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Optimal scheduling of household appliances with a battery storage system and coordination

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ABSTRACT

This paper demonstrates an optimal household appliance scheduling problem with a battery as an energy storage system under time of use electricity tariff. Power consumption measurements of individual appliances considered were performed and demand profiles were obtained. In this work, a mixed integer nonlinear programming mathematical model with more practical operation constraints for appliance and battery scheduling is formulated and solved. The simulation results show effectiveness of the algorithm in that by optimally scheduling appliances and battery, cost saving, peak shaving and valley filling are achieved through load shifting. The energy cost saving that might be beneficial to consumers; and peak shaving and valley filling, which are of great importance to the utility. It is found that consideration of appliance coordination yields smaller cost saving because of interdependent operation. Without the battery and coordination, a cost saving of 22% and peak reduction from 10.355 kW to 8.405 kW are realized. Consideration of appliance coordination gives a further cost saving of 1% and a relatively smaller peak reduction to 8.30 kW. The battery bank system promotes peak shaving and valley filling and a further cost saving of about 6% and peak reduction to 5.175 kW. Sensitivity analysis, however, reveals that the energy cost saving is sensitive to consumer's willingness to pay.

1. Introduction

Energy consumption in the residential sector accounts for more than 18% of total electricity demand in South Africa[1] [1,2]. According to the US Energy Information Administration's 2013 Annual Energy Outlook report,[2] the residential sector currently makes up 20% of total energy demand and is increasing by 24% worldwide. This shows that residential energy use makes up a sizeable portion of the energy pie. Since demand response (DR) was initially created to manage peak load, it has been found in the USA that the residential segment simply cannot be ignored as part of any utility's energy management strategy.[2] Residential DR (RDR) diverts money that would generally go to a fossil fuel power plant to homeowners instead through peak shifting/shaping and better management of demand. Literature extensively covers the definition and different types of DR programs and the reader is referred to the references[3] [3].

Battery energy storage systems (BESS) are an option to provide peak shaving and valley filling of the residential load profile [4,5]. Electric vehicles and conventional batteries have over the years been used as residential energy storage devices [5–7]. There are two main applications of BESS in the residential sector. First is the off-grid hybrid energy solution, where integrated operation of two or more different types of renewable energy sources and a storage device is employed. This method is mostly applied to rural settlements where there is no access to the grid power [8–10]. This has been extensively studied in literature [9,10]. The second application of BESS is a backup system for a household connected to the grid.[4] This application is motivated by unreliable and intermittent electrical power supply. In this application the BESS is connected to the grid. It can be available as a compact backup electronic power supply system, uninterruptible power supply (UPS). Usually in an African set-up, buying a UPS is not affordable to many because of its high cost due to its technological enhancement features such as

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[1] The Eskom factor: Power politics and the electricity sector in South Africa, Greenpeace report, 2012. http://www.greenpeace.org.

[2] Residential demand response infographic. http://www.comverge.com.

[3] FERC, Demand response compensation in organized wholesale energy markets, FERC Docket RM101700, 18 March 2010. http://www.ferc.gov.

[4] PowerGen renewable energy http://powergen-renewable-energy.com/.

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0378-7788/

Nomenclature

i	appliances index
t	index of the time period
A	total number of appliances
T	the control horizon (24 h)
Δt	sampling time (10 min)
P_i	rated power of appliance i (kW)
N_i	duration of appliance i being on (min)
k_i	additional run time of appliance i (min)
η_c	battery charging efficiency
η_d	battery discharge efficiency
ρ_t	time of use electricity price at time t (R)
C	the maximum cost that the consumer is willing to pay (R)
d_i	the on-time start of appliance i
e_i	the on-time end of appliance i
$u_{i,t}^{bl}$	baseline on/off status of appliance i at time t
$u_{i,t}$	the switching status of the ith appliance at time interval t
SOC	state of charge of the battery
E_t	state of the battery at time t (kWh)
E_0	the initial state of charge of the battery at time t
E^{min}	minimum allowable battery capacity (kWh)
E^{max}	maximum allowable battery capacity in (kWh)
$\underline{P}_{b,t}$	the battery charging power (kW)
$\overline{P}_{b,t}$	the battery discharging power (kW)
DOD	depth of discharge
$P_{m,t}$	grid power at time t (kW)
$P_{A,t}$	power demanded by all appliances excluding battery at t (kW)
$P_{D,t}$	total power demanded from the grid t (kW)
P_D	the total power demanded from the grid in a day (kW)
$Rand(R)$	South African currency (1 Rand = 0.086USD), as at 02 Feb. 2015.

longer life and less maintenance. The ideal solution is to build the system. These systems can be designed in any size, based on the application.

This paper presents the household energy cost minimization problem through appliance scheduling with a battery as a grid-connected storage device in order to promote further energy balance in the power system network and save consumer cost. The motivation for consumers to participate in DR programs is to minimize energy cost because DR allows energy users of all kinds to act as "virtual power plants," adding stability to the grid by lowering their demand for electricity. Participants get paid for providing demand response capacity[5] [3]. The contribution of this paper is the formulation of a practical mixed integer nonlinear program (MINLP) optimization model with more practical operational constraints for a household to determine the optimal scheduling of household appliances under time of use (TOU) electricity prices with a battery as a storage device. Literature has to some extent provided related work, albeit with some shortfalls. In contrast to references [5,6], our study focuses on a single household and we formulate a cost minimization optimization mathematical model under a demand response program with time differentiated electricity tariff. The model also presents scheduling of household appliances. Both references however do not provide an optimal solution to the problem. Similar work is demonstrated in [7], where appliance scheduling is considered with a battery storage and PV system. In contrast to the reference, which models the household scheduling problem as a mixed integer programming (MIP) problem, we formulate the problem as a more complex and practical problem as an MINLP optimization mathematical model. In our work, the nonlinearity of the problem is brought by the inconvenience, continuous operation of appliances and the battery exclusive operation, which are not captured in the paper. We have, in addition, incorporated coordination of appliances that are not modeled in [7]. These constraints are crucial to the appliance scheduling problem because practically appliances do not operate in isolation. In the reference, the objective function shows that the consumer is charged for both charging and discharging of the battery. This is in contrast with the practical situation because the consumer is only billed for charging the battery. The power balance equation is also not presented in the reference, though it is crucial to ensure a system power balance. [11] provides a study on scheduling of appliances using physical models where the activation of appliances is controlled by a proposed scheduling policy; a storage device is not considered. In [12], the optimization model considers activity scheduling of the electric vehicle against the aggregated appliance schedule. The shortfall of this model is that the specific appliances considered are not stated and the objective function excludes the inconvenience level that gauges the disparity between the baseline and optimal schedule. The model also excludes the switching status of appliances under consideration and the sampling time of 1 h is not practical for household appliance scheduling. The model also excludes a number of practical constraints, such as appliance operation time, appliance continuous operation and coordination. This work demonstrates the use of the battery for both peak shaving and valley filling, and a sampling time of 10 min is used. This may promote behavior change as a result of a shorter waiting period. Experimental work has been performed to validate the performance of the algorithm.

