Electrical Power and Energy Systems 79 (2016) 150–160

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

# Combined residential demand side management strategies with coordination and economic analysis

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ARTICLE INFO

*Article history:*
Received 31 August 2015
Received in revised form 23 November 2015
Accepted 2 January 2016

*Keywords:*
Residential demand response
Appliance scheduling
PV system
Storage system
Carbon emissions
Economic analysis

ABSTRACT

In this paper combined demand side management strategy for residential consumers is studied for five households in South Africa. This study is twofold; the first part proposes an energy management system that combines demand side management strategies with a view of minimizing the consumer's cost and reducing the power consumption from the grid. Appliance scheduling with a dedicated photovoltaic and storage system under time-of-use tariff shows that customers can realize cost savings and the power demanded from the grid is reduced by optimal scheduling of power sources. In the second part of this study, a model is developed to investigate the joint influence of price and $CO_2$ emissions. It is found that $CO_2$ emissions could give customers an environmental motivation to shift loads during peak hours, as it would enable co-optimization of electricity consumption costs and carbon emissions reductions. It is also demonstrated that the consumer's preferences on the cost sub-functions of energy, inconvenience and carbon emissions affects the consumption pattern. These results are important for both the consumer and the electricity suppliers, as they illustrate the optimal decisions considered in the presence of trade-offs between multiple objectives. A further study crucial to the consumer on economic analysis of PV and battery system showed that the consumer could recoup their initial investment within 5 years of their investment.



## Introduction

Demand side management (DSM) programs enable utility companies to manage the user-side electrical loads and also consumers to voluntarily lower their demand for electricity. Alternative to connecting more conventional generation to the electrical power system, DSM programs pay electrical energy users to lower their energy consumption. The utilities around the world pay for DSM capacity because it is generally economical and uncomplicated to acquire than conventional generation.[1] DSM is a set of flexible and interconnected programs that permits customers a substantial role in decreasing their general usage of electricity and shifting their load during peak times and this fosters better efficiency and operations in electrical energy systems.[2] DSM activities, which are classified into; energy response (energy efficiency and conservation (EEC)) and demand response (DR), are becoming more popular due to technological advances in smart grids and electricity market deregulation [1,2].

Energy efficiency and conservation programs entail encouraging customers to give up some of their energy usage [3–7] in order to gain some economic benefits. The energy reduction can be achieved through activities such as reducing the settings of thermostat [8,9] or retrofitting projects [10–12].

Demand response (DR) on the other hand is a highly flexible program that can be customized to the energy consumption and financial objectives of participants. DR is defined as the reduction in the consumption of electrical energy by customers from their expected consumption in response to an increase in the price of electrical energy or to incentive payments.[3,4] DR options are generally categorized as price-based and incentive-based programs [13]. It is expected that demand response will be an important stepping stone towards practical deployments of the smart grid [14]. Residential demand response (RDR) is used as an energy DSM strategy to

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[1] Enernoc, What is demand-side management? <http://www.enernoc.com/our-resources/term-pages/what-is-demand-side-management>.

[2] Sustainable energy regulation and policymaking for Africa, Module 14; Demand side management.< http://africa-toolkit.reeep.org/modules/Module14.pdf>.

[3] FERC, Demand Response Compensation in Organized Wholesale Energy Markets. <http://www.ferc.gov/eventcalender>.

[4] V.E. CapGemini Consulting Tech., Demand Response: A Decisive Breakthrough for Europe CapGemini Consulting Tech., 2009. <http://www.capgemini.com/insights-and-resources/by-publication//>.

http://dx.doi.org/10.1016/j.ijepes.2016.01.016
0142-0615/

**Nomenclature**

| | |
|---|---|
| $i$ | appliances index |
| $t$ | an index of the time period |
| $h$ | an index of household |
| $k$ | an index of controllable appliances |
| $A$ | a set of all household appliances |
| $H$ | a set of all households |
| $T$ | the control horizon (24 h) |
| $K$ | a set of controllable appliances |
| $\Delta t$ | sampling time (15 min) |
| $P_i$ | rated power of appliance $i$ (kW) |
| $N_i^h$ | duration of appliance $i$ being on in household $h$ (min) |
| $\rho_t$ | time of use electricity price at time $t$ (R) |
| $C^h$ | the maximum cost that household $h$ is willing to pay (R) |
| $d_i^h$ | the on-time start of appliance $i$ in household $h$ |
| $e_i^h$ | the on-time end of appliance $i$ in household $h$ |
| $u_{i,t}^{bl,h}$ | baseline commitment status of appliance $i$ at time $t$ in household $h$ |
| $u_{i,t}^h$ | optimal commitment status of the $i^{th}$ appliance at time $t$ |
| $E_t^h$ | state of the battery at time $t$ in household $h$ (kW h) |
| $E_0$ | the initial state of charge of the battery at time $t$ |
| $E^{min}$ | minimum allowable battery capacity (kW h) |
| $E^{max}$ | maximum allowable battery capacity in (kW h) |
| $P_{b,t}^h$ | the battery charging power in household $h$ (kW) |
| $\bar{P}_{b,t}$ | the battery discharging power in household $h$ (kW) |
| $\eta_c$ | battery's charging efficiency |
| $\eta_d$ | battery's discharging efficiency |
| $DOD$ | depth of discharge |
| $P_{m,t}^h$ | grid power at time $t$ in household $h$ (kW) |
| $P_{flex,t}^h$ | power consumed by flexible appliances (kW) |
| $P_{inflex,t}^h$ | power consumed by inflexible appliances (kW) |
| $P_{ngt,t}^h$ | power consumed by night time appliances (kW) |
| $P_{A,t}^h$ | power demanded by all appliances excluding battery at time $t$ in household $h$ (kW) |
| $P_{D,t}$ | total power demanded from the grid by all at time $t$ (kW) |
| $P_D$ | the total power demanded from the grid in a day (kW) |
| $\lambda_c$ | the carbon emission price (R/kg) |
| $M_c^h$ | mass of carbon dioxide emission in household $h$ (kg) |
| $\alpha_{grid}$ | $CO_2$ emission rate of the grid (kg/kW h) |
| $w_1, w_2, w_3$ | sub-objective functions weighting factors |
| $DPV$ | discounted present value |
| $FV$ | future value of the cash flow amount ($R$) |
| $r$ | discount or interest rate |
| $n$ | time before the future cash flow occurs (yr) |
| $AEO$ | annual energy output (kW h) |
| $AEC$ | annual energy consumption (kW h) |
| $AES$ | annual energy cost saving (R) |
| $Rand(R)$ | South African currency ($1Rand = 0.080USD$), as at 16 Mar. 2015. |

manage the peak load by use of time differentiated prices and incentive payments to control the demand[5] at household level. It has been shown that the impact of RDR is significant and most appreciable at aggregated households than individual household.[6]

