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Optimal dispatch for a microgrid incorporating renewables and demand response

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A B S T R A C T

This paper proposes an optimal economic dispatch of a grid connected microgrid. The microgrid consists of solar photovoltaic, diesel and wind power sources. An Incentive Based Demand Response Program is incorporated into the operations of the grid connected microgrid. The optimal dispatch strategy is obtained by minimizing the conventional generators fuel cost, the transaction costs of the transferable power and maximizing the microgrid operator's demand response benefit whilst simultaneously satisfying the load demand constraints amongst other constraints. The developed mathematical model is tested on two practical case studies and sensitivity analysis of the model to key parameters was also performed. Case study 1 consists of three conventional generator units, one wind generator, one solar generator and three rural customers. Case study 2 is a much larger microgrid and was chosen to test the applicability of our model to larger microgrids and also to verify the scalability of our algorithm. Results show that the demand response program curtails significant grid relieving amounts of energy in the two case studies considered and integration of an incentive based demand response programs into the microgrid energy management problem introduces optimality at both the supply and demand spectrum of the grid.

1. Introduction

Microgrids as distinct from a major power grid consists of distributed generation units, storage devices and controllable loads sited close to the customer and spanning a limited physical area [1]. The generation units in micro grids can either be conventional power generators or renewable energy sources. Examples of renewable energy sources are wind power or solar power. Conventional power generators can either be thermal generators or diesel generators. Storage devices in microgrids include batteries, flywheels and pumped storage [1,3]. Typically modern microgrid systems can either be operated in the grid connected mode or in the islanded mode. In the grid connected mode, the microgrid is connected with the main grid, whilst in the islanded mode, the microgrid can be disconnected from the main grid in the event of a system emergency and still supply local load. Thus microgrids are also able to ensure localized power system operation in the event of a blackout or brownout. Advantages of microgrids include improvement of reliability of electricity supply, sustainability, power quality and lower electricity costs, transmission and distribution line losses [1]. As stated earlier, the generation units in micro grids can either be conventional power generators or renewable energy sources. However, in recent times Renewable Energy Sources (RES) have become preferred for use in microgrids because of their long term environmental and cost benefits over conventional generation sources [4]. They are used either singly or in conjunction with other RES. Recently, the focus of researchers has been on the optimal operation and control of microgrids. This field of research endeavour is commonly referred as the energy management of microgrids and involves minimizing or maximizing some predetermined objective function (minimizing cost, maximizing microgrid reliability, etc) and determining the optimal dispatch (economic dispatch) and commitment (unit commitment) of the conventional generators, RES and storage devices. An optimal control strategy for a microgrid operating in the islanded mode and containing RES is investigated [5]. The objective is to minimize the electricity generation cost and determine the optimal operational schedule of the microgrid considering the stochastic nature of RES. Grid connected interconnected microgrids with variable electricity

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prices and having the objectives of maximizing financial gain and PV energy consumption are investigated [6]. A microgrid consisting of wind, PV energy sources with battery storage is researched [7] with the objective of maximizing the overall economic benefit of the system and determining the optimal output of power sources whilst satisfying load balance constraints. In Ref. [8], a microgrid made up of wind, PV energy sources with batteries is considered. The microgrid is grid connected and investigations are carried out under different grid market policies and Particle Swarm Optimization (PSO) is utilized in solving the obtained mathematical model. The optimal control strategy for a hybrid microgrid consisting of PV and diesel power source and a battery storage system was proposed [9]. The objective function is to minimize the cost of the diesel generators and determine the optimal power output for the power sources under winter and summer conditions. This work was further expanded and improved [10] with the inclusion of wind power sources and the application of a Model Predictive Control (MPC) strategy to handle variations in demand. Another work proposes a switched model predictive control strategy for a PV, diesel and battery hybrid power system [11]. The advantage of the switched MPC over conventional MPC is that it is able to efficiently handle cases when the battery is not permitted to charge and discharge simultaneously. Other works that deal with the energy management of microgrids are [1,2,7]. However, the aforementioned works do not incorporate Demand Response (DR) into the optimal energy management problem of microgrids. Failing to include DR into the energy management problem of micirogrids can lead to suboptimal operation of the microgrid. This is because the energy management problem is concerned with the optimal commitment and dispatch of conventional generators, RES and storage devices at the supply side whilst DR programs are concerned with providing demand relief at the demand side [12]. Inclusion of DR programs would make for a better and more reliable microgrid as this would ensure optimal operating conditions at both the supply side and demand side of the microgrid [12]. It has been observed that DR programs lead to reduced microgrid operational cost and improved operations [12,13]. Furthermore the addition of DR programs into the microgrid mix provides some degree of grid flexibility and helps to mitigate the effect of having intermittent RES [13].

A few works have incorporated DR into the energy management problem of microgrids like [12,13]. While in Ref. [13] DR is incorporated into the microgrid and provides reserve capacity, in Ref. [12], DR is modelled with detailed residential household appliances consumption information incorporated into a microgrid. The model setup is investigated under a single consumer and under multiple consumers. Both works have as their objective the minimization of the microgrid fuel costs. Other recent examples of the integration of DR programs into microgrid problems include [14,15,22]. There is still the need to investigate and provide a comprehensive practical framework for incorporating DR into the energy management problem of a microgrid in a way that is beneficial to participating DR customers and does not just seek to minimize microgrid fuel costs. It is imperative that DR programs accurately captures the customers outage cost and factor these costs in the design of the DR programs to be incorporated into the energy management problem of microgrids. The DR program presented in this work is an incentive based DR program [23] and one of the core constraints in the DR model is that there should be incentive compatibility, that is customers must see economic benefit in participating in the DR program and that they are adequately compensated for their level of participation. This work builds on the work done in Ref. [23] where a DR program was incorporated into the Dynamic Economic Emission Dispatch (DEED) problem [24,26]. In this work we incorporate this incentive based DR program into the microgrid energy management problem under the grid connected operational mode. It is important we provide in our model instances when the microgrid is in a grid connected mode and there is need to import or export power from the main grid into the microgrid. To the best of the knowledge of the authors of this paper, there has been no work that has provided this nature of DR program integrated into the microgrid energy management problem. The developed model is able to provide grid flexibility and helps to mitigate the effect of having intermittent RES whilst simultaneously using DR to provide relief to the system. The DR model actively incentivises customers to participate in the DR program and ensures that their incentive is greater than the cost of curtailment. Furthermore practical constraints like budgetary and customer maximum load constraints are built into the model. The rest of the paper is organized as follows: Section 2 presents the mathematical models for the microgrid incorporating the demand response model. Section 3 focuses on the methodology deployed in the numerical simulations whilst Section 4 presents obtained results. The paper is concluded in Section 5.