In this work, sensitivity analysis is performed to determine the effect of the customer's willingness to pay on the energy cost saving. Sensitivity analysis is used to determine how sensitive the solution is to changes in the value of the parameters of the model [13]. This analysis has not been performed in any of the literature in this area.

The remainder of this paper is structured as follows: Section 2 gives the problem layout. Section 3 focuses on the formulation of the optimization model. Section 4 presents the data. Section 5 presents the solution method based on solving integer constraint problems (SCIP) algorithms. Measurement and simulation results are discussed in Section 6 and lastly a conclusion is drawn.

2. Problem description

The layout of the problem is shown in Fig. 1. The energy flows are indicated by the arrows. The reader will notice that the battery bank consumes power from the mains. This will happen during off-peak times, while it feeds the load during peak times.

The optimal control problem of household appliance scheduling with storage entails control inputs as the energy demand, the desired time of starting and completing tasks, appliance rated power, the baseline schedule, TOU tariff, battery input and output efficiencies, as well as capacity. The control decisions are the scheduling status of appliances, power flows from the grid and battery state of charge (SOC), which has battery charging and discharging power as control variables. The main objective is to determine the minimum cost of scheduling these appliances and the battery, taking into account the necessary constraints and inconvenience level. This problem is of great importance because worldwide research on DR, of which the main purpose is to reduce energy consumption, particularly during peak times, has opened new possibilities

[5] Enernoc http://www.enernoc.com/.

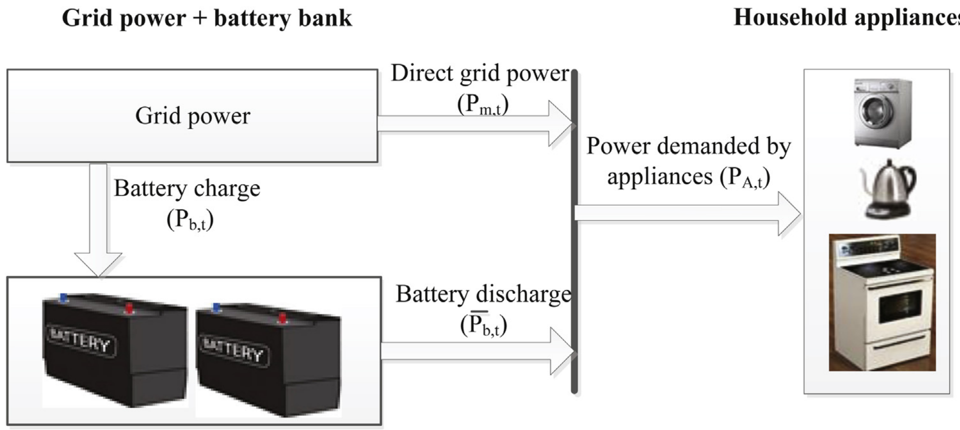

Fig. 1. Layout of the presented problem.

for advanced planning and control of supply and demand, especially at residential level where appliance scheduling plays a major role. A major benefit of scheduling is that users can compare the cost benefit among different inconvenience levels that come with an optimal solution against baseline schedule [14].

3. Mathematical model formulation

3.1. Optimization model

In this section, we formulate the mathematical model as an MINLP optimization problem for the household appliance scheduling problem with a battery as storage device. First we present the energy cost model, then the battery model and finally we formulate the problem's objective function, incorporating the battery and scheduling inconvenience.

3.1.1. Energy cost

An electricity-consuming household's objective is to minimize its electricity cost during a dynamic price tariff. The current work is an improvement of our previous work [14] and those of [15–17] in that a number of practical operational constraints have been incorporated and the battery has been considered.

$$J_e = \sum_{t=1}^{T}\sum_{i=1}^{A} P_i \Delta t \rho_t u_{i,t}, \tag{1}$$

$$P_i > 0, \quad \rho_t > 0, \quad i = 1, \ldots, A, \quad t = 1, \ldots, T,$$

$$u_{i,t} = \begin{cases} 1, & \text{when appliance } i \text{ is on at } t; \\ 0, & \text{when appliance } i \text{ is off at } t; \end{cases}$$

where the notations are listed and described in the nomenclature. In a household scheduling problem there are three main types of constraints: appliance operation time, continuous operation and maximum cost or maximum energy constraint. Additional constraints can be added, such as; coordination, inconvenience and comfort constraints, if there are any [16,18]. The following constraints are formulated to the objective function (1):

(a) Maximum cost

$$\sum_{t=1}^{T}\sum_{i=1}^{A} P_i \rho_t u_{i,t} \Delta t \le C. \tag{2}$$

This constraint models the maximum cost that the consumer is willing to incur within the control horizon. The parameter C is obtained from the consumer's bill.