The use of renewable energy sources (RES) has become inevitable in today's electrical energy system because of their sustainability and their environmental advantage. In smart grid applications, use of RES at residential level cannot be ignored as many countries including South Africa, have rolled out such systems mainly through roof-top connections. RDR models integrated with renewable energy sources is an active current global research area for smart grid applications. Electricity use in a household is mostly dependent upon the activities of the occupants and their associated use of electrical appliances [15–19], hence modeling such systems is complex. General models on household appliance scheduling without storage or renewable energy generators are presented in [20–26]. These models primarily present household appliance scheduling under demand response programs for smart grid applications. In [27,28], the scheduling problem is presented with a storage system either as a battery or plug-in hybrid electric vehicle (PHEV); the models of storage systems are also presented in [29,30]. A number of times the application of photovoltaic (PV) and battery storage is considered without appliance scheduling, hence as optimal scheduling of power supply sources of various combinations of PV/wind/diesel/battery system [31–38] on a distribution network. However, the shortfall of these models is that they are presented as a simplified problem as linear problem (LP) or mixed integer programming (MIP) problems, thereby forgoing some practical sub-functions and constraints. In our case we have considered a nonlinear inconvenience cost sub-function and nonlinear constraints such as appliance's continuous operation and the battery's exclusive operation.

South Africa has over the years implemented residential rooftop PV systems; however grid connection of small-scale renewable electricity generation is yet to be implemented because South Africa's national energy regulator (NERSA) is currently in the process of developing the regulatory framework on small-scale renewable embedded generation and the guidelines on electricity reseller tariffs.[7] Some of the challenges with small-scale renewable generation grid tie include but not limited to reverse power flows and metering tariff solutions. For this reason, in this work, we consider households with dedicated solar PV and storage systems, without infeed to the grid. Therefore the purpose of the PV is to charges the battery, which will in turn discharge during peak times to relieve the grid.

In the second part of this study we develop a model to investigate the joint influence of price and $CO_2$ emissions in a DR program and the motivation for this is that consumption habits may require other incentives to change rather than the proposed financial incentive. This joint influence is rarely covered by the literature. Knowledge of carbon emissions cost can incentivise investment in renewable energy at household level. By putting a price on carbon emissions, governments can save lives and protect communities from the threat of climate change.[8] In [39], the problem is presented as a multi-objective problem between two sub-functions of cost minimization through appliance scheduling and carbon emissions. The model is solved as a Markov-chain load model in order to forecast the power demands of residential consumers and a scheduling program for providing optimal schedules for smart appliances. In this paper, the problem is presented as an LP problem, as both sub-functions and constraints are linear. In [40], the thesis evaluates two formulations to schedule smart home appliances with respect to economic benefits and environmental benefits. The thesis also

[5] USA Department of energy <http://energy.gov/oe/technology-development/smart-grid/demand-response>.

[6] The Battle Group, Quantifying demand response benefits, Energetics, 27 January 2007 <http://sites.energetics.com/MADRI/battlegroupreport.pdf>.

[7] NERSA, response benefits, Energetics, 27 January 2007 <http://www.nersa.org.za/>.

[8] S. Blaine, SA first African country to introduce carbon emissions tax, BDLive, 28 February 2013 <http://www.bdlive.co.za/national/science/2013/02/28/>.

focuses on the reduction of computational time for the scheduling of smart home appliances as a mixed integer linear programming (MILP) problem. In [40], the dynamic data for carbon footprint is obtained from the Institution of Ecology at the Royal Institute of Technology. In South Africa, however, there is currently a fixed rate of carbon emissions. Ref. [41] presents a similar model to this work where a solution is proposed that models a multi-carrier energy system in a smart grid with appliances scheduling, gas and carbon emissions. The goal is to find an optimal policy that achieves numerous rewards over the long run, where the Monte Carlo method is used. Unlike [40,41], we consider one-way flow of electricity from the grid because of the reason in the foregoing paragraph. Also, our model is presented as a more practical problem as mixed integer nonlinear programming (MINLP) with all practical constraints and we also consider the inconvenience brought by the suggested optimal solution against the baseline appliance status.

When dealing with renewable energy sources (RES), the length of time required to recover the cost of investing in them becomes very interesting to consumers because a major obstacle to the adoption of such systems is customer uncertainty on both technology performance and its economic benefits [38]. The payback period of investing in such a system is an important determinant of whether to undertake the project, as longer payback periods are typically not desirable for investment positions. Hence, in this work, economical analysis is also carried out to aid the consumer. In literature, an extensive work on analysis of the renewable energy sources from a technical and economical point of view mainly looking at system sizing has been carried out [42–44]. Although techno-economic analysis of RES system is one of the ongoing research topics, the work has been inclined towards stand alone hybrid and non-hybrid [45,46] systems. Our work considers optimal control of an integration of RES to the grid under DR program which is hardly covered by the literature.

The purpose of this paper, therefore, is to develop an applicable optimal control model of residential resources management for smart grid applications. The paper studies coordinated scheduling of appliances under demand response in multiple households with a dedicated PV-battery system with grid supply under time differentiated electricity tariffc. The importance of this is that in current years, the use of RES is inevitable due to challenges attached to conventional power generation sources and the short falls in energy supply. Modeling such systems is a critical issue in smart grid applications to allow practical models of electrical energy usage patterns [47]. This paper advances previous research done in [20,27,28] which considered optimal control of household appliances while minimizing the energy and inconvenience costs in one household with and without a storage system. However, it is important to also give consumers information about reduction of carbon emissions as this could give them an environmental motivation to control their loads. For further environmental sustainability, the use of PV systems is encouraged in many countries to promote near net zero energy buildings. These motivations are also in line with the current ongoing global environmental awareness campaigns and trainings. Finally economic analysis is carried out to determine the length of time required to recover the cost of investing in the PV-battery system because a major obstacle to the adoption of such systems is customer uncertainty on both technology performance and its economic benefits [38]. The above points are the main contributions in this work and the adoption of this optimal control strategy will go along way in conserving the environment and ensuring energy security in developing nations.

The remainder of this paper is organized as follows: Section "Problem definition" focuses on defining the problem and optimization model formulations. Section "Optimization model" provides information on the data used in this study. The solution methodology and simulation results are presented and discussed in Section "Data". Section "Solution methodology" covers the economical analysis of such a system and lastly a conclusion and further study are presented in Section "Simulation results and discussion".

## Problem definition

We consider a set of households $H$ with an index $h$ as shown in Fig. 1. The households under study are assumed to be connected at a distribution bus $P_{bus}$. Fig. 2 shows the power flows in one household with a dedicated $PV$ and storage system.

