor (α). With equal weighting value ($\alpha = 0.5$) for the EC and the IC, the BILP model consumes much more time to compromise between both electricity cost and scheduling inconvenience.

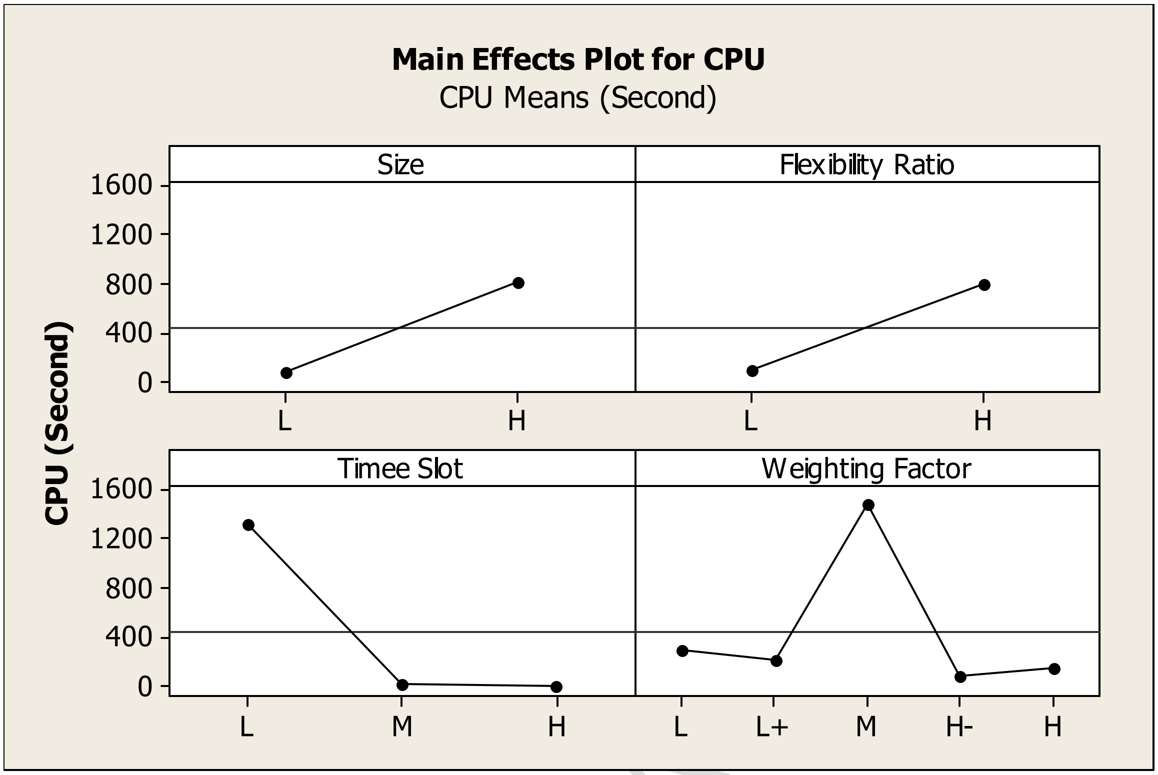

Fig. 4: Main effect plots for the CPU

4.3.5. The interaction effect on the computation time

In order to investigate the interaction effect of the four design factors on the computation time performance measure, the interaction plots for CPU is illustrated in Figure 5. It emerges that the flexibility ratio slightly increases CPU for small-scale problems; however, it's impact is significant for the large-scale case. Also, the effect of time slot length is minimal in the small-scale case and the low flexibility rate scenario. However, it's effect is significant in the large-scale case and the high flexibility ratio scenario. Furthermore, the dramatic increase in computation time is obvious in large-scale cases, high flexibility ratio scenarios, and instances in which time slot length is low.