(b) Appliance operation time

Given the predetermined parameters d_i, e_i and N_i, in order to provide the needed consumption for each appliance, in times within interval $[d_i,e_i]$ it is required that,

$$\sum_{t=d_i}^{e_i} u_{i,t} = N_i + k_i, \forall i, \tag{3}$$

where $N_i \le (e_i - d_i)$ and $k_i \in \mathbb{Z}$ is the additional run time of appliance i. Note that this constraint has been modified from the standard one that appears in [14–18]. It now offers flexibility to consumers in that they can choose to increase or reduce the run time wherever possible. For example, if the estimated cooking time is 50 min, the consumer can choose to increase or reduce it by k_i.

(c) Appliance continuous operation

This constraint ensures continuous operation of appliances. The importance of this constraint is that it avoids interruption of appliance operation [19].

$$\sum_{t=d_i}^{e_i} u_{i,t} \cdot u_{i,t+1} \cdot u_{i,t+2} \cdots u_{i,t+(N_i-1)} = 1. \tag{4}$$

(d) Appliance coordination

Coordination between household appliance commitment is very important because some household appliances are committed relative to others, that is, operating one appliance may necessitate operating the other at the same or at a delayed time. The following algebraic constraint examples are used to model appliance coordination and reference is made to Table 1 for clarity.

Inequality (5) could be applied to an appliance with multiple operational tasks where the first task cannot be performed concurrently with the second one. This constraint is also applied to appliances that are not to be committed at the same time. An example from a set of laundry appliances would be a washer/dryer combination machine; the washing (with index $i = 10$) cannot be done at the same time as drying ($i = 11$).

$$u_{10,t} + u_{11,t} \le 1, \quad t = 1, \ldots, T. \tag{5}$$

Table 1
Appliances data.

No.	Appliance	Rated power, P_i (kW)	Run-time N_i (min)	Baseline $u_{i,t}^{bl}$ avg. $d_i - e_i$ (h)
Lights				
1	Kitchen	0.011		As kitchen appliances
2	TV room	0.011		As TV
3	Laundry room	0.011		As laundry appliances
Kitchen				
4	Dishwasher	1.8	150	115–129
5	Breadmaker	1.5	150	117–131
6	Stove	2.0	30, 50	31–33, 112–116
Swimming pool				
7	1 hp pump	0.75	120	103–114
Heating				
8	Space heating	2.4	120	108–119
9	EWH	3.0	120, 120	30–41, 103–114
Laundry				
10	Washing machine	2.0	60	108–113
11	Clothes dryer	2.0	30	115–117
Entertainment				
12	Television	0.133	180	103–120
13	DVD player	0.025	180	103–120
14	Decoder	0.07	180	103–120

The following inequality is necessary to ensure that, for example, the dryer follows the washing machine:

$$d_{10} + N_{10} \leq d_{11}. \tag{6}$$

If two appliances are on at the same time, such as the television ($i = 12$) and the decoder ($i = 14$), then the equality is modeled as,

$$u_{12,t} - u_{14,t} = 0, \qquad t = 1, \ldots, T. \tag{7}$$

If one appliance is off while the other is on, this is represented by the inequality constraint (11). An example would be a DVD player and a decoder. The DVD player ($i = 13$) is off when the decoder is on with the same television set. This is represented by;

$$u_{13,t} + u_{14,t} \geq 1, \qquad t = 1, \ldots, T. \tag{8}$$

An example of a television being off, then the DVD player is off, is represented by (12). Another example would be television room lights being switched off when the television is off.

$$u_{13,t} = 0 \quad \text{if}\, u_{12,t} = 0 \tag{9}$$

To coordinate the lighting with the appliances used in their respective rooms, we use the constraint with reference to the laundry room, as indicated in Table 1. The only time the laundry lights are off is if neither the washing machine nor the dryer is on.

$$u_{3,t} = \begin{cases} 1, & \text{when}\, u_{10,t} \quad \text{or} \quad u_{11,t} = 1, \\ & or\, u_{10,t} = u_{11,t} = 1, \\ 0, & \text{when}\, u_{10,t} = u_{11,t} = 0. \end{cases} \tag{10}$$

(e) Appliance power consumption limits

$$0 \leq P_{i,t} \leq P_i^{\max}. \tag{11}$$

3.1.2. Battery model

In our current work it is assumed that the household under study has a battery bank as a storage device. The BESS is characterized by continuous charging and discharging power, therefore $P_{b,t}$ and $\overline{P}_{b,t}$ are considered continuous variables. The general battery dynamics are presented by the battery's state of charge (SOC) [19,20];

$$E_t = E_0 + \eta_c \sum_{\gamma=1}^{t} P_{b,t} \Delta t - \eta_d \sum_{\gamma=1}^{t} \overline{P}_{b,t} \Delta t, \quad 1 \leq t \leq T, \tag{12}$$

where E_t is the SOC of the battery, E_0 is the initial SOC, whereas $\eta_c \sum_{\gamma=1}^{t} P_{b,t} \Delta t$ is the battery energy during the charging period and $\eta_d \sum_{\gamma=1}^{t} \overline{P}_{b,t} \Delta t$ is the battery energy during the discharge period. Note that at a time when the battery is consuming power, it is treated as an appliance, whereas during discharging it acts as a source. The objective is to minimize the cost of charging and maximize the cost of discharging the battery. Therefore the cost objective function for the battery is as follows:

$$J_b = \sum_{t=1}^{T} P_{b,t} \rho_t \Delta t, \tag{13}$$

with continuous control variables $P_{b,t}$ being the battery power during the charging period.