2. Mathematical model of microgrid

The microgrid used in this work, consists of conventional generators and RES at the supply side and demand response formulations at the customer side. The RES consists of a PV system and a wind energy system. The hourly energy output of a PV generator S_t is given as [10]:

$$S_t = n_{pv} A_c Ipv_t, \tag{1}$$

where n_{pv} is the efficiency of the solar PV generator/array, Ipv_t (kW h/m^2) is the hourly solar irradiation incident on the solar PV array, A_c is the area of the PV array and S_t is the hourly energy output from a solar generator [10]. The hourly output of a wind generator is highly dependent on the wind speed and the wind speed is given as [10]:

$$vhub_t = vref_t \left(\frac{hhub}{href}\right)^{\beta}, \tag{2}$$

where $vhub_t$ is the hourly wind speed at the desired height $hhub$, $vref_t$ is the hourly wind speed at the reference height $href$ and β is the power law exponent that ranges from $\frac{1}{7}$ to $\frac{1}{4}$. For the purpose of this work, $\frac{1}{7}$ is used. The mathematical formula used to convert hourly wind speed to electrical power is as follows [10]:

$$W_t = 0.5 n_w \rho_{air} C_p A V^3, \tag{3}$$

where V is the wind velocity at hub height, ρ_{air} is the air density, C_p is the power coefficient of the wind turbine, depending on the design, A is the area of the wind turbine rotor swept area, n_w the efficiency of the wind generator and W_t is the hourly energy output from the wind generator.

The mathematical models for the microgrid at the supply side and the demand response model at the demand side are presented in the following subsections.

2.1. Grid-connected microgrid

In this work, we assume that a trading scheme exists whereby power can either be transferred or sold from the main grid to the microgrid and vice versa. This trading scheme exists to cater for the intermittent nature of RES. Thus if W_t is the forecast (maximum) wind power obtainable from the wind generator while S_t is the forecast (maximum) solar power obtainable from the solar generator, we define Pw_t as the power generated by the wind generator and Ps_t as the power generated by the solar generator in the microgrid at time t. If the microgrid's supply cannot meet its demand, then power has to be purchased from the main grid, and if the microgrid's supply exceeds its demand, then the excess power can be sold to the main grid. We thus denote Pr_t as the transferable power between the microgrid and the main grid at time t.

If an assumption is made that Locational Marginal Prices (LMP's) [25] are used to purchase power between the main and micro grid from a specific interface bus (given as γ_t), then the total transaction cost for trading transferable power is $C_r(Pr_t)$ and is given as:

$$C_r(Pr_t) = \begin{Bmatrix} \gamma_t \times Pr_t & Pr_t > 0 \\ 0 & Pr_t = 0 \\ -\gamma_t \times Pr_t & Pr_t < 0 \end{Bmatrix}. \tag{4}$$

The objective function in the grid connected mode is thus to minimize the fuel cost of the conventional generators and the transaction costs of the transferable power and is given as:

$$min \sum_{t=1}^{T} \sum_{i=1}^{I} C_i(P_{i,t}) + \sum_{t=1}^{T} C_r(Pr_t), \tag{5}$$

s.t.

$$\sum_{i=1}^{I} P_{i,t} + Pw_t + Ps_t + Pr_t = D_t - \sum_{j=1}^{J} X_{j,t}. \tag{6}$$

$$P_{i,min} \le P_{i,t} \le P_{i,max}, \tag{7}$$

$$0 \le Pw_t \le W_t, \tag{8}$$

$$0 \le Ps_t \le S_t, \tag{9}$$

$$-Pr_{max} \le Pr_t \le Pr_{max}, \tag{10}$$

$$-DR_i \le P_{i,t+1} - P_{i,t} \le UR_i, \tag{11}$$

where

- Pr_t is the transferable power between the main grid and the microgrid at time t;
- $C_r(Pr_t)$ is the transaction cost for trading transferable power at time t;
- W_t is the forecast (maximum) wind power obtainable from the wind generator while S_t is the forecast (maximum) solar power obtainable from the solar generator;
- $P_{i,t}$ is the power generated from conventional generator i at time t;
- Pw_t is the power generated from the wind generator at time t;
- Ps_t is the power generated from the solar generator at time t;
- C_i is the fuel cost of conventional generator i;
- D_t is the total system demand at time t;
- $P_{i,min}$ and $P_{i,max}$ are the minimum and maximum capacity of generator i respectively;
- Pr_{max} is the maximum power that can be transferred between the main grid and microgrid;
- DR_i and UR_i are the maximum ramp down and up rates of conventional generator i respectively;
- a_i and b_i are the fuel cost coefficients of conventional generator i respectively;
- I and T are the number of conventional generators and the dispatch interval respectively.

The following is a brief description of the constraints:

- Constraint (6) is the power balance constraint and ensures that at any time t, the total power generated from the conventional, wind and solar generators and the power transferred from the main grid equals the total demand.
- Constraint (7) is the generation limits constraint for the conventional generators and ensures that the generator limits are not exceeded.
- The third and fourth constraints are the generation limits constraint for the renewable generators (constraints (8) and (9)). They ensure that the optimal values for the wind and solar generators are less than or equal to the forecast or maximum values.
- Constraint (10) is the limit for the transferable power between the main grid and microgrid. This is dictated by the physical characteristics of the transmission facilities between the main grid and microgrid; and
- Constraint (11) is the conventional generator ramp rate limits constraint and ensures that the generator ramp rate limits are not violated.

For the sake of simplicity, the conventional generator fuel cost in equation (12) is assumed to be a quadratic function of the generators active power output [9] and is given as:

$$C_i(P_{i,t}) = a_i P_{i,t}^2 + b_i P_{i,t}, \tag{12}$$

Other types of conventional generators can be used as long as they have similar fuel cost functions and ramp rate constraints.

2.2. Demand response model

Let $c(\theta, x)$ be defined as the cost incurred by a customer of type θ who decreases power consumption by x MW. The benefit function of the customer is given as:

$$V_1(\theta, x, y) = y - c(\theta, x), \tag{13}$$

where y is the value of monetary compensation the customer receives. It follows logically, that the customer would only participate if $V_1 \ge 0$. Similarly, the benefit function of the utility is given as:

$$V_2(\theta, \lambda) = \lambda x - y. \tag{14}$$

λ is the cost of not supplying power to a particular location on the grid. Under certain conditions, it might be costly for the power utility to supply electric power to some load buses on the grid [18]. The electric utility can easily calculate this cost of not supplying power. This calculated value has hitherto been defined as: the value of power interruptibility (λ) [17,19,20] and is typically calculated from optimal power flow (OPF). The objective of the utility is to maximize its benefit function:

$$\max_{x,y} [\lambda x - y], \tag{15}$$

where

- θ is the “customer type”, normalized in $[0, 1]$.
- x is the quantity of power reduced by a participating customer.
- $c(\theta, x)$ is the cost of reducing x kW by customer of type θ.
- λ is the “value of power interruptibility” and can be calculated via OPF (LMP).

2.2.1. Customer cost function

As stated before, $c(\theta,x)$ is the cost incurred by a customer of type θ who decreases power consumption by x MW. In this work, it is assumed that the mathematical function is given as in Ref. [20]:

$$c(\theta,x) = K_1x^2 + K_2x - K_2x\theta, \tag{16}$$

where K_1 and K_2 are cost co-efficients. θ is the customer type [17,19,21] and is used to categorize the different kinds of customers based on their desire/readiness to curb electric power. θ is normalized in the interval $0 \le \theta \le 1$, thus $\theta = 1$ for the most willing customer and $\theta = 0$ for the least willing. We provide a summary of all the conditions that the cost function must satisfy:

- Assumed form $c(\theta,x) = K_1x^2 + K_2x - K_2x\theta$.
- $K_2x\theta$ term sorts customers by way of θ.
- As θ increases marginal cost decreases: The most willing customer ($\theta = 1$) has the least marginal cost and thus has the highest marginal benefit, whilst the least willing customer ($\theta = 0$) has the highest marginal cost and thus the lowest marginal benefit.
- $\partial c/\partial x = 2K_1x + K_2 - K_2\theta$.
- Non-negative Marginal cost.
- Increasing Marginal cost (Convex cost function).
- Zero curtailment: curbing zero power should cost ($c(\theta,0) = 0$).