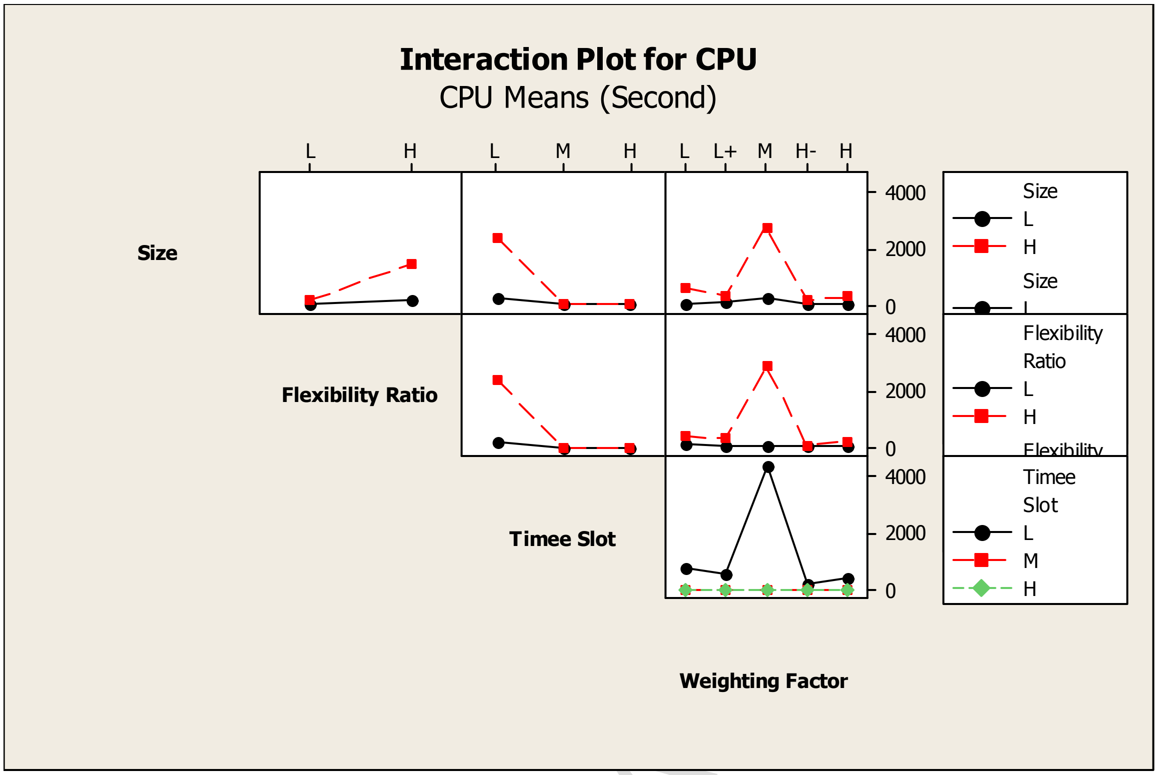

Fig. 5: Interaction effect plots for the CPU

Table 4: The small-scale case study numerical results

Comb. #	Δt	α	Low Flexibility ratio				High Flexibility ratio			
			EC		IC (Slots)	CPU (Sec.)	EC		IC (Slots)	CPU (Sec.)
			Cost (R)	% Reduction			Cost (R)	% Reduction		
1	L	L	14.47	38.4	18720	42	10.44	55.5	18720	47
2	L	L+	14.47	38.4	370	71	10.44	55.5	586	522
3	L	M	14.47	38.4	370	64	10.92	53.5	526	1244
4	L	H-	23.05	1.8	0	59	23.05	1.8	0	194
5	L	H	23.05	1.8	0	58	23.05	1.8	0	63
6	M	L	14.53	38.1	3744	6	10.45	55.5	3744	11
7	M	L+	14.53	38.1	74	3	10.45	55.5	118	7
8	M	M	14.53	38.1	74	3	10.45	55.5	118	8
9	M	H-	14.53	38.1	74	3	10.45	55.5	118	7
10	M	H	23.11	1.5	0	3	23.11	1.5	0	4
11	H	L	14.89	36.6	1872	1	10.51	55.2	1872	2
12	H	L+	14.89	36.6	38	1	10.51	55.2	60	2
13	H	M	14.89	36.6	38	1	10.51	55.2	60	2
14	H	H-	14.89	36.6	38	1	10.51	55.2	60	2
15	H	H	23.47	0.0	0	1	23.47	0.0	0	2
Average				**29.9**		**21**		**40.8**		**141**
Average Cost for the small-scale case					**R15.40**					
Average IC for the small-scale case					**≈ 1690 time slots**					
Average CPU for the small-scale case					**114 second**					