The nature of renewable energy sources makes it a challenge to integrate them in a power system. The two main characteristics of renewable energy sources that present challenges are their intermittency and their unpredictability. The impact of both these characteristics can be mitigated by the application of batteries in the system. Each house has a dedicated PV-battery system and the purpose of the paper is to formulate an optimal control model that seeks to minimize energy cost, the inconvenience and carbon emissions.

## Optimization model

In this section mathematical model is formulated for the optimal control of the system presented in Section "Problem definition". This model is an enhancement of our previous work [27] with augmented features of; multiple households rather than a single household, consideration of carbon emissions for the co-optimization of the energy and carbon emissions, PV system, and economic analysis which is performed in Section "Economic analysis". The formulations are presented as model objective function followed by formulation of constraints.

### *Model objective function*

In order to obtain an optimal operational scheme that balances the objectives in (1), a weighting method is employed to integrate the sub-objectives into one. The advantage of this approach is that the consumer has an option to choose the objective to use to control their consumption. Each household seeks to minimize the following combined cost function:

$$\min J = w_1 J_e + w_2 J_I + w_3 J_c, \tag{1}$$

where $w_1, w_2$ and $w_3$ are the weighting attached to these objectives according to the consumer's preference, and $\sum_{j=1}^{3} w_j = 1$. $J_e$ is the energy cost function as in (2), $J_I$ is the inconvenience cost function shown in (4) while $J_c$ is the carbon emissions cost objective function given in (5).

### *Energy cost model*

The energy cost objective function (2) minimizes the cost of energy consumed by households through optimal scheduling of appliances and the battery using TOU electricity tariff.

$$J_e = \rho_t \Delta t \sum_{h=1}^{H} \sum_{t=1}^{T} \left( P_{inf,t}^h + P_{ngt,t}^h + \sum_{k=1}^{K} P_{k,t}^h u_{k,t}^h + \eta_c P_{b,t}^h \right) \tag{2}$$

$$P_{k,t}^h \geqslant 0,\ \rho_t > 0,\ k = 1, \ldots, K,\ t = 1, \ldots, T,\ h = 1, \ldots, H,$$

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

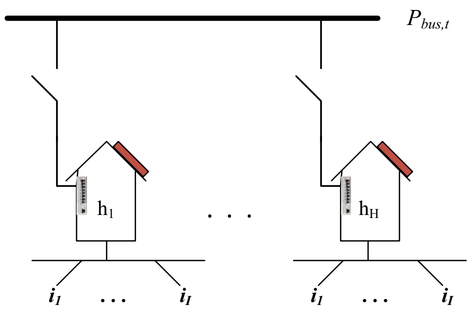


**Fig. 1.** Problem layout.

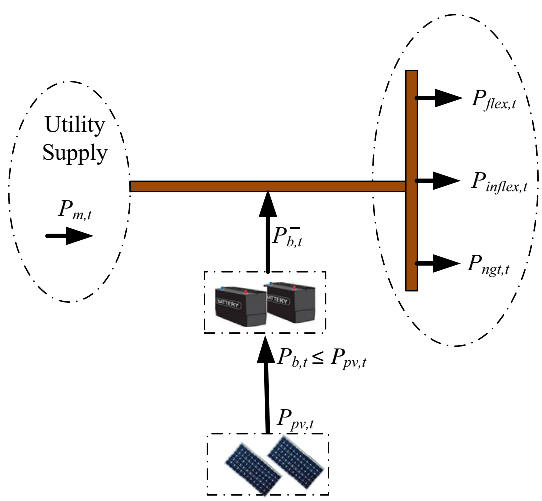


**Fig. 2.** Power flows in a household.

$P^h_{inf}, P^h_{flex}$ and $P^h_{ngt}$ are appliance classifications denoting inflexible, flexible and night-time load, respectively, and each household consists of these three types of loads. Flexible loads can be adjusted according to the consumer's preferences and night-time loads can be committed during the night (22:00–0:500), while inflexible appliances are non-shiftable. $k$ is an index of controllable appliances.

*Inconvenience cost model*

The scheduling inconvenience, $I$, minimizes the disparity between the baseline and the optimal schedule [27]. The consumer therefore also minimizes the inconvenience given by:

$$I_h := \sum_{t=1}^{T}\sum_{k=1}^{K}\left(u^{bl,h}_{k,t} - u^h_{k,t}\right)^2, \tag{3}$$

$$J_I = \rho_t \Delta t \sum_{h=1}^{H}\sum_{t=1}^{T}\sum_{i=1}^{K}\left(u^{bl,h}_{k,t} - u^h_{k,t}\right)^2. \tag{4}$$

The baseline $u^{bl,h}_{k,t}$ of controllable appliances is obtained from the measured results as explained in data section.

*Carbon emissions cost model*

The carbon emissions model is the carbon footprint of the consumer from the grid electricity usage offset by the injection of emission-free electricity from the *PV* battery system. The objective function is to minimize the cost of carbon emissions by a household.

$$J_c = \sum_{h=1}^{H}\sum_{t=1}^{T}\lambda_C M^h_{C,t}\Delta t, \tag{5}$$

where $J_c$ is the $CO_2$ emission cost, $\lambda_C$, is the emission price and $M^h_{C,t}$ is the mass of $CO_2$ emission in kilogram, which is computed as follows;

$$M^h_{C,t} = \left(\sum_{i=1}^{A} P^h_{i,t} + P^h_{b,t} - \overline{P^h_{b,t}} - P^h_{pv,t}\right) * \alpha_{grid}, \tag{6}$$

and with $P^h_{b,t} = P^h_{pv,t}$, therefore, (6) reduces to;

$$M^h_{C,t} = \left(\sum_{i=1}^{A} P^h_{i,t} - \overline{P^h_{b,t}}\right) * \alpha_{grid}, \tag{7}$$

where $\alpha_{grid}$ is the $CO_2$ emission rate of the grid, which is 0.99 kg of $CO_2$/kW h for South Africa's utility,[9] and is charged at $\lambda_C = R0.1323$/kg. Note that the charging of the battery is taken care of by the PV system.