The concept of contract formulations to more than one customer is given as in Refs. [19,20]: Thus, if y_j is the amount of payment paid to customer j, the customer benefit is obtained from:

$$u_j = y_j - \left(K_1x^2 + K_2x - K_2x\theta\right), for\ j = 1,\ldots,J, \tag{17}$$

The utility benefit is determined from:

$$u_o = \sum_{j=1}^{J} \lambda_j x_j - y_j. \tag{18}$$

The objective is thus to maximize the expected utility benefit:

$$max_{x,y} \sum_{j=1}^{J} \left[\lambda_j x_j - y_j\right], \tag{19}$$

s.t.

$$y_j - \left(K_1x_j^2 + K_2x_j - K_2x_j\theta_j\right) \ge 0, for\ j = 1,\ldots,J, \tag{20}$$

$$y_j - \left(K_1x_j^2 + K_2x_j - K_2x_j\theta_j\right) \ge y_{j-1} - \left(K_1x_{j-1}^2 + K_2x_{j-1} - K_2x_{j-1}\theta_{j-1}\right), for\ j = 2,\ldots,J,. \tag{21}$$

The mathematical formulation presented above has two variables; the power curtailed (x MW) and the incentive paid (\$ y). Furthermore, the two constraints are defined and described below:

The "individual rationality constraint" (constraint (20) ensures that each customer benefit is greater than or exceeds zero.).
The "incentive compatibility constraint" (constraint (21) ensures that customers are appropriately compensated for their level of load curbed).

The demand management contract formulations (equations 19–21) is extended to more than one time interval. We also modify the individual rationality constraint and the incentive compatibility constraint and enforce it over the total optimization horizon (a day) instead of a single time interval (every hour). This we believe makes more practical and economic sense. Finally, we add maximum power targets and total budget as practical constraints into the model. The final mathematical model is given as:

$$max_{x,y} \sum_{t=1}^{T} \sum_{j=1}^{J} \left[\lambda_{j,t} x_{j,t} - y_{j,t}\right], \tag{22}$$

s.t.

$$\sum_{t=1}^{T} \left[y_{j,t} - \left(K_{1,j}x_{j,t}^2 + K_{2,j}x_{j,t} - K_{2,t}x_{j,t}\theta_j\right)\right] \ge 0, for\ j = 1,\ldots,J, \tag{23}$$

$$\sum_{t=1}^{T} \left[y_{j,t} - \left(K_{1,j}x_{j,t}^2 + K_{2,j}x_{j,t} - K_{2,t}x_{j,t}\theta_j\right)\right] \ge \sum_{t=1}^{T} \left[y_{j-1,t} - \left(K_{1,j-1}x_{j-1,t}^2 + K_{2,j-1}x_{j-1,t} - K_{2,j-1}x_{j-1,t}\theta_{j-1}\right)\right], for\ j = 2,\ldots,J,\ . \tag{24}$$

$$\sum_{t=1}^{T} \sum_{j=1}^{J} y_{j,t} \le UB, \tag{25}$$

$$\sum_{t=1}^{T} x_{j,t} \le CM_j, \tag{26}$$

where UB is the utility's total budget and CM_j is the daily limit of interruptible power for customer j;Constraint (23) ensures that the total daily incentive received by a customer exceeds or equals his daily cost of interruption.Constraint (24) ensures that the greater the customer power curtailed, the greater the customer benefit.Constraint (25) ensures that the total incentive paid by the utility is less than the utility's budget.Constraint (26) ensures that the total daily power curtailed by each customer is less than its daily limit of interruptible power.

2.3. Combined grid-connected microgrid with demand response model

For the grid connected microgrid with a demand response model, there are two objective functions. One objective function seeks to minimize the fuel cost of conventional generators and the transaction cost for trading transferable power. The second objective function seeks to maximize the grid operator's DR benefit. Fig. 1 shows the representation of the grid connected microgrid with demand response programs.

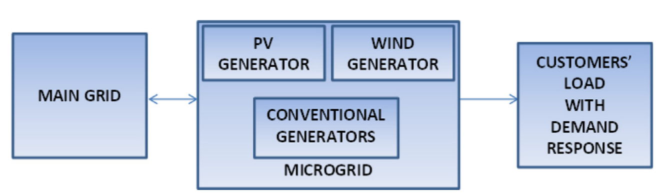

Fig. 1. Set-up of a grid connected microgrid with a demand response model.

The mathematical formulation is presented below:

$$\min w\left[\sum_{t=1}^{T}\sum_{i=1}^{I} C_i(P_{i,t}) + \sum_{t=1}^{T} C_r(Pr_t)\right] + (1-w)\left[\sum_{t=1}^{T}\sum_{j=1}^{J}\left[y_{j,t} - \lambda_{j,t}x_{j,t}\right]\right], \tag{27}$$

subject to the network constraints in (equations 6–11) and (equations 23–26) where w and $1-w$ are the objective function weights and the following condition is required to be satisfied when choosing weights:

$$w + (1-w) = 1. \tag{28}$$

The variables to be determined by the optimization model are $x_{j,t}$, $y_{j,t}$, Pw_t, Ps_t, Pr_t and $P_{i,t}$.

3. Methodology

Case study 1 is designed to validate the grid connected microgrid coupled with a demand response model. It consists of three conventional (diesel) generator units, one wind generator, one solar generator and three rural customers. A scheduling interval of 24 h is considered, however for the solar generator a scheduling interval of 8 h (8 a.m.–6 p.m.) is considered. The decision variables are $x_{j,t}$, $y_{j,t}$, Pw_t, Ps_t, Pr_t and $P_{i,t}$. Table 1 shows the conventional generator parameters (fuel cost coefficients, output power limits and ramp rates limits). Table 2 gives the initial hourly microgrid demand and the hourly values of power interruptibility ($\lambda_{j,t}$). The wind and solar generators have maximum output power ratings of 11 kW and 15 kW respectively and the maximum power that can be transferred between the main grid and microgrid is given as 4 kW. Values for W_t and S_t are adapted from Ref. [10] and shown in Table 3. Solar radiation data is calculated from stochastically generated values of hourly global and diffuse irradiation using the simplified tilted-plane model [10] for a site in Harare, Zimbabwe (latitude 17.80 °S) [10]. The wind speed data used in this work is obtained at 1480 m altitude above sea level and anemometer height of 10 m [10]. The generator cost coefficients are specified by the manufacturer [10]. For this microgrid it is initially assumed that all three customers have equal values of power interruptibility. Table 4 details the cost function coefficients, customer type and daily customer power limit. The assumption is that the microgrid operator knows the customers daily limit of interruptible energy (CM_j) which it then uses to rank the customers in order of increasing willingness to curb electric power. In other words, CM_j aids the microgrid operator in determining θ_j. Also, the microgrid operator knows the outage cost function coefficients of participating customers ($K_{1,j}$ and $K_{2,j}$) and the microgrid operator's daily budget (UB) is $ 500.