(a) Battery energy capacity limits

The battery capacity limits provide the upper and lower bounds to the battery capacity.

$$E^{\min} \leq E_t \leq E^{\max}, t = 1, \ldots, T, \tag{14}$$

where E^{min} and E^{max} are related through depth of discharge (DOD) as follows;

$$E^{\min} = (1 - \text{DOD}) E^{\max}. \tag{15}$$

(b) Avoiding charging while discharging

We consider that battery charging and discharging operations are mutually exclusive. Therefore the battery cannot charge and discharge at the same time; the constraint below is applied. This constraint also allows the state of the battery to be idle while it is not charging or discharging.

$$P_{b,t} * \overline{P}_{b,t} = 0; \tag{16}$$

(c) System power balance

The power demanded by the load at time t should be met by both the discharging battery and the mains supply;

$$\overline{P}_{b,t} + P_{m,t} = P_{D,t}, \tag{17}$$

where

$$0 \le P_{m,t} \le P_m^{\max}.$$

$\overline{P}_{b,t}$ is the battery power during discharge, $P_{m,t}$ is the power from the grid and $P_{D,t}$ is the aggregated power demanded by the appliances together with the battery at time t. Without the battery, the power supplied by the grid is equivalent to the power consumed by the aggregated household load, $P_{m,t} = P_{A,t}P_{D,t}$. Aggregated power consumed by appliances excluding the battery is;

$$P_{A,t} = \sum_{i=1}^{A} P_i u_{i,t}, \tag{18}$$

while the aggregated consumption of the appliances and the battery is given by,

$$P_{D,t} = P_{A,t} + \eta_c P_{b,t}. \tag{19}$$

The total power consumption of appliances under consideration and the battery, P_D in a day is given by:

$$P_D = \sum_{t=1}^{T} (P_{A,t} + \eta_c P_{b,t}). \tag{20}$$

3.1.3. The inconvenience level

The scheduling inconvenience (I) seeks to minimize the disparity between the baseline and the optimal schedule [14]. The consumer therefore also minimizes the inconvenience given by:

$$I := \sum_{t=1}^{T}\sum_{i=1}^{A} (u_{i,t}^{bl} - u_{i,t})^2. \tag{21}$$

The baseline $u_{i,t}^{bl}$ is obtained from the measured results as shown in Table 1.

3.2. The overall objective

The inconvenience cost and the battery objective are incorporated in the main objective, therefore the final objective function that the consumer seeks to minimize is expressed as follows:

$$J = (J_e + J_b) + \alpha I \Delta t, \tag{22}$$

where J_e is the energy cost function as in (1) and J_b is the battery energy cost function as shown in (14). It is to be noted that the inconvenience as presented in (21) is a unit less value. Therefore to express all sub-functions within the overall objective function (22) with the same unit, there is a need to use some form of cost coefficient to express all sub-functions in the same units. In this work we use the tariff $\alpha = \rho(t)$ as an assumption.

The model obtained in (1)–(22) is the MINLP model with control variables $u_{i,t}$, $P_{b,t}$, $\overline{P}_{b,t}$ and $P_{m,t}$.

4. General data

4.1. Appliance data

A typical household in South Africa is used as a case study. Fourteen appliances are selected and studied and results are shown in Table 1. Field measurements are conducted to obtain baseline commitment and the profile of appliances under consideration. Appliance rated power is specified by the appliance manufacturers and can be obtained from the appliances. Data on appliance usage in the household under study were collected, as well as information on the allowable time duration required to finish the normal operation of the appliance, N_i. The information on d_i and e_i as the beginning and end of the time interval in which the appliance is scheduled is specified by the user, based on the usual or preferred usage. This is shown in the last column of Table 1 where, for example appliance 4, d_i = 115 (19:10) and e_i = 129 (21:30) are the average time ranges at which the appliance is normally switched on. This is typical of a working class household where most activities occur in the morning and after work. Appliances considered are shown with their rated power and normal operation time ranges. The baseline on appliance operation time is also shown.

4.2. Tariff

The tariff used is based on South Africa's TOU Homeflex 1 tariff structure for residential consumers. The Homeflex 1 tariff has five charge components[6] as service charge, network charge, environmental levy, peak charge and off-peak charges. We model these into fixed and variable charges as follows:

$$\rho_t = F_C + V_C,$$

where F_C is a fixed charge and consist of service charge, network charge and environmental levy, while V_C are peak and off-peak energy charges.

$$F_C = R(2.96 + 3.68 + 2.00)/100,$$

and

$$V_C = \begin{cases} R1.7487, & \text{peak time}, t \in [07:00, 10:00), [18:00, 20:00) \\ R0.5510, & \text{off-peak time}, t \in [00:00, 07:00), [10:00, 18:00], [20:00, 00:00]. \end{cases}$$

4.3. Battery data

The household under consideration is assumed to have a battery bank consisting of lead acid batteries, which are the most common devices used to store energy because of their relatively low price, relatively low investment cost, high availability, reasonable performance and life characteristics [20]. Most literature states that the lead acid battery has a discharge efficiency of 100%, whereas the charging efficiency is in the range of 65–85% [5,20,21]. A point to note about the battery is that for it to work with an AC network, there has to be conversion and inversion from AC to DC and DC to AC. It is acknowledged that there are some losses within these electronic modules. However, for our work the net efficiency has been used, that is, converter/battery as charging efficiency and battery/inverter as discharging efficiency. Therefore the battery data used are shown in Table 2. The minimum discharge capacity of 50% has been shown to sustain the lifespan of the battery [20].

[6] Eskom tariffs and charges 2011/2012. http://eskom.com.

Table 2
Battery data.

Battery capacity	10 kWh
η_c	75%
η_d	100%
DOD	50%

Table 3
Other data

Daily maximum bill (C)	R25
Maximum power from the grid (P_m^{max})	$230V * 60A * 0.75 * 0.5 = 5.2$ kW

Other data shown in Table 3 are the maximum cost that the consumer is willing to incur. This value is obtained from the consumer's bill. The maximum power from the grid has an assumed power factor of 0.75. It is assumed that the appliances considered can consume a maximum of 50% of the household maximum power at any time *t*.

A point to note on battery cost is that it entails capital cost, operational and maintenance (O&M) costs. Since our study horizon is one day, we only consider O&M costs. However, the impact of investment cost cannot be ignored during longer study periods [22–24]. In [25–27], the O&M cost of a lead acid battery has been estimated to a specific annual value or some online sources estimate the annual O&M cost to be less than or equal to 2% of capital cost. In this work, our estimate is guided by [25–27] that use a fixed value of 22 EUR/kW/year and we convert to a daily equivalent of R 0.8178 kW/day.