*Model constraints*

*Battery model*

The PV-battery system is considered in this work because of their numerous benefits to both the consumer and the utility. The PV system typically has a peak generation around mid-day, which generally does not align well with on-site demand with more consumption in the evening. Storage at the PV system is used to store this energy. PV energy, like other renewable energy sources, is subject to rapid weather variations, and the resultant of this is significant grid instability. In this work, storage system is optimally charged and discharged to compensate for these fluctuations. This improves the interconnection of PV systems to the grid, and support grid stability. The battery model is presented with general battery dynamics presented by the battery's state of charge (SOC) [27,33]. The battery energy storage system is characterized by continuous charging and discharging power, therefore $P^h_{b,t}$ and $\bar{P}^h_{b,t}$ are considered continuous variables at time step $t$.

$$E_t = \sum_{h=1}^{H}\left(E_0 + \Delta t \sum_{\gamma=1}^{t}\left(\eta_c P^h_{b,\gamma} - \eta_d \bar{P}^h_{b,\gamma}\right)\right), 1 \leqslant t \leqslant T, \tag{8}$$

where $E_t$ is the SOC of the battery, $E_0$ is the initial SOC of the battery, whereas $\eta_c \sum_{\gamma=1}^{t} P^h_{b,\gamma}\Delta t$ and $\eta_d \sum_{\gamma=1}^{t} \bar{P}^h_{b,\gamma}\Delta t$ are the battery energy during the charging and discharge period, respectively.

The following constraints are applied to the battery model:

$$E^{min} \leqslant E^h_t \leqslant E^{max}, \quad t = 1, \ldots, T, \tag{9}$$

$$E^{min} = (1 - DOD)E^{max}, \tag{10}$$

$$P^h_{b,t} * \bar{P}^h_{b,t} = 0, \quad t = 1, \ldots, T, \tag{11}$$

where (9) is the battery energy capacity limits, (10) is the relation between $E^{min}$ and $E^{max}$ through the battery's depth of discharge (DOD) that describes how deeply the battery is discharged. (11) presents the exclusive operation of the battery because the battery cannot charge and discharge at the same time. This constraints also allows the battery to be in idle mode.

*Power flows*

The total power consumed by a set of all appliances ($A$) in one household at time step $t$ is given by:

$$\sum_{i=1}^{A} P^h_{i,t} = P^h_{inf,t} + P^h_{flex,t} + P^h_{ngt,t}, \tag{12}$$

$$\left(P^h_{inf,t}, P^h_{flex,t}, P^h_{ngt,t}\right) \geqslant 0,$$

[9] Eskom Integrated report,2014 <http://http://www.integratedreport.eskom.co.za//>.

while the total power demanded by a household $h$ at each time step is given by,

$$P_t^h = \sum_{i=1}^{A} P_{i,t}^h + P_{b,t}^h, \tag{13}$$

and $P_{b,t}^h$ is the power consumed by the battery while charging at $t$.

The total power demanded by the load in household $h$ at time $t, P_t^h$, is satisfied by the battery power output $\overline{P_{b,t}^h}$, grid power $(P_{m,t}^h)$ and the output $(P_{pv,t})$ charges the battery, hence the power balance equation is given by,

$$\bar{P}_{b,t}^h + P_{m,t}^h = P_t^h, \tag{14}$$

where

$$0 \leqslant P_{m,t}^h \leqslant P_m^{max}, \tag{15}$$

The grid's power upper bound is estimated as, $P_m^{max} = 230V * 60A * 0.75 = 10.35$ kW, with nominal single phase voltage and current ratings of 230 V and 60 A, and an assumed power factor of 0.75.

$$0 \leqslant P_{b,t}^h \leqslant P_{pv,t}. \tag{16}$$

Constraint (16) bounds the battery charge to the PV output. The total power consumption in each household in a day is given by (17). $k$ is the controllable appliance index and $K$ is a set of controllable appliances. $P_{k,t}$ is the rated power of controllable appliance $k$ at time $t$. $u_{k,t}^h$ is the commitment status of appliance $k$ in household $h$ at time $t$ and $\rho_t$ is the TOU electricity price at $t$.

$$P^h = \sum_{t=1}^{T} \left( P_{inf,t} + P_{ngt,t} + \sum_{k=1}^{K} P_{k,t} u_{k,t} + \eta_c P_{b,t} \right). \tag{17}$$

The aggregated consumption as seen by the distribution bus from a set of serviced households is given by;

$$P_{bus,t} = \sum_{h=1}^{H} \sum_{t=1}^{T} \left( P_{inf,t}^h + P_{ngt,t}^h + \sum_{k=1}^{K} P_{k,t} u_{k,t}^h + \eta_c P_{b,t}^h - \eta_d \overline{P_{b,t}^h} \right). \tag{18}$$

Note that the battery's power during charging is met by the PV. The individual household energy consumption at time step $t$ is capped to the capacity of the distribution board installed in the house as in (19).

$$P_{inf,t}^h + P_{ngt^h,t} + \sum_{k=1}^{K} P_{k,t} u_{k,t}^h + \eta_c P_{b,t} \leqslant P_m^{max}. \tag{19}$$

*Appliance operational constraints*

Given the predetermined parameters of the controllable appliances; $d_k^h, e_k^h$ and $N_k^h$, as the beginning and end of time to which each flexible appliance is to be scheduled, and duration required to finish the normal operation of each controllable appliance in household $h$, the following; inequality (20) holds.

$$\sum_{t=d_k^h}^{e_k^h} u_{k,t}^h = N_k^h, \quad \forall h, \ \forall k, \tag{20}$$

where

$$N_k^h \leqslant (e_k^h - d_k^h), \tag{21}$$

$$\sum_{t=d_k^h}^{e_k^h} u_{k,t} \cdot u_{k,(t+1)} \cdot u_{k,(t+2)} \cdots u_{k,(t+(N_k-1))} = 1, \quad t = 1, \ldots, T, \tag{22}$$

$$u_{2,t} - u_{6,t} - u_{7,t} = 0, \tag{23}$$

$$d_6 + N_6 \leqslant d_{7+1}, \tag{24}$$

$$0 \leqslant P_{k,t} \leqslant P_k^{max}, \tag{25}$$

**Table 1**
Flexible appliances data.

| Index ($i$) | Appliance | Rated power $P_i$ (kW) | | | | |
|---|---|---|---|---|---|---|
| | | $h_1$ | $h_2$ | $h_3$ | $h_4$ | $h_5$ |
| | *Flexible* | | | | | |
| 1 | Kitchen lights | 0.11 | | | | |
| 2 | Laundry room lights | 0.11 | | | | |
| 3 | Microwave | 0.8 | 1.5 | 0.6 | 1.2 | 0.6 |
| 4 | Stove | 2.2 | 2.0 | 2.4 | 2.0 | 2.0 |
| 5 | EWH | 2.0 | 2.0 | 2.0 | 2.0 | 2.0 |
| 6 | Washing machine | 2.0 | 2.4 | 2.2 | 2.0 | 2.0 |
| 7 | Clothes dryer/spin | 2.0 | 0.6 | 2.0 | 0.6 | 0.6 |
| 8 | Vacuum cleaner | 0.8 | 0.8 | 0.4 | 0.8 | 0.35 |
| 9 | DVD player | 0.025 | 0.025 | 0.025 | 0.015 | 0.015 |
| | *Inflexible* | | | | | |
| 10 | TV room lights | 0.11 | | | | |
| 11 | Refrigerator | 0.35 | 0.4 | 0.25 | 0.35 | 0.15 |
| 12 | Television | 0.133 | 0.1 | 0.25 | 0.1 | 0.09 |
| 13 | Decoder | 0.07 | | | | |
| | *Night loads* | | | | | |
| 14 | Breadmaker | 1.5 | 1.5 | 1.6 | 1.2 | - |
| 15 | Dishwasher | 1.5 1.2 | 1.2 | 1.5 | 1.5 | - |