Case study 2 is a setup designed to test the applicability of our model to larger microgrids and to verify the scalability of our algorithm. It consists of aggregated wind and solar generators with maximum power ratings of between 170 MW and 150 MW respectively. The maximum power that can be transferred between the main grid and microgrid is given as 150 MW. There are ten conventional generators and their parameters are given in Table 5 (fuel cost coefficients, output power limits and ramp rates limits). Fig. 2 shows the initial hourly demand and the hourly values of

Table 1
Data of the three-unit system (Case study 1).

i	a_i	b_i	$P_{i,min}$	$P_{i,max}$	DR_i	UR_i
1	0.06	0.5	0	4	3	3
2	0.03	0.25	0	6	5	5
3	0.04	0.3	0	9	8	8

Table 2
Total initial hourly demand and λ values (Case study 1).

Time(h)	D_t (kW)	$\lambda_{j,t}$ ($)
1	31.83	1.57
2	31.40	1.40
3	31.17	2.20
4	31.00	3.76
5	31.17	4.50
6	32.10	4.70
7	32.97	5.04
8	34.10	5.35
9	37.53	6.70
10	38.33	6.16
11	40.03	6.38
12	41.17	6.82
13	39.67	7.30
14	41.70	7.80
15	42.10	8.50
16	41.67	7.10
17	40.70	6.80
18	40.07	6.30
19	38.63	5.80
20	36.40	4.20
21	34.10	3.80
22	32.80	3.01
23	32.50	2.53
24	32.00	1.42

Table 3
Forecast power from the wind and solar generators (Case study 1).

Time(h)	W_t (kW)	S_t (kW)
1	7.56	0
2	7.50	0
3	8.25	0
4	8.48	0
5	8.48	0
6	9.42	0
7	9.82	0
8	10.35	7.99
9	10.88	10.56
10	11.01	13.61
11	10.94	14.97
12	10.68	15
13	10.42	14.78
14	10.15	14.59
15	9.67	13.56
16	8.98	11.83
17	8.37	10.17
18	7.61	7.66
19	6.70	0
20	5.72	0
21	7.21	0
22	7.75	0
23	7.88	0
24	7.69	0

Table 4
Customer cost function coefficients, customer type and daily customer curtailable energy limit (Case study 1).

j	$K_{1,j}$	$K_{2,j}$	θ_j	$CM_j(kWh)$
1	1.079	1.32	0	30
2	1.378	1.63	0.45	35
3	1.847	1.64	0.9	40

Table 5
Data of the ten-unit system (Case study 2).

i	a_i	b_i	$P_{i,min}$	$P_{i,max}$	DR_i	UR_i
1	0.00043	21.6	30	370	80	80
2	0.00063	21.05	35	360	80	80
3	0.000394	20.81	33	240	80	80
4	0.0007	23.9	30	200	50	50
5	0.00079	21.62	33	143	50	50
6	0.00056	17.87	37	60	50	50
7	0.00211	16.51	20	30	30	30
8	0.0048	23.23	27	120	30	30
9	0.10908	19.58	20	80	30	30
10	0.00951	22.54	25	55	30	30

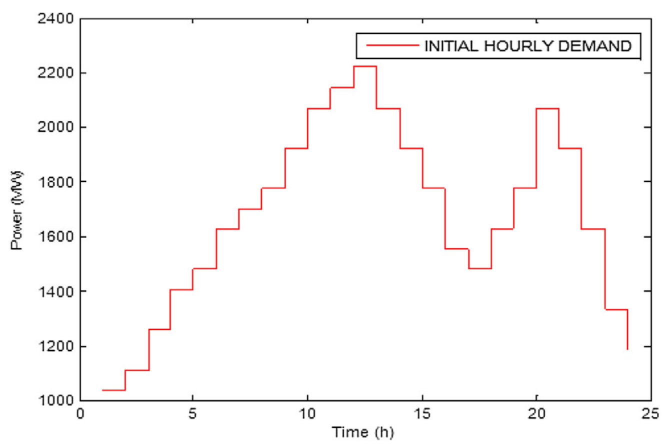

Fig. 2. Total Initial Hourly Demand (Case study 2).

power interruptibility ($\lambda_{j,t}$) are shown in Fig. 3. Table 6 shows the forecast output power from the wind and solar generators over the 24 h scheduling interval. Table 7 details the cost function coefficients, customer type and daily customer power limit. The case study parameters (ten unit generator parameters, initial demand, hourly values of power interruptibility and customer parameters) have been used in prior research works [27,28] to investigate various demand response models. It is also similarly assumed in case study 2 that the grid operator knows the outage cost function coefficients of participating customers ($K_{1,j}$ and $K_{2,j}$) and the customers daily limit of interruptible energy (CM_j) which it then uses to rank the customers in order of increasing willingness to curb electric power θ_j. The microgrid DR operator's daily budget (UB) is given as \$ 150000.

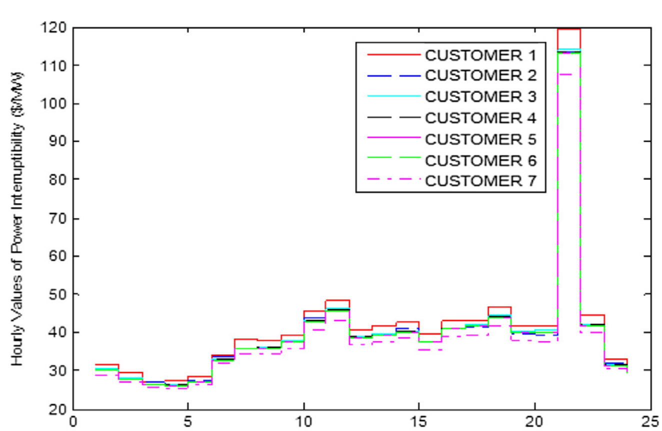

Fig. 3. Hourly Values of Power Interruptibility for different customers (Case study 2).

Table 6
Total forecast power from the wind and solar generators (Case study 2).

Time(h)	W_t (MW)	S_t (MW)
1.00	113.44	0.00
2.00	112.55	0.00
3.00	123.76	0.00
4.00	127.21	0.00
5.00	127.33	0.00
6.00	141.44	0.00
7.00	147.39	0.00
8.00	155.38	79.94
9.00	163.33	105.69
10.00	165.28	136.18
11.00	164.23	149.75
12.00	160.32	150.00
13.00	156.31	147.89
14.00	152.30	145.92
15.00	145.05	135.65
16.00	134.80	118.36
17.00	125.64	101.71
18.00	114.20	76.68
19.00	100.63	0.00
20.00	85.95	0.00
21.00	108.26	0.00
22.00	116.38	0.00
23.00	118.33	0.00
24.00	115.38	0.00

Table 7
Customer cost function coefficients, customer type and daily customer energy limit (Case study 2).

j	$K_{1,j}$	$K_{2,j}$	θ_j	$CM_j(MWh)$
1	1.847	11.64	0	180
2	1.378	11.63	0.14	230
3	1.079	11.32	0.26	310
4	0.9124	11.5	0.37	390
5	0.8794	11.21	0.55	440
6	1.378	11.63	0.84	530
7	1.5231	11.5	1	600

The Advanced Interactive Multidimensional Modelling System (AIMMS) [29] is utilized to build and solve the resulting mathematical models using the CONOPT solver on a computer with Intel (R) core processor and 8 GB of RAM. AIMMS is an Algebraic

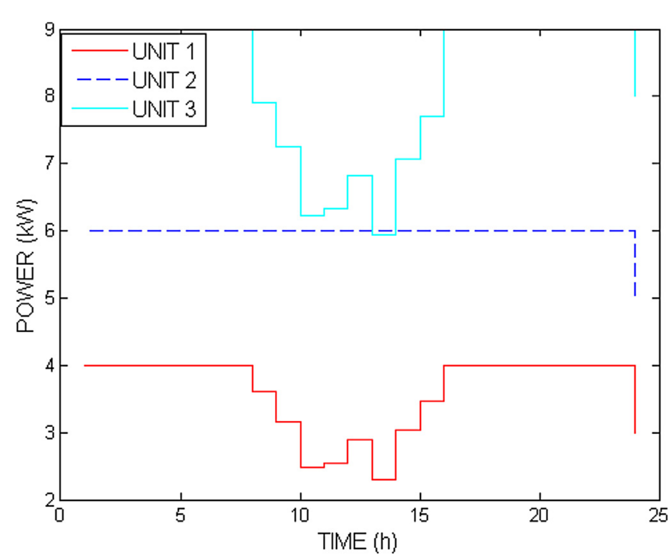

Fig. 4. Optimal power from conventional generators.