5. Solution methodology

Field measurements were conducted to obtain the baseline commitment and the profile of appliances under consideration. During these measurements the TOU tariff was used. The MINLP optimization problem (1)–(22) is solved with an optimization solver, SCIP, available in the Matlab interface OPTI toolbox. SCIP is currently one of the fastest non-commercial solvers for MIP and MINLP. It is also a framework for constraint integer programming and branch-cut-and-price.[7,8] It uses Interior Point Optimizer (IPOPT) and SoPlex as nonlinear and integer algorithms. SoPlex is an advanced implementation of the revised simplex algorithm for solving linear programs. It features preprocessing, exploits sparsity, and provides primal and dual solving routines. It is the default LP solver in SCIP. IPOPT is an open-source solver for large-scale nonlinear programming. IPOPT implements a primal-dual interior point method and uses line searches based on filter methods.[7,9] The solver offers solutions to problems of the form:

$$\min f(x), s.t., \begin{cases} Ax \le b, A_{eq}x = b_{eq}(\text{linear constraints}) \\ c(x) \le d, c_{eq}(x) = d_{eq}(\text{nonlinearconstraints}) \\ Lb \le x \le Ub(\text{variable bounds}) \\ x_i \in \mathbb{Z}(\text{integer decision variables}) \\ x_j \in \{0, 1\}, i \ne j(\text{binary decision variables}) \end{cases}$$

The measured results are compared with simulation results to demonstrate the effectiveness of the algorithm.

[7] SCIP: Solving Constraint Integer Programs. http://scip.zib.de/.
[8] T. Berthold, et al., Solving mixed integer linear and nonlinear problems using the SCIP Optimization Suite, ZIB-Report 12-27 (July 2012), Takustraße 7, D-14195 Berlin-Dahlem, Germany. file:///C:/Users/User/Downloads/ZR-12-27%20(1).pdf.
[9] Opti Toolbox solvers. http://www.i2c2.aut.ac.nz/Wiki/OPTI/index.php/Solvers.

Fig. 2. Efergy E2 Classic energy monitor components.

Fig. 3. Connection at the DB.

6. Measured and simulation results

The consumption of the appliances considered is monitored using an Efergy E2 Classic energy monitor. The Efergy E2 Classic is a wireless electricity monitor that allows monitoring of electrical energy consumption trends over time in households. It includes an innovative software package that allows tracking energy usage on a computer. The measuring device has three components, as shown in Fig. 2, and a typical connection is shown in Fig. 3.

Sensor unit: The unit is clipped onto the electricity meter's feed cable for aggregated household energy measurement but for individual appliance measurements, it is connected to the live wire of the appliance three-core cable. This excludes the electric water heater (EWH), which is supplied directly at the distribution board (DB); hence its measurements are made at the DB. *Transmitter unit*: The transmitter links to the sensor cable and sends information to the display unit. This unit captures data at least every 6 s. *Display unit*: The unit displays the information on energy usage and demand profile and the cost of the energy in monetary units being consumed. The numerical hourly average data are provided for analysis. This device is kept at a distance of not more than 70 m from the transmitter unit.[10]

[10] http://www.sustainable.co.za/efergy-e2-optical-wireless-electricity-monitor.html.

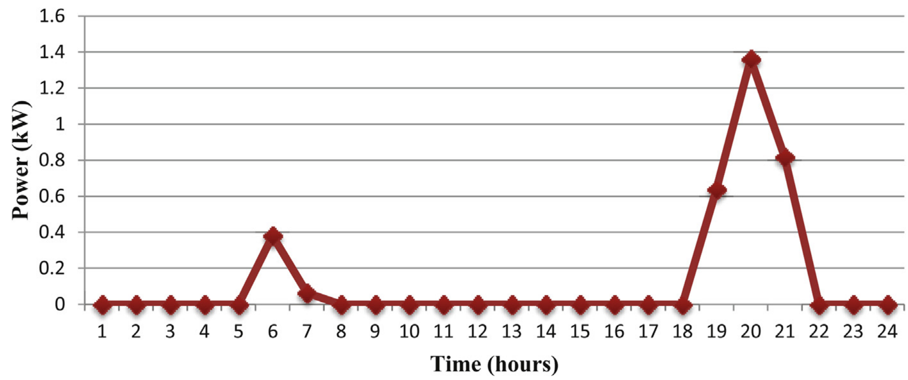

Fig. 4. Demand profile for the stove.

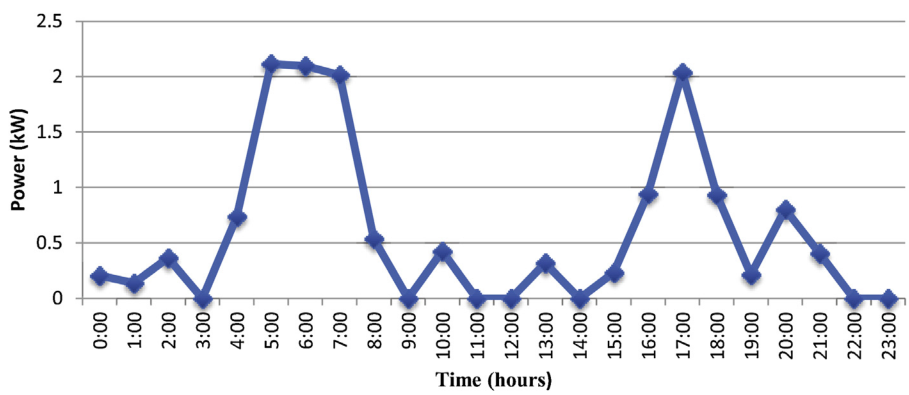

Fig. 5. Demand profile for the EWH.

The Efergy E2 Classic monitor has been shown to have 2% error,[11] which makes the results reliable. South Africa's residential load management (RLM) program, which enables the municipal control of residential EWH, necessitates that the EWH be supplied differently from other household appliances for ease of external control.[12] This residential unit is located in a block of houses where the EWH control devices are located at a localized meter box, hence the invisibility in the DB. Typical profiles of two appliances are shown in the figures below. These are for the stove and the EWH. The aggregated profile for the appliances considered is shown as the baseline profile in Fig. 6.