where nonlinear constraint (22) models the non-interruptible operation of appliances. (23) and (24) are coordination constraints. (23) coordinates lighting with the appliances used in their respective rooms, using the the laundry room as a reference. The time the laundry lights are off is when neither washing machine nor drier is on. (24) ensures that, for example, the dryer follows the washing machine. The numerical indices in equality (23) and inequality (24) correspond to appliance index as provided in Table 1. The laundry room lights has index $i = 2$, washing machine, $i = 6$, and dryer has index $i = 6$. (25) is the appliance power consumption limit.

$$\sum_{t=1}^{T} \left( P_{inf,t}^h + P_{ngt,t}^h + \sum_{k=1}^{K} P_{k,t} u_{k,t}^h + \eta_c P_{b,t}^h \right) = C^h. \tag{26}$$

This constraint models the maximum cost that each household is willing to incur within the control horizon. The parameter $C$ is obtained from the consumer's bill and provided in the data section, Table 2.

The formulated model is MINLP optimal control problem with control variables $u_{i,t}^h, P_{b,t}^h, \overline{P_{b,t}^h}$, and $P_{m,t}^h$.

## Data

Five typical apartments in South Africa have been used as a case study which are connected to a common point as shown in Fig. 1. Each household has a dedicated PV and battery system.

*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[10] 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.

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

[10] Eskom tariffs and charges 2011/2012 <http://eskom.com>.

**Table 2**
Appliance baseline data for flexible appliances.

| Appliance | Duration $(d_k, e_k)$, | | | | | Run-time $N_k$ (min) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $h_1$ | $h_2$ | $h_3$ | $h_4$ | $h_5$ | $h_1$ | $h_2$ | $h_3$ | $h_4$ | $h_5$ |
| Kitchen lights | As kitchen appliances | | | | | | | | | |
| Laundry room lights | As laundry appliances | | | | | | | | | |
| Microwave | 06:00–21:00 | 04:00–18:00 | 08:00–11:00 | 05:30–09:00 | 01:00–19:00 | 6 | 8 | 6 | 6 | 9 |
| Stove | 06:30–15:00 | 06:00–15:00 | 08:00–11:00 | 05:30–09:00 | 01:00–15:00 | 54 | 45 | 48 | 62 | 36 |
| EWH | 06:00–15:00 | 09:15:00 | 23:00–04:00 | 16:00–23:00 | – | 180 | 120 | 180 | 180 | 180 |
| Washing machine | 10:00–15:00 | 18:00–22:00 | 15:00–17:00 | 16:00–22:00 | 01:00–19:00 | 60 | 60 | 60 | 60 | 60 |
| Clothes dryer | 10:00–15:00 | 18:00–22:00 | 15:00–17:00 | 16:00–22:0 | 01:00–19:00 | 30 | 30 | 30 | 30 | 15 |
| Vacuum cleaner | 10:00–18:00 | 09:00–12:00 | 08:00–15:00 | 08:00–14:00 | 01:00–19:00 | 12 | 24 | 16 | 18 | 10 |
| DVD player | 10:00:23:00 | 08:00–23:00 | 08:00–23:00 | 08:00–22:00 | 01:00–19:00 | 120 | 180 | 120 | 120 | 120 |

and

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

*Appliance data*

Appliance maximum rated power is specified by the appliance manufacturers and can be obtained from the appliances. One month's weekday data on appliance usage in the households under study were collected. Table 1 shows common flexible, inflexible and night-time loads. Different power ratings are due to different appliance brands and sizes. It must be noted that depending on the type of consumer, flexibility of appliances differs as shown in Table 2 for the duration at which appliances may be committed and this is also depicted in Fig. 3. In Table 2, for example; stove usage commitment time ranges varies in all households. Household 1, $h_1$, proposes to commit stove usage any time from 06:00 to 21:00 making them more flexible on this appliance whereas $h_4$ is less flexible compared to the former with time ranges of 05:30–09:00. One of the practical reasons is that household with non-working family members may be willing to have a less stringent/time scheduling horizon while working class families or families school-going children, may have to cook within specified times. This observation motivates for further research into actual classification of appliance usage based on family types. Table 2 also shows the measured maximum run-time, $N_k$, of appliance $k$.

Individual households shows that most of them portray different consumptions; $h_1$ displays different consumption behavior with one evening peak. However, household $h_5$ is the lowest consumer with missing data for EWH which was non functioning at a time of data collection.

Based on the data obtained, we estimated the percentage of flexible load in each household as $\frac{\sum_t^T P_{flex,t}}{\sum_t^T P_{A,t}} * 100$, and it is found that it ranges from 20% to 42%. Fig. 4 shows the baseline load profile for aggregated total load of the five households and the load for inflexible and night loads. It is observed that the baseline has three peaks, morning, lunch and evening peak, with morning as the highest peak at 09:00–10:00. This shows that the highest consumers are stay-home families, as also revealed in Fig. 3 with $h_2$, $h_1$ and $h_3$ as morning peak high contributors.

Table 3 provides data for the maximum budget that each household is willing to incur in the study horizon. This data is obtained from the bill of each household (see Table 4).

*$P_{pv}$ and battery data*

Each household is assumed to have the same battery and PV. The battery bank data is provided in Table 2 and the data for *PV* is shown in Fig. 5; this data is adopted from [31]. The battery capacity is an assumed value of 10 kW h. The minimum discharge capacity of 50% has been shown to sustain the lifespan of the battery [32].