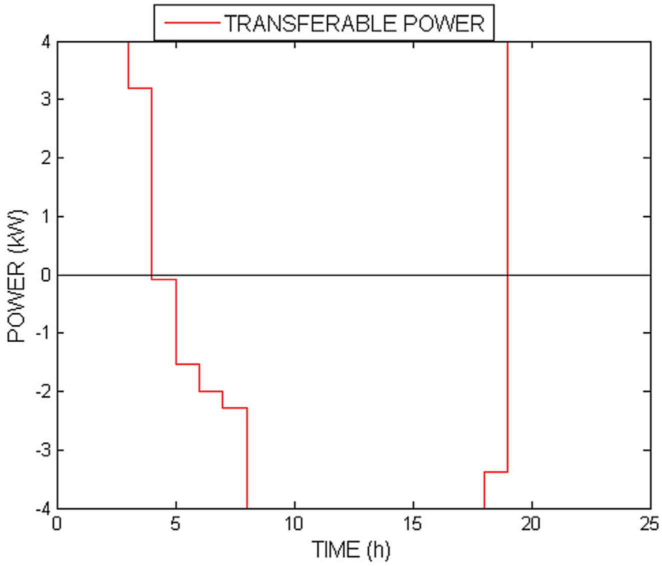

Fig. 5. Optimal power transferred between main grid and microgrid.

Modelling language (AML) used for solving optimization and scheduling type mathematical problems. A major advantage of using AIMMS is the similarity of the software's syntax to the mathematical representation of optimization problems. The software supports the solution of a large number of optimization problem types and allows for an easy reproduction of their results. CONOPT is a feasible path solver based on the generalized reduced gradient (GRG) method and is a suitable solver for large-scale nonlinear optimization problems like the models presented in this work.

4. Results

4.1. Case study 1

In the simulations for the grid connected microgrid (equations 27 and 28), $w = 0.5$. This is done to give equal weights to both objective functions. Fig. 4 shows the optimal output power from the three conventional (diesel) generators, Fig. 5 shows the optimal transferred power between the main grid and micro grid. Fig. 6 shows the optimal customer power curtailed and incentive received for curtailment by each microgrid consumer. Table 8 gives the total daily energy curtailed and incentive received by each of the customers. The complete model results detailing the optimal power generated by conventional generators, optimal power generated by wind and solar generators, optimal power transferred between the main grid and microgrid, optimal power curtailed by the customers and optimal incentive by the customers is shown in Tables A.16–A.19.

4.2. Case study 2

For the second case study (case study 2), Fig. 7 shows the optimal output power from the renewable energy sources (wind and solar) and the power transferred or traded between the main grid and the microgrid. The total energy curtailed by each of the customers over the 24 h period with the corresponding optimal incentive received by each customer is shown in Table 9.

4.3. Sensitivity analysis

In simulations performed, it is assumed that the grid operator places equal preference to the two objective functions ($w = 0.5$), thus satisfying equation (28). This is known as the Base Case. However it is crucial in multi-objective optimization problems to analyse and view the impact of giving varied preference weights to objectives and how they influence the microgrid solutions. Thus (w is varied from 0 to 1). When ($w = 1$), it means that the objective is to minimize fuel cost/transaction cost with no attention paid to the grid operator DR benefit. When ($w = 0$), it means the objective is to maximize the grid operator DR benefit and ignore the minimization

Table 8
Total energy curtailed and customer incentive received (Case study 1).

j	Energy saved (kWh)	Incentive received ($)
Customer 1	30	103.27
Customer 2	35	122.66
Customer 3	40	145.32
Total	**105**	**371.25**

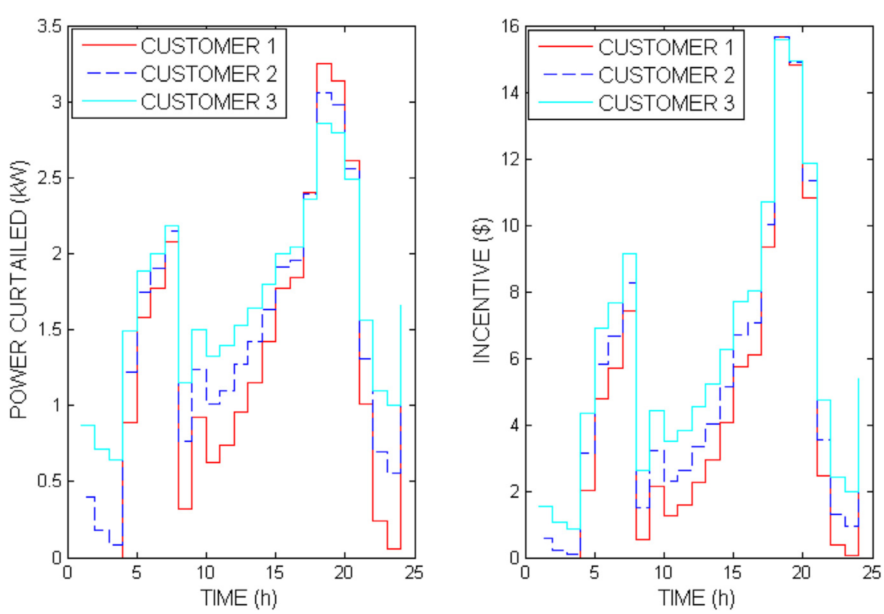

Fig. 6. Customer power curtailed and incentive paid.

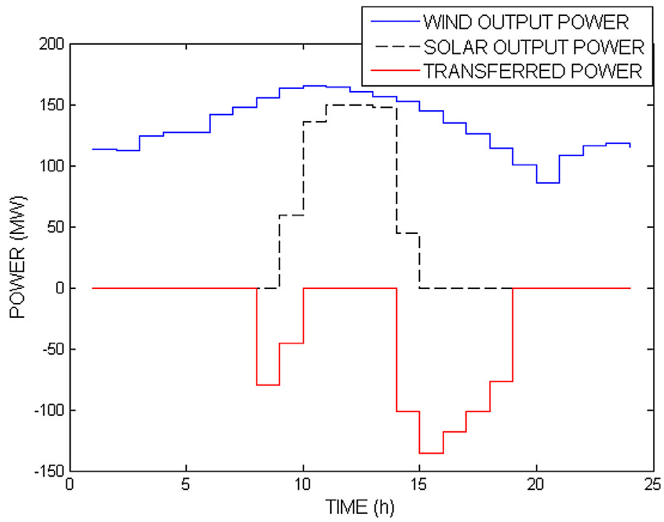

Fig. 7. Output power from the wind generator, solar generator and transferred power between the main grid and microgrid.