Since the occupants of the house are working class people and consumption that occurs at night and during daytime when the occupants are not around or not active, it is the opinion of the writers that the consumption is due to the EWH standby losses.[13] It is clearly seen, particularly in the evening, for both the stove and EWH that the consumption is during peak times between 18:00 and 20:00. One of the challenges of using this measuring device is that the cost comparison can only be made at monthly level.

The measured baseline cost of the EWH is R 11.82 and stove is R 6.0629 for the profiles shown in Figs. 4 and 5 and the TOU tariff as in Section 4.2. The effectiveness of the algorithm is demonstrated in the results obtained from our simulation results. The optimization solution with the TOU tariff shows a shift in the consumption profile of appliances. Because of load shifting, for example, the EWH shows one day's cost of R 8.33. This shows a cost saving for this appliance of 29.5%. The stove shows R 4.70; this gives a cost saving of 22.48%. It is to be noted that our simulation results may show an overestimation because, for example, for the stove we assume fixed power consumption whereas in practice the appliance is a heat regulator, hence the actual consumption is variable.

The other challenge with this meter, however, is that when performing individual appliance measurements, the live wire from a three-core cable has to be exposed in order to monitor the consumption and this may pose safety issues. Another challenge is that the monitoring device can be used to make a cost comparison for one month for different tariffs. Since our study horizon is 24 h, the daily estimates may not reflect a true cost value for the day in consideration. It is to be noted that for simplicity, in our simulation results we have excluded standby losses.

The simulation results provided are with additional run time $k_i = 0$ and $\alpha = \rho(t)$. In our previous work [14] we tested different values of alpha where it was discovered that the simulation result was sensitive to the value of alpha. The high value of alpha generated the highest cost value and smallest value of inconvenience. For alpha = 0, the consumer's decision is not influenced by the inconvenience and at that time the inconvenience assumes the highest value, while the cost is at its lowest value. It is to be noted that the selection of the proper value of alpha is subjective, as it is dependent on the user's preference. At this stage we can only make an assumption. In order to differentiate this current work with the previous one, instead of assuming a fixed inconvenience cost coefficient, we now use the TOU tariff, that is $\alpha = \rho(t)$, that is, the consumers opts to go with the utilities' price. The trade-off between cost and inconvenience can help consumers in making a choice on how much they are willing to be inconvenienced, which may affect the level of participation in the program.

Fig. 6 shows simulation results obtained with coordination considered. The appliances' baseline and optimal appliance schedules

[11] http://efergy.com/manuals/e2classic_instructions_web2011.pdf.
[12] R.S. Pandaram, Residential load management (RLM) in South Africa: challenges and solutions. http://active.cput.ac.za/energy/past_papers/DUE/Pandaram.pdf.
[13] Q. Caherine, J. Wheeler, R. Wilkinson, G. De Jager, Hot water usage profiling to improve geyser efficiency. http://www.erc.uct.ac.za/23-jesa-catherine-etal.pdf.

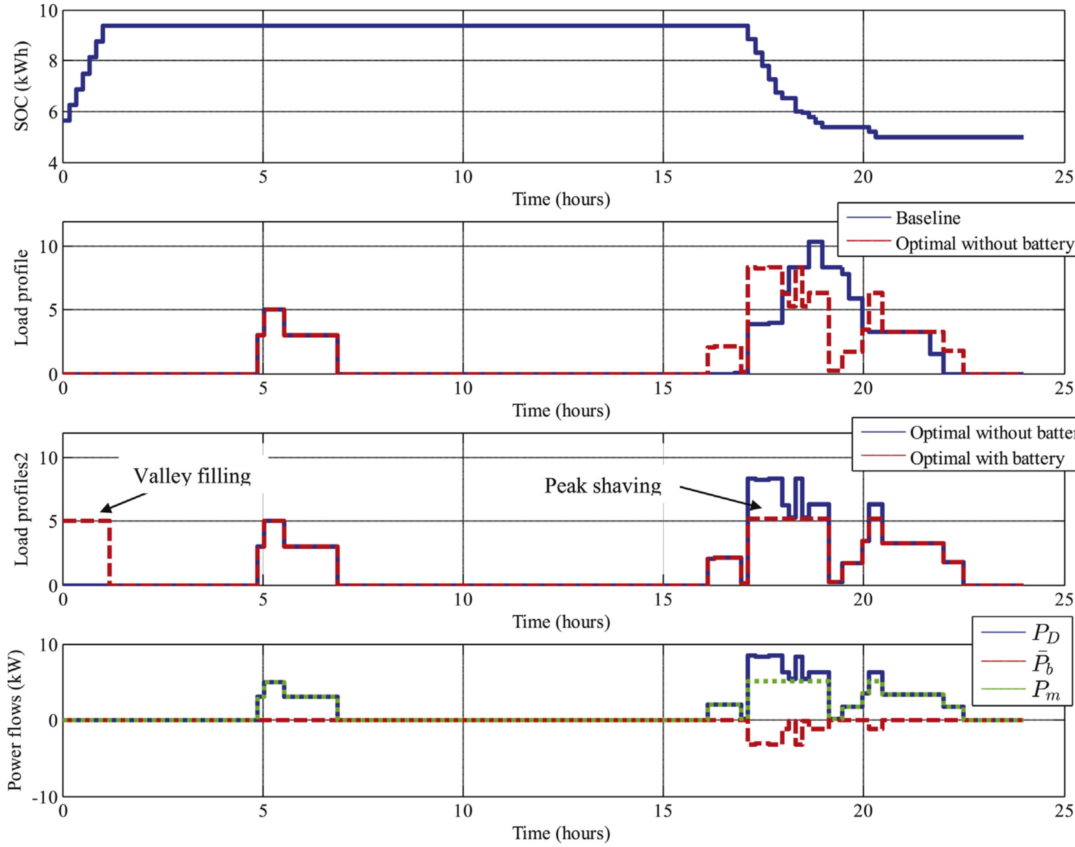

Fig. 6. Simulation results.

are shown. The profile shows the baseline and optimal load profiles both with and without battery. It shows that the optimal solution without battery offers shifted consumption and a reduced peak of 8.405 kW at t = 103, 106 and 107 (17:10, 17:40 and 17:50). The baseline has a peak of 10.355 kW at t=112–113 (18:40–18:50). This shows a shifted peak consumption from peak. The energy consumed at peak has also reduced by 18%. The baseline energy cost is R 31.77, while the optimal cost realized without battery is R 24.76, a saving of 22%. This saving is relatively higher compared to most results obtained with the TOU tariff owing to the high disparity between the peak and off-peak Eskom prices; the latter is 30% of the former.