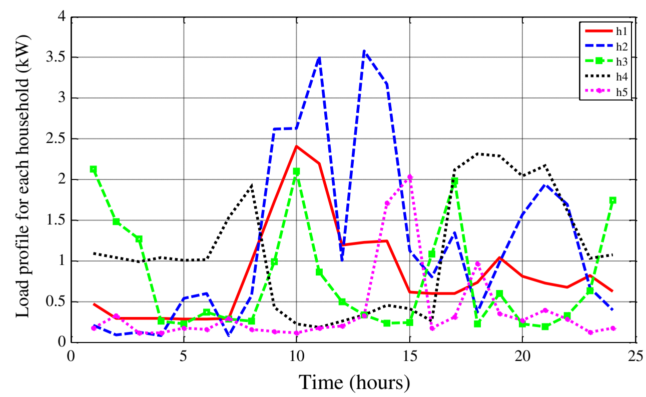


**Fig. 3.** Baseline demand for each household.

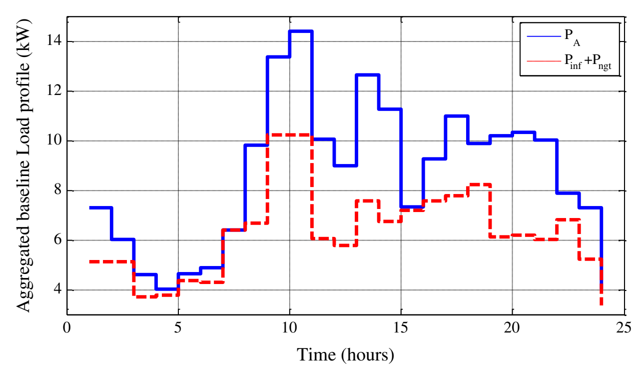


**Fig. 4.** Aggregated baseline demand for five households.

**Table 3**
Other data.

| Household | $h_1$ | $h_2$ | $h_3$ | $h_4$ | $h_5$ |
|---|---|---|---|---|---|
| Daily maximum bill (C) (R) | 15.90 | 23.08 | 12.16 | 22.57 | 10.23 |

**Table 4**
Battery data.

| | |
|---|---|
| Battery capacity | 10 kW h |
| $\eta_c$ | 75% |
| $\eta_d$ | 100% |
| DOD | 50% |

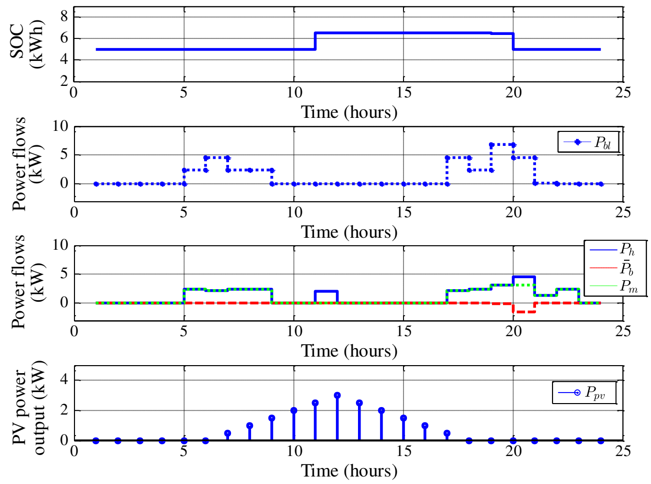


**Fig. 5.** Simulation results for $h_3$ with $w_1 = 0.2, w_2 = 0.8$.

## Solution methodology

The MINLP optimization problem (1)–(26) is solved with an optimization solver, SCIP, available in the Matlab interface OPTI toolbox. The simulation study is performed for 24 h at a sampling time of 15 min. 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.[11,12] 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.[7,13] The solver offers solutions to problems of the form:

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

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

## Simulation results and discussion

This section presents simulation results of two cases. Case 1 demonstrates an energy management system that combines DSM strategies with a dedicated PV and storage system under TOU tariff. Case 2 presents the results of an investigation on the joint influence of dynamic electricity price and $CO_2$ emissions in a DR program. These two cases give two typical scenarios for residential houses with DR.

### *Case 1*

To make this case concise, we start looking at one household then aggregated households with an objective; $\min J = w_1 J_e + w_2 J_I$ where $w_1 + w_2 = 1$. The purpose of this approach is for the consumer to appreciate the trade off between the energy cost and the inconvenience in the presence of a PV-battery system. This is in contrast to our previous work [27] where we did not consider the PV. Simulation results are given at assumed consumer's preference of $w_1 = 0.2$ and $w_2 = 0.8$.

The results in Fig. 5 show one household's results with the battery's SOC, power flows and $P_{pv}$. The battery charges at hour 11; at that time it is charged by the *PV* power. $P_h, \bar{P}_b$ and $P_m$ are the power consumed in the household according to (17) but for $h_3$, power discharge from the battery and power from the grid, respectively. The morning household load (05:00–09:00) is covered by the grid power as at that time the grid power is cheaper to acquire. The battery discharges at a time when the load within the house is high. The baseline cost of flexible appliances excluding the battery is R28.96. The cost due to load shifting, battery and PV is R20.03, a cost saving of 30.84%. This is comparably a significant amount of savings compared to previous work where the savings without PV-battery system reported are in the ranges of 15–25% [27,20]. Note that the contribution share between the sub-costs is sensitive to the weighting factors as demonstrated in case 2, therefore the consumers' preferences affect the savings. The inconvenience cost at these weighting factors however is R11.41, which one can argue that it is a relatively large value that may not be economical to the electricity suppliers. The power is reduced from 6.794 kW at hour 19 to 4.58 kW owing to appliance shifting and battery discharge.

Fig. 6 shows the results of the aggregated households assumed to have the same weighting factors of $w_1 = 0.2$ and $w_2 = 0.8$. The baseline power as seen by the distribution bus and the optimal power seen by the same bus after optimal control: shows a total power reduction seen by the distribution bus from 205.50 kW to 176.44 kW, a reduction of 14%. A total energy cost reduction from R164.18 to R139.21 of 15.21% is realized by aggregated households. The DR combined with PV and battery show that the aggregated strategy can reduce the power demanded from a distribution system by a significant amount and thus relieve the power system network and according some residential members significant collective savings. It must be noted in Fig. 6 that the maximum peak present in the morning still occurs after optimal control because it appears during off-peak and this also observed for the mid-day peak. In addition, this is due to unavailability of PV power where the battery starts charging at around 11:00. However, in the evening peak a significant reduction is realized, since the TOU tariff is high during those times and the battery is fully charged. This also shows the effectiveness of the optimizer in scheduling both appliances and the battery.