Table 9
Total energy curtailed and customer incentive received (Case study 2).

	Energy saved (MWh)	Incentive received ($)
Customer 1	180.00	10872.69
Customer 2	230.00	13419.17
Customer 3	310.00	17718.74
Customer 4	390.00	22052.58
Customer 5	440.00	24292.13
Customer 6	530.00	27858.47
Customer 7	600	32498.73
Total	**2680**	**148712.50**

of the fuel cost/transaction cost. Results of this experiment is presented in Table 10 for case study 1 and Table 10 for case study 2. The analysis is done by collecting six parameters from the model. The parameters collected are the total conventional power cost (i.e. the total cost of power from the conventional generators), total transferred power transaction cost (i.e. the total cost of power transferred between the main grid and microgrid), total customer incentive (i.e. daily total monetary amount received by the customers as incentive for shedding power), total customer energy curtailed (i.e. total energy all customers curtailed over a 24 h period), total conventional energy generated (i.e. total energy generated by the conventional generators) and total transferred energy (i.e. total energy transferred between the main grid and the microgrid). The results of the simulations are shown in Table 10 for case study 1 and Table 11 for case study 2. They show the trade off's between the two objectives. The results show that lower costs are achieved in the microgrid when the grid operator's DR benefit is maximized at the expense of minimizing fuel/transaction costs.

To further investigate the robustness of our model, we perform sensitivity analysis of the model in case study 1 to the values of power interruptibility ($\lambda_{j,t}$). It is initially assumed that in the microgrid, all three customers have equal $\lambda_{j,t}$, however we investigate the effect of varying $\lambda_{j,t}$ on obtained results. We assume that Customer 1 has a $\lambda_{j,t}$ that is 90% of it's initial $\lambda_{j,t}$, while Customer 3 has a $\lambda_{j,t}$ that is 110% of their initial $\lambda_{j,t}$. Fig. 8 shows the different values of power interruptibility for each customer. From Table 12 we see this effect on the results on of the microgrid and especially on the customers. We observe that a clear link between λ and the customer is shown as the customer who had a λ decrease, also had a reduction in incentive for the same amount of power curtailed, the customer with the same λ had essentially the same incentive whilst the customer with λ increase had an increase in incentive. It is worth noting that the incentive compatibility constraint from game theory still holds and is not violated.

Finally we investigate the effect of CM_j on the grid connected microgrid model. In the default case C3 in Table 13, the total daily energy curtailed by all three customers is 105 kWh. We vary the total value from between 95 kWh and 115 kWh and check the sensitivity of the microgrid via our obtained solutions to CM_j. From Table 14 we see very clearly the effect. As the load customers agree to curtail increases, the conventional energy generated by conventional generators reduces and thus the cost reduces. Again as more energy is curtailed by the customers, the incentive increases. This is perfectly rational and expected. Furthermore as the energy curtailed by customers increases, there is an increase in the energy

Table 10
Investigating the effect of w on the grid connected microgrid (Case study 1).

	$w = 0$	$w = 0.1$	$w = 0.2$	$w = 0.3$	$w = 0.4$
Total Conventional Power Cost ($)	237	240	241	244	246
Total Transferred Power Transaction Cost ($)	417	383	381	393	407
Total Customer Incentive ($)	340	349	360	361	363
Total Customer Energy Curtailed (kWh)	101	103	105	105	105
Total Conventional Energy Generated (kWh)	411	416	417	420	423
Total Transferred Energy (kWh)	83.5	76.9	76.2	78.2	80.8
			$w = 0.5$		
Total Conventional Power Cost ($)			**250**		
Total Transferred Power Transaction Cost ($)			**427**		
Total Customer Incentive ($)			**371**		
Total Customer Energy Curtailed (kWh)			**105**		
Total Conventional Energy Generated (kWh)			**428**		
Total Transferred Energy (kWh)			**84.5**		
	$w = 0.6$	$w = 0.7$	$w = 0.8$	$w = 0.9$	$w = 1.0$
Total Conventional Power Cost ($)	256	264	270	270	270
Total Transferred Power Transaction Cost ($)	443	436	454	450	450
Total Customer Incentive ($)	391	433	500	500	500
Total Customer Energy Curtailed (kWh)	105	105	105	105	105
Total Conventional Energy Generated (kWh)	434	443	450	450	450
Total Transferred Energy (kWh)	87.9	86.9	89.9	88.9	88.9

Bold text indicates the base case when equal preference is given to both objective functions.

Table 11
Investigating the effect of w on the grid connected microgrid (Case study 2).

	$w = 0$	$w = 0.1$	$w = 0.2$	$w = 0.3$	$w = 0.4$
Total Conventional Power Cost ($)	729826.44	730823.94	730415.71	729819.10	729840.56
Total Transferred Power Transaction Cost ($)	8675.54	25175.31	25662.75	26320.40	26943.09
Total Customer Incentive ($)	143321.61	144093.87	145183.94	147259.31	148194.14
Total Customer Energy Curtailed (MWh)	2585.80	2606.70	2633.17	2669.07	2680.00
Total Conventional Energy Generated (MWh)	33202.01	33578.26	33563.54	33543.48	33547.56
Total Transferred Energy (MWh)	4320.19	3923.05	3911.30	3895.46	3880.44
			w = 0.5		
Total Conventional Power Cost ($)			**730195.39**		
Total Transferred Power Transaction Cost ($)			**27670.01**		
Total Customer Incentive ($)			**148712.50**		
Total Customer Energy Curtailed (MWh)			**2680.00**		
Total Conventional Energy Generated (MWh)			**33565.08**		
Total Transferred Energy (MWh)			**3862.92**		
	$w = 0.6$	$w = 0.7$	$w = 0.8$	$w = 0.9$	$w = 1.0$
Total Conventional Power Cost ($)	730696.33	731603.04	731794.63	731853.06	731885.74
Total Transferred Power Transaction Cost ($)	28637.28	30117.25	30385.28	30458.37	30495.34
Total Customer Incentive ($)	149508.42	150000.00	150000.00	150000.00	150000.00
Total Customer Energy Curtailed (MWh)	2680.00	2680.00	2680.00	2680.00	2680.00
Total Conventional Energy Generated (MWh)	33588.40	33623.24	33629.67	33631.57	33632.62
Total Transferred Energy (MWh)	3839.60	3804.76	3798.33	3796.43	3795.38

Bold text indicates the base case when equal preference is given to both objective functions.

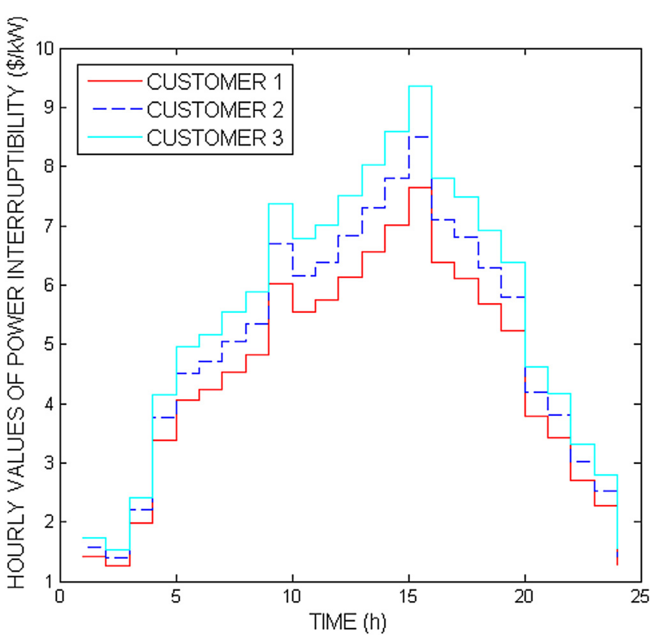

Fig. 8. Varying values of power interruptibility.