Table 5: The large-scale case study numerical results

Comb. #	*Δt*	*α*	*Low Flexibility ratio*				*High Flexibility ratio*			
			EC		IC	CPU	EC		IC	CPU
			Cost (R)	% Reduction	(Slots)	(Sec.)	Cost (R)	% Reduction	(Slots)	(Sec.)
1	L	L	31.25	53.2	37440	1062	26.29	60.6	37440	2196
2	L	L+	31.56	52.7	530	307	27.53	58.7	666	1572
3	L	M	31.56	52.7	530	308	28.00	58.0	606	16168
4	L	H-	38.95	41.6	200	307	37.10	44.4	220	449
5	L	H	45.73	31.5	80	308	45.31	32.1	80	1294
6	M	L	31.31	53.1	7488	12	26.28	60.6	7488	171
7	M	L+	31.32	53.1	158	10	26.29	60.6	294	43
8	M	M	31.56	52.7	110	10	27.12	59.3	170	26
9	M	H-	31.62	52.6	106	10	27.54	58.7	142	10
10	M	H	45.49	31.8	16	11	44.00	34.0	16	7
11	H	L	31.67	52.5	3744	3	26.34	60.5	3744	44
12	H	L+	31.68	52.5	80	3	26.35	60.5	148	8
13	H	M	31.92	52.2	56	3	26.59	60.1	124	11
14	H	H-	31.98	52.1	54	2	27.60	58.6	72	4
15	H	H	45.55	31.7	8	3	44.36	33.5	8	3
Average				**48.9**		**157**		**53.4**		**1467**
Average Cost for the large-scale case					**R32.99**					
Average IC for the large-scale case					**≈ 3370 time slots**					
Average CPU for the large -scale case					**1215 seconds**					

5. Conclusion

This study discussed an experimental study of the home appliance scheduling problem that incorporates realistic aspects. This paper has examined the factors that might affect the scheduling of residential loads and has tested the performance of the proposed BILP optimization model under different experimental scenarios. It has also proposed a conceptual definition of a new parameter in the home appliances scheduling problem, the so-called "flexibility ratio". Furthermore, the paper presented a data set for future use in literature pertaining to the home appliance scheduling problem. It was found that the objective function minimized the weighted sum of electricity cost (and earned the relevant incentives) and scheduling inconvenience.

In comparison to the preferred schedule defined by the consumer, the experimental results showed that the BILP optimization model could reduce electricity costs by around 35% (from R23.47 to R15.4) for the small-scale case study and by around 50% (from R66.71 to R32.99) for the large-scale case study. Numerical experiments were conducted which showed that the BILP model solution outperforms the MINLP model solution. An electricity cost saving of 31% compared to the schedule resulting from the MINLP model (from the literature) can be realized. Furthermore, the BILP model reduced the computation time in a significant superior way. Furthermore, the results showed that the problem size, flexibility ratio and objective function weighting factor have a significant effect on EC. However, only problem size and objective function weighting factor have a significant effect on IC. Also, the results illustrate that all four factors have a significant interaction effect on the model computation time.

In future research, uncertainty in appliance operations time should be considered, the length of usage duration could be different from consumer to another and from time to time. Also, non-linearity of scheduling preferences should be modeled, i.e., by considering different preference weights to each of the appliances at a time. Extending the model to consider multi-consumer is an important aspect, which would enable leveling and analyzing the peak loads on a micro-grid level. Furthermore, a dynamic load scheduling system should be developed to enable customers, utility companies and policy makers to use it and take decisions on real-time.

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Optimal load scheduling of household appliances considering consumer preferences: an experimental analysis

Highlights

- The proposed model could eliminate electricity cost by around 35% to 50%.
- The proposed linear formulation can reduce the computation time in a superior way.
- Flexibility ratio has a moderate negative effect on cost function and inconvenience.
- Flexibility ratio has a significant positive effect on the computation time.
- Short time-slot enlarges the problem size and has a significant impact on computation time.