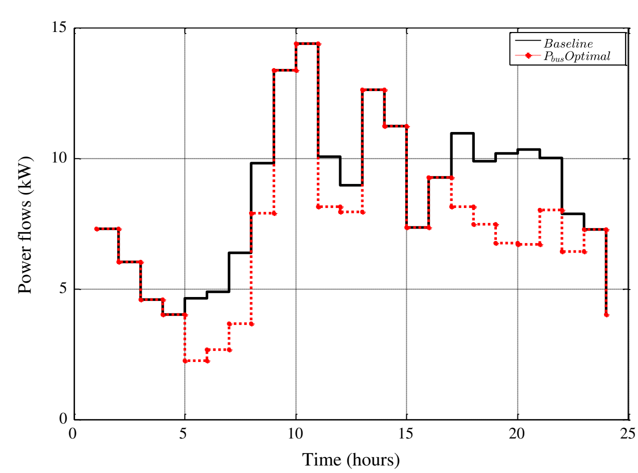


**Fig. 6.** Simulation of aggregated households for case 1.

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

*Case 2*

In this case we consider carbon emissions with the objective $\min J = w_1 J_e + w_2 J_I + w_3 J_c$ where $w_1 + w_2 + w_2 = 1$. We investigate the joint influence of dynamic electricity price and $CO_2$ emissions. As in case 1, we also look at one typical household with typical controllable loads. We compare two scenarios with different preferences. Fig. 7 shows the results of the same household in case 1 with $w_1 = w_2 = w_3 = 0$, where the consumer does not place value on any of the sub-functions. In Fig. 7, the battery charges between 07:00–10:00 and significant discharge of the battery is noticed at 18:00 and a slight discharge late at 23:00. This demonstrates the effectiveness of the optimizer where most contribution from the battery is needed during peak times. The power discharge from the battery is shown by $\bar{P_b}$.

Simulation results in Fig. 8 are given at $w_1 = 0, w_2 = 0$ and $w_3 = 1$, that is, the case of an environmentally sensitive consumer places high importance on carbon emissions. Both figures show that for different preferences, the consumption profile is different, hence the costs also vary accordingly.

The effect of different combinations of the weighting factors on costs, considering extreme cases, is summarized in Table 5. It is demonstrated that the consumer's preferences on the cost sub-functions of energy, inconvenience and carbon emissions affects the consumption pattern. These results are important for both the consumer's cost and environmental impact reduction and the electricity suppliers' main interest of achieving both power usage reduction and mitigation of environmental impact, as they illustrate the optimal decisions considered in a case of multiple sub-objectives.

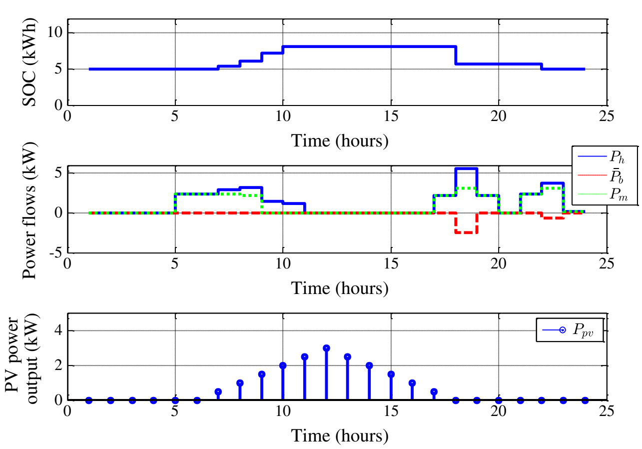


**Fig. 7.** Simulation results for $h_3$ with $w_1 = w_2 = w_3 = 0$.

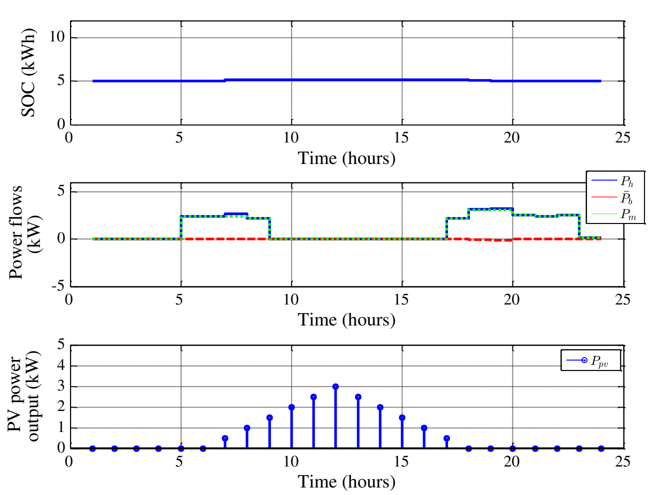


**Fig. 8.** Simulation results for $h_3$ with $w_1 = w_2 = 0$ and $w_3 = 1$.

**Table 5**
Effect of weighing factors on energy ($J_e$), inconvenience ($J_I$) and carbon emissions ($J_c$) costs for a typical household.

| Scenario | $w_1$ | $w_2$ | $w_3$ | $J_e$ (R) | $J_I$ (R) | $J_c$ (R) |
|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 0 | 21.76 | 10.31 | 3.53 |
| 2 | 1 | 0 | 0 | 18.60 | 9.45 | 3.52 |
| 3 | 0 | 1 | 0 | 27.92 | 4.89 | 3.88 |
| 4 | 0 | 0 | 1 | 27.89 | 10.42 | 3.40 |
| 5 | 0.2 | 0.4 | 0.4 | 21.44 | 5.21 | 3.46 |

In Table 5, five cases of preferences are presented, of which four are extreme and for comparison, an additional non-extreme scenario is included. In the first scenario, the consumer does not place any priority on any of the cost sub-functions. In the second scenario, the consumer's priority is the energy cost and he does not care about the other two. The results concur with practical expectation in that; where the consumer places more value, the respective cost will be minimal. High value on energy cost, scenario 2, gives the lowest cost of R18.60, while high value on inconvenience, scenario 3, gives the lowest inconvenience cost of R4.89 and high value on carbon emissions cost gives the lowest value of R3.40. Scenario 5 is a typical non-extreme preference with in-between values.

The simulation results for the aggregated households $h_1$ to $h_H$ show carbon emissions saving under the weighting factors that are assumed to be same for all households. The baseline aggregated carbon emissions is 203.44 kg while the optimal solution gives a less carbon emission of 174.67 kg, 14.14% savings. Carbon costs are respectively R26.91 and R23.11. This shows that carbon emissions could give customers an environmental motivation to shift or reduce loads during peak hours, as it would enable co-optimization of electricity consumption, inconvenience and carbon emissions costs reductions. This could also be used to motivate consumers to opt for more usage of renewable resources.

*Economic analysis*

Since the problem modeled in this work entails combined DSM strategies, It is assumed that the consumer does not bear the cost of demand response which is usually covered by the utility, therefore, this economical analyses is performed on the usage of PV and battery system on such a strategy.