The battery SOC shows that the battery charges during off-peak from t = 0 (00:00) to t = 7 (01:00) and discharges from t = 102 (17:00) to t = 120 (20:00). Load profile 1 as a relation between the baseline and the optimal load profile without a battery is included here for ease of comparison. Load profile 2 shows the load profiles obtained from the model solution with and without the battery. It shows the contribution of the battery in peak shaving and valley filling. The battery reduces the peak to 5.1750 kW (10% reduction) and cost reduction to R 23.28. The utilization of the battery brings about a further cost reduction of 6% due to the battery discharge during peak times to aid the power from the grid. a further saving of 6%.

Consideration of appliances coordination yields relatively smaller cost saving because of operation independence. Without coordination, constraints (5)–(10) are ignored. Consideration of appliance coordination gives a further cost saving 1% and a relatively smaller peak reduction to 8.305 kW. This shows that the work that excludes coordination constraints may show inflated residential demand response simulation cost savings.

The figure with power flows shows the power demanded by the load P_D, the power from the grid P_m and the power from the battery $\overline{P_b}$. It is shown that the power demanded by the load is met by both P_m and $\overline{P_b}$, for example at t = 110 (18:20), P_D = 8.305 kW and this load is met with P_m = 5.1750 kW and $\overline{P_b} = 3.13$ kW. These power flows satisfy constraint (19).

6.1. Sensitivity analysis of parameter C on the solution.

A sensitivity analysis is carried out to investigate the solution's dependence on parameter C, the consumer's willingness to pay. The results obtained are shown in Table 4. We can deduce from these results that the solution obtained is sensitive to how much the consumer is willing to spend. When parameter C increases, the energy cost increases, the inconvenience cost decreases, the cost saving decreases while the battery contributes more to cost reduction until solution convergence. These results are commensurate with practical expectation in that if the budget or willingness to pay is less, the minimization algorithm is stringent on the energy cost and the inconvenience cost will henceforth be higher. This, however, shows that the consumer can also use the cost to regulate the algorithm's outcome. Thus in the determination of energy cost saving by the consumer, the amount of savings is affected by the consumer's budget.

6.2. Further discussion

The problem presented above is deterministic, one could easily use the model at hand, optimize it numerically off-line and implement the optimal inputs in an open-loop fashion. However, because of uncertainty, additional information such as uncertainty description or plant measurements must be included in order to achieve real time implementation.

Table 4
Sensitivity of parameter C on the results.

C (R)	Energy cost, ($J_e + J_b$) (R)	Energy cost saving (%)	Cost contribution by battery (R)	Inconvenience cost (R)
20	Infeasible			
21	Infeasible			
22	Infeasible			
23	23.0708	27.3779	0.1569	16.1621
24	23.5728	25.7977	−0.2421	13.8411
25	24.5189	22.8196	−0.2421	12.5148
26	25.3298	20.2671	−0.5424	11.1886
27	25.4425	19.9123	−1.3307	10.5254
28	26.3096	17.1829	−1.3307	10.0437
29	27.2731	14.150	−1.3307	9.5620
30	28.5395	10.1636	−1.1553	9.1709
40	29.7478	6.3601	−2.1317	8.4796
50	29.7478	6.3601	−2.1317	8.4796
100	29.7478	6.3601	−2.1317	8.4796

In an effort to work toward real time implementation, we are currently working on formulating the model as stochastic to account for uncertain parameters because in practice, optimization is complicated by the presence of uncertainty in the form of plant-model mismatch and unknown disturbances. The main challenge of real time implementation is in accurate prediction of the load because of its uncertainty. In this case the uncertainty of the load is practically attributed to both the appliance operation time and power consumption, since they are dependent on; using the stove as an example, such things as the type of event, food, heat regulation, environmental temperatures and even types of cooking devices used. The television may also depend on the day and time of day usage. Comfort level also brings about uncertainty on the load where the consumer may wish to schedule at a different time, hence the need to allow for manual operation. The efficiency of the battery may also be uncertain.

The complexity of dynamic optimization problems makes it hard for general purpose solvers to compute solutions fast enough for a real-time implementation. The simulation package, SCIP we are using is relatively fast with solution time of 7 s. SCIP is regarded as one of the fastest non-commercial solvers for MIP and MINLP. However, tailored numerical algorithms may be needed to overcome these challenges in real-time application. Real time implementation require computers that are specifically designed for this purpose, which can be done in faster and more effective tools that offer a platform to integrate software and hardware while capitalizing on the latest computing technologies such as Labview or Matlab combined with DSP.

7. Conclusion and further study

The paper gives our results from a study using the MINLP household appliance optimization scheduling problem with the necessary constraints and a battery storage. The optimal results show that consumers reschedule their appliances in response to variable electricity prices, as demonstrated through a TOU tariff. The optimization solution shows consumers can minimize energy cost by shifting their consumption from peak to off-peak times. This brings about a cost saving of 22%. Consideration of appliance coordination brings variation in the results obtained. A further energy cost reduction of 6% is achieved by using a battery, which promotes peak shaving as it discharges during peak times. However, since the battery charges during off-peak times, it provides valley filling. This not only affects an energy cost saving for the household, but also promotes energy balance in the power system, which the utility pursues as a global need. The battery does not bring about a significant improvement when compared with load shifting, which yields a significant energy cost saving because of the charging component of the battery, which has a power consumption cost. Consideration of appliance coordination reduces the cost by a further 1%. It has been found that the solution obtained is sensitive to input parameter C, the amount the consumer is willing to pay. When C increases the energy cost also increases and the inconvenience cost reduces. This is in line with practical expectations in that if the consumer has a higher budget he is likely to have less inconvenience and high energy consumption cost. This, however, shows that the consumer can also use the cost to regulate the algorithm's outcome.