Table 12
Total customer energy curtailed and incentive paid for grid connected microgrid with varying lambda (Case study 1).

j	Total energy curtailed (kWh)	Total incentive ($)
1	30	102.42
2	35	122.49
3	40	146.92

to be transferred between the main grid and the microgird (see Fig. 9). This also leads to a corresponding increase in the total transferred power transaction cost. A breakdown of this transferred power in Table 15 shows that as CM_j increases the power bought from the main grid reduces while there is an increase in the power

Table 13
Varying CM_j (Case study 1).

j	C1 (kWh)	C2 (kWh)	C3 (kWh)	C4 (kWh)	C5 (kWh)
1	27.5	28.75	**30**	31.25	32.5
2	32.5	33.75	**35**	36.25	37.5
3	35	37.5	**40**	42.5	45
Total	95	100	**105**	110	115

Bold text indicates the base case.

Table 14
Effect of Varying CM_j on the Grid Connected Microgrid (Case study 1).

	C1	C2	C3	C4	C5
Total Conventional Power Cost ($)	255	252	**250**	248	246
Total Transferred Power Transaction Cost ($)	414	420	**427**	433	438
Total Customer Incentive ($)	320	345	**371**	399	428
Total Customer Energy Curtailed (kWh)	95	100	**105**	110	115
Total Conventional Energy Generated (kWh)	434	431	**428**	425	423
Total Transferred Energy (kWh)	82.4	83.4	**84.4**	85.1	85.5

Bold text indicates the base case.

sold by the microgrid to the main grid. Thus it follows that if we want to be able to sell more power to the microgrid (reduce the instances of Pr_t having positive values in Figs. 5 and 9) we have to curtail more power. This insight is very important especially in instances where the price for selling power to the main grid differs from the buying price.

4.4. Discussion of results

A close look at results obtained from the simulations provides interesting underlying perspectives on the operational mode of the microgrid. For case study 1, Fig. 4 shows that the conventional generators are operating throughout the 24 h scheduling interval, and are supported by the RES. That is why when the solar generator comes on stream, conventional generators 1 and 3 reduce their power output (See Fig. 4). It is observed that the conventional generators in the microgrid cannot satisfy demand alone. This now makes it imperative that the microgrid deploys the DR program and

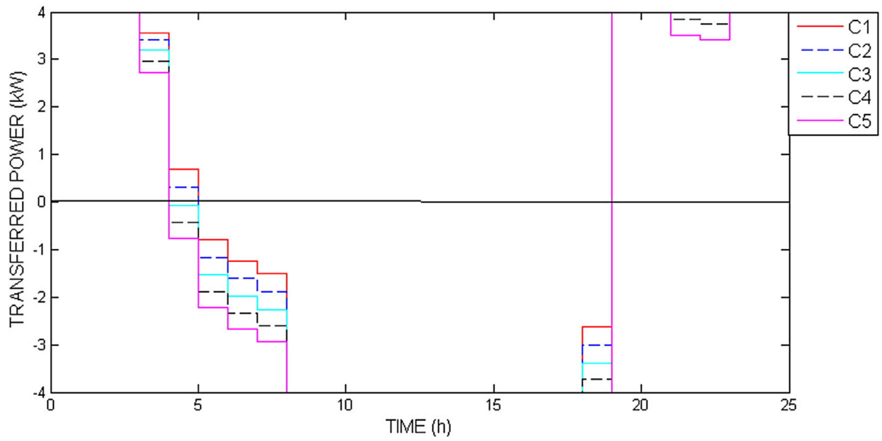

Fig. 9. Effect of varying CM_j on Pr_t.

Table 15
Breakdown of the effect of varying CM_j on the power transferred between main grid and microgrid (Case study 1).

	C1	C2	C3	C4	C5
Total Energy Bought from Main Grid (kWh)	36.25	35.72	**35.19**	34.55	33.66
Total Energy Sold to the Main Grid (kWh)	−46.13	−47.67	**−49.18**	−50.57	−51.83

Bold text indicates the base case.

transacts with the main grid. Fig. 5 shows that when Pr_t is negative, power is being sold to the main grid whilst if it is positive, power is being bought from the main grid. Thus from the Figure, it is observed that power is bought in the early hours of the morning and late at night when the renewable energy sources are not producing at their maximum. When the renewable energy sources are fully on stream, there is power available to sell to the main grid especially when the solar generator comes on stream. Due to the fact that power from the conventional generators costs less than power transferred from the main grid, the conventional generators have to produce close to their maximum output (see Fig. 4).

Fig. 6 shows the power curtailed and incentive received by each customer. Table 8 sheds more light on these results as they show that the customers receive incentive payments in line with the amount of load they curtail (i.e. customer willingness). Thus, Customer 3 has a greater incentive than Customers 1 and 2, as Customer 3 curtails the greatest amount of energy and is thus the most willing customer. Customer 1 curtails the least amount of energy and thus receives the least amount of incentive. This shows that the incentive compatibility constraint is not violated. These results are fully shown in Tables A.16–A.19 in the Appendix. Results from case study 2 corroborate our findings from case study 1 which is significant as case study 2 is a much larger system than 1. Fig. 7 shows the optimal output power from the wind generators and solar generators, it is observed that the operation of the RES in addition to the DR program provides enough power to be transferred or be traded from the microgrid to the main grid (negative transferred power in Fig. 7). In this case study, the microgrid does not buy any power from the main grid but instead supplies or sells to the main grid. Table 9 also mirrors results from case study 1 as again customers receive incentive payments in proportion to the amount of load they curtail. Thus customers with the highest customer willingness, shed the most load and also receive the highest compensation. Full details of these results are shown in the Appendix (Table A.21 which show the hourly output power of the conventional generators and Table A.20 which shows the power curtailed by all the seven customers throughout the scheduling horizon).

5. Conclusion and future work

In this work, the energy management problem for a microgrid incorporating a demand response program was investigated. The demand response program is a game theory based demand response program (GTDR) and the grid connected operational mode for a microgrid is investigated. The objective is to minimize the fuel cost of conventional generators and the transaction cost for trading transferable power and at the same time maximize the grid operator DR's benefit. The optimization model has a scheduling interval of 24 h and determines the optimal customer power curtailed, optimal customer incentive, optimal power generation schedule for the conventional generators and optimal power to be transferred between the main grid and microgrid. The Advanced Interactive Multidimensional Modelling System (AIMMS) is used to solve the developed model, and obtained results indicate that incorporating DR programs into the energy management of microgrid problem is helpful and introduces optimality at both the supply and demand side of the microgrid. Furthermore, there was a significant energy reduction of 105 kWh and 2680 MWh in the two case studies considered. Sensitivity analysis of obtained results to the weighting factor, value of power interruptibility and total value of customer power curtailed was performed to validate the robustness of obtained solutions. The results show that lower costs are achieved in the microgrid when the grid operators DR benefit is maximized at the expense of minimizing fuel/transaction costs. Results also proved that both the incentive compatibility constraints and the individual rationality constraints from game theory were also satisfied. Future work will include incorporating penalty factors into the demand response microgrid energy management problem.