There are different methods used to perform economic analysis of systems in the literature. These methods include but not limited

**Table 6**
Approximate cost of components.

| Component | Approximate cost (R) |
|---|---|
| Solar modules | 59550.00 |
| Deep cycle battery | 11559.00 |
| Inverter and accessories | 7172 |
| Energy controllers | 9557 |
| Installation cost | 5430 |
| Sub total | 93,268 |
| Operation and maintenance cost (@2.5% fixed annual) | 2331.70 |
| TOTAL | 95600.00 |

**Table 7**
Energy cost saving due to PV-battery system for $h_3$.

| *AEO* (kW h/yr) | *AEC* (kW h/yr) | *%S* | *AES* (R) |
|---|---|---|---|
| 2086 | 7080 | 0.2946 | 28 582 |

**Table 8**
Payback period.

| Years | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|---|
| Capital cost | (93 268.00) | | | | | | |
| O&M (@2.5% capital cost) | | (2331.70) | (2331.70) | (2331.70) | (2331.70) | (2331.70) | (2331.70) |
| Optimal benefit | | 28 582 | 28 582 | 3 28 582 | 28 582 | 28 582 | 28 582 |
| | (93 268.00) | 26 250.3 | 26 250.3 | 26 250.3 | 26 250.3 | 26 250.3 | 26 250.3 |
| Discount factor @5.75% | 1 | 0.95 | 0.89 | 0.85 | 0.80 | 0.576 | 0.72 |
| Discounted cash flows | (93 268.00) | 24 822.98 | 23 473.27 | 22 196.94 | 20 990.02 | 19 848.71 | 18 769.47 |
| Discounted PBP | Years | D-cashflows | C-cashflows | | | | |
| | 0 | (93 268.00) | (93 268.00) | | | | |
| | 1 | 24 822.98 | (68 445.02) | | | | |
| | 2 | 23 473.27 | (44 971.76) | | | | |
| | 3 | 22 196.94 | (22 774.81) | | | | |
| | 4 | 20 990.02 | (1 784.80) | | | | |
| | 5 | 19 848.71 | 18 063.92 | | | | |
| | 6 | 18 769.47 | 36 833.39 | | | | |
| Payback period | 4.09 years | | | | | | |

to net present value (NPV), pay back period (PB) and discounted present value (DPV) [48,49,11,7,50–52]. In this paper we adopt the DPV method provided in[14] which is also presented in [48] to calculate the length of time to recoup an investment on usage of PV and battery system based on the investment's discounted cash flows. By discounting each individual cash flow, the discounted payback period takes into consideration the time value of money because the approach first determines the present value of the future cash flows for the given investment and then uses these discounted values to determine the payback period.

$$DPV = \frac{FV}{(1+r)^n}, \tag{27}$$

where $FV$ is the future amount of money that must be discounted, $n$ is the number of compounding periods between the present date and the date where the sum is worth $FV$, and $r$ is the discount or interest rate given as 5.75% for the current month, July 2015 as South African inflation rate.[15] In order to make economical analysis of the PV-battery system, certain assumptions are made.

The PV and battery costs entails capital cost, operational and maintenance (O&M) costs as shown in Table 6. Since our study horizon is one day we annualize our costs.

In [50,53–55], the O&M cost of a PV-battery has been estimated to a specific annual value or some online sources estimate the annual O&M cost to be around 2–2.5% of capital cost and in this work we use less conservative value of 2.5%. Calculation of savings brought by the optimal use of the PV-battery system is performed as follows.

Although practically, daily energy consumptions are variable depending on the behavior of the consumer in terms of the way they commit their appliances, in this work, however, we estimate an annualised energy from the PV-battery system utilized by the consumer as the energy output to consumer (AEO) with the assumption that all days are identical. This is computed using equality (28);

$$AEO = \sum_{t}^{T} \bar{P}_{b,t} * \Delta t * 365. \tag{28}$$

Then equality (29) is used to determine the percentage energy saving that is brought by the use of PV-battery system;

$$\%S = \frac{AEO}{AEC}, \tag{29}$$

the percentage of the consumers electric bill that is covered by the PV-battery system is $\%S$; obtained from the system's annualised energy output, $AEO$ and annualised energy consumption $AEC$. $AEC$ is obtained from the monthly electric bill from municipality which coincides with the measured values determined from Fig. 4. The annualised cost savings (AES) due to PV-battery system is determined from the product of the annual bill charge and $\%S$.

$$AES = \%S * AEC * \xi. \tag{30}$$

Note that the monthly bill charge of $R1.36$/kW h for South Africa is used as a flat electricity price prior to DR, otherwise $\xi = \rho_t$. The energy cost saving for a typical household, say $h_3$ is shown in Table 7.

The results in Table 7 show that the use of PV-battery system yields an annual energy cost saving of R28,582.00 to the consumer. This is within reasonable values of 20–45% reported in most literature. Then this value of AES is used as the optimal benefit of using PV-battery system in calculating the discounted present value. Table 8 shows the revenue for $h_3$ from solar energy sales and the household's benefit on cost savings emanating from the proposed optimal control strategy.

As can be seen in Table 8, the assumptions made are that the operation and maintenance costs and optimal benefits are constant throughout the projected years into the future. This assumption implies that exclusion of weighted sum of capital cost the pay back period is reduced. It can be seen from the table that in this case, the payback period of $h_3$ is 4.09 years. It is however acknowledged that this is an estimate based on the assumptions made. A more precise results could be obtained from the actual sizing of the PV-battery system and consideration of the weighted average cost of capital (WACC) which cannot be reliably estimated at this point.

## Conclusion

Optimal control strategy through optimal scheduling of resources during a demand response program has been studied in this paper. In this study, the first part, proposes an energy management system that combines DSM strategies with a view to minimize the consumer's cost and reduce the power consumed from the grid, thereby promoting power system stability. A combination of appliance scheduling, dedicated PV and a storage system under TOU tariff shows that power drawn from the distribution bus reduces by 14% while cost savings are 15.21%. This strategy of DR

[14] Discounted present value calculator, <http://www.aqua-calc.com/page/discounted-present-value-calculator>.
[15] Current market rates, South African reserve bank, July 2015, <http://www.resbank.co.za/Research/Rates/Pages/CurrentMarketRates.aspx>.

combined with PV and battery shows that the aggregated strategy can reduce the power demanded from a distribution system by a significant amount and thus relieve the power system network and afford some residential members significant collective savings. The second part of this study shows that consumption habits may require other incentives to change in addition to the proposed energy and inconvenience cost. The results for the aggregated households $h_1$ to $h_H$ show carbon emissions reduction from 203.44 kg to 174.67 kg was achieved. This shows that carbon emissions could give customers an environmental motivation to shift or reduce loads during peak hours, as it would enable co-optimization of electricity consumption, inconvenience and carbon emissions costs reductions. Knowledge on carbon emissions can incentivize investment in renewable energy at household level. It is also demonstrated that the consumer's preferences on the cost sub-functions of energy, inconvenience and carbon emissions affects the consumption pattern. These results are important for both the consumer and the electricity suppliers, as they illustrate the optimal decisions considered in the presence of trade-offs between conflicting objectives. In the measured data, it was however discovered that the level of flexibility on the 'assumed' controllable appliances may vary between households. Economical analysis on consideration of PV and battery system has also been studied where it has been shown that the payback period 4.09 years has been estimated based on the assumptions made.

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