In further work that is currently in progress we consider residential demand response under uncertainty using a stochastic optimization approach. For example, in our on-going work we consider, among other uncertain parameters, appliances' power consumption P_i to be stochastic. There is also a need to develop a more scientific method to determine the value of inconvenience cost coefficient α.

References

[1] D. Krueger, A background to major power usage areas, in: E. Van Zyl (Ed.), in: Energy Efficiency Made Simple, vol. II, Crown Publications, 2009, pp. 6–9.

[2] R. Inglesi-Lotz, N.J. Blignaut, Estimating the price elasticity of demand for electricity by sector in South Africa, South Afr. J. Econ. Manage. Sci. 14 (4) (2011) 449–465.

[3] X. Xia, D. Setlhaolo, J. Zhang, Residential demand response strategies for South Africa, in: IEEE PES Power Africa 2012 – Conf. and Exhib., Johannesburg, South Africa, 9–13 July, 2012.

[4] H. Chen, T.N. Cong, W. Yang, C. Tan, Y. Li, Y. Ding, Progress in electrical energy storage system: a critical review, Prog. Nat. Sci. 19 (3) (2009) 291–312.

[5] J. Leadbetter, L. Swan, Battery storage system for residential electricity peak demand shaving, Energy Build. 55 (2012) 685–692.

[6] A. Purvins, I.T. Papaioannou, L. Debarberis, Application of battery-based storage systems in household-demand smoothening in electricity-distribution grids, Energy Convers. Manage. 65 (2013) 272–284.

[7] T. Yu, D.S. Kim, S.Y. Son, Optimization of scheduling for home appliances in conjunction with renewable and energy storage resources, Int. J. Smart Home 7 (4) (2013) 261–272.

[8] M.S. Adaramola, S.S. Paul, O.M. Oyewola, Assessment of decentralized hybrid PV solar–diesel power system for applications in northern part of Nigeria, Energy Sustain. Dev. 19 (2014) 72–82.

[9] J. Dekker, M. Nthontho, S. Chowdhury, S.P. Chowdhurry, Economic analysis of PVdiesel hybrid power systems in different climatic zones of South Africa, Int. J. Electr. Power Energy Syst. 40 (1) (2012) 104–112.

[10] N. Tutkun, Minimization of operational cost for an off-grid renewable hybrid system to generate electricity in residential buildings through the SVM and the BCGA methods, Energy Build. 76 (2014) 470–475.

[11] D. Caprino, M.L.D. Vedova, T. Facchinetti, Peak shaving through real-time scheduling of household appliances, Energy Build. 75 (2014) 133–148.

[12] L. Breierova, M. Choudhari, An Introduction to Sensitivity Analysis, vol. 10, Massachusetts Institute of Technology, 2001, pp. 41–107.

[13] J.M. Lujano-Rojas, C. Monteiro, R. Dufo-López, J.L. Bernal-Agustín, Optimum residential load management strategy for real time pricing (RTP) demand response programs, Energy Policy 45 (2012) 671–679.

[14] D. Setlhaolo, X. Xia, J. Zhang, Optimal scheduling of household appliances for demand response, Electr. Power Syst. Res. 116 (2014) 24–28.

[15] P. Du, N. Lu, Appliance commitment for household load scheduling, IEEE Trans. Smart Grid 2 (2) (2011) 411–419.

[16] C.C. Wang, Y. Zhou, J. Wang, P. Peng, A novel traversal-and-pruning algorithm for household load scheduling, Appl. Energy 102 (2013) 1430–1438.

[17] M. Rastegar, M. Firuzabad, F. Aminifar, Load commitment in a smart home, Appl. Energy 96 (2012) 45–54.
[18] A. Saad al-sumaitia, M.H. Ahmed, M.M.A. Salamaa, Smart home activities: a literature review, Electr. Power Compon. Syst. 42 (3–4) (2014) 294–305.
[19] U.E. Ekpenyong, J. Zhang, X. Xia, An improved robust model for generator maintenance scheduling, Electr. Power Syst. Res. 92 (2012) 29–36.
[20] M. Durr, A. Cruden, S. Gair, J.R. McDonald, Dynamic model of a lead acid battery for use in a domestic fuel cell system, Power Sources 161 (2006) 1400–1411.
[21] H. Tazvinga, X. Xia, J. Zhang, Minimum cost solution of photovoltaic–diesel–battery hybrid power systems for remote consumers, Solar Energy 96 (2013) 292–299.
[22] M. Esen, T. Yuksel, Experimental evaluation of using various renewable energy sources for heating a greenhouse, Energy Build. 65 (2013) 340–351.
[23] H. Esen, I. Mustafa, M. Esen, A techno-economic comparison of ground-coupled and air-coupled heat pump system for space cooling, Build. Environ. 42 (5) (2007) 1955–1965.
[24] H. Esen, M. Inalli, M. Esen, Technoeconomic appraisal of a ground source heat pump system for a heating season in eastern Turkey, Energy Convers. Manage. 47 (9) (2006) 1281–1297.
[25] B. Battke, T.S. Schmidt, D. Grosspietsch, V.H. Hoffmann, A review and probabilistic model of lifecycle costs of stationary batteries in multiple applications, Renew. Sustain. Energy Rev. 25 (2013) 240–250.
[26] J. Hoppmann, J. Volland, T.S. Schmidt, V.H. Hoffmann, The economic viability of battery storage for residential solar photovoltaic systems: a review and a simulation model, Renew. Sustain. Energy Rev. 39 (2014) 1101–1118.
[27] J. Weniger, T. Tjaden, V. Quaschning, Sizing of residential PV battery systems, Energy Proc. 46 (2014) 78–87.