Acknowledgements

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Appendix A

Table A.16. Optimal power produced by conventional generators and transfer power between the microgrid and main grid Case study 1.

	$P_{j,t}$ (kW)			Pr_t (kW)
	$i=1$	$i=2$	$i=3$	
$t=1$	4	6	9	4
$t=2$	4	6	9	4
$t=3$	4	6	9	3.19
$t=4$	4	6	9	−0.08
$t=5$	4	6	9	−1.54
$t=6$	4	6	9	−1.99
$t=7$	4	6	9	−2.27
$t=8$	3.60	6	7.90	−4
$t=9$	3.16	6	7.25	−4
$t=10$	2.49	6	6.23	−4
$t=11$	2.55	6	6.33	−4
$t=12$	2.89	6	6.83	−4
$t=13$	2.30	6	5.95	−4
$t=14$	3.04	6	7.06	−4
$t=15$	3.47	6	7.71	−4
$t=16$	4	6	9	−4
$t=17$	4	6	9	−4
$t=18$	4	6	9	−3.38
$t=19$	4	6	9	4
$t=20$	4	6	9	4
$t=21$	4	6	9	4
$t=22$	4	6	9	4
$t=23$	4	6	9	4
$t=24$	3	5	8	4

Table A.17. Optimal power from the wind and solar generators Case study 1.

Time(h)	Pw_t (kW)	Ps_t (kW)
1	7.56	0
2	7.50	0
3	8.25	0
4	8.48	0
5	8.48	0
6	9.42	0
7	9.82	0
8	10.35	7.99
9	10.88	10.56
10	11.01	13.61
11	10.94	14.97
12	10.68	15
13	10.42	14.78
14	10.15	14.59
15	9.67	13.56
16	8.98	11.83
17	8.37	10.17
18	7.61	7.66
19	6.70	0
20	5.72	0
21	7.21	0
22	7.75	0
23	7.88	0
24	7.69	0

Table A.18. Optimal power curtailed by the customers (Case study 1).

	$x_{j,t}$ (kW)		
$t=1$	0.00	0.40	0.87
$t=2$	0.00	0.18	0.71
$t=3$	0.00	0.08	0.64
$t=4$	0.89	1.22	1.49
$t=5$	1.58	1.75	1.89
$t=6$	1.77	1.90	2.00
$t=7$	2.08	2.15	2.18
$t=8$	0.32	0.77	1.15
$t=9$	0.92	1.24	1.50
$t=10$	0.63	1.01	1.33
$t=11$	0.74	1.10	1.40
$t=12$	0.96	1.27	1.53
$t=13$	1.15	1.42	1.64
$t=14$	1.42	1.63	1.80
$t=15$	1.77	1.91	2.00
$t=16$	1.84	1.96	2.04
$t=17$	2.40	2.39	2.36
$t=18$	3.25	3.06	2.86
$t=19$	3.14	2.98	2.80
$t=20$	2.61	2.56	2.49
$t=21$	1.01	1.31	1.56
$t=22$	0.24	0.70	1.10
$t=23$	0.06	0.56	1.00
$t=24$	1.19	1.45	1.66

Table A.19. Optimal incentive received by customers (Case study 1).

	$y_{j,t}$ (\$)		
	$j=1$	$j=2$	$j=3$
$t=1$	0.00	0.57	1.56
$t=2$	0.00	0.21	1.06
$t=3$	0.00	0.09	0.87
$t=4$	2.04	3.13	4.33
$t=5$	4.78	5.81	6.89
$t=6$	5.69	6.67	7.68
$t=7$	7.42	8.27	9.13
$t=8$	0.53	1.50	2.64
$t=9$	2.13	3.22	4.42
$t=10$	1.27	2.32	3.51
$t=11$	1.57	2.64	3.83
$t=12$	2.27	3.36	4.55
$t=13$	2.95	4.04	5.22
$t=14$	4.07	5.13	6.26
$t=15$	5.73	6.71	7.72
$t=16$	6.10	7.05	8.03
$t=17$	9.36	10.04	10.71
$t=18$	15.67	15.65	15.60
$t=19$	14.82	14.90	14.95
$t=20$	10.83	11.36	11.87
$t=21$	2.45	3.54	4.73
$t=22$	0.37	1.31	2.43
$t=23$	0.08	0.93	2.00
$t=24$	3.12	4.21	5.37

Table A.20. Optimal customer power curtailed ($x_{j,t}$) (Case study 2).

$x_{j,t}$	$j=1$	$j=2$	$j=3$	$j=4$	$j=5$	$j=6$	$j=7$
$t=1$	0.00	0.00	0.00	0.00	0.00	7.22	11.77
$t=2$	0.00	0.00	0.00	0.00	0.00	6.38	11.06
$t=3$	0.00	0.00	0.00	0.00	0.00	5.83	10.65
$t=4$	0.00	0.00	0.00	0.00	0.00	6.20	10.95
$t=5$	0.00	0.00	0.00	0.00	0.00	6.22	10.99
$t=6$	0.00	0.00	0.00	0.00	0.00	9.79	14.13
$t=7$	0.00	0.00	0.00	0.00	0.00	10.30	14.44
$t=8$	0.00	0.00	0.00	0.00	0.00	10.37	14.43
$t=9$	0.98	0.40	2.05	4.36	7.46	16.48	19.89
$t=10$	6.81	8.30	11.72	15.86	19.23	24.00	26.63
$t=11$	12.48	15.83	21.62	27.53	31.34	31.72	33.49
$t=12$	19.63	25.45	33.98	42.13	46.59	41.45	42.45
$t=13$	6.49	7.70	11.34	15.35	18.79	23.71	26.42
$t=14$	2.72	2.88	4.75	7.68	10.68	18.53	21.88
$t=15$	0.00	0.00	0.00	0.00	0.00	11.67	15.51
$t=16$	0.00	0.00	0.00	0.00	0.00	11.30	15.12
$t=17$	0.00	0.00	0.00	0.00	0.00	11.56	15.31
$t=18$	0.00	0.00	0.00	0.00	1.08	12.41	16.07
$t=19$	0.16	0.00	0.69	2.75	5.77	15.40	18.85
$t=20$	26.71	34.76	46.25	56.58	61.69	51.09	50.97
$t=21$	21.34	26.18	35.13	43.32	47.75	42.19	41.98
$t=22$	13.43	16.91	23.09	29.23	33.25	32.94	34.76
$t=23$	21.09	27.63	36.60	45.27	49.88	43.55	44.66
$t=24$	48.17	63.96	82.79	99.93	106.49	79.68	77.59

Table A.21. Optimal power generated by generators ($P_{i,t}$) (Case study 2).

$P_{i,t}$	$i=1$	$i=2$	$i=3$	$i=4$	$i=5$	$i=6$	$i=7$	$i=8$	$i=9$	$i=10$
$t=1$	86.63	351.94	240.00	30.00	33.00	60.00	30.00	27.00	20.00	25.00
$t=2$	166.63	338.38	240.00	30.00	43.00	60.00	30.00	27.00	20.00	25.00
$t=3$	246.63	346.13	240.00	30.00	93.00	60.00	30.00	27.00	20.00	25.00
$t=4$	326.63	360.00	240.00	30.00	143.00	60.00	30.00	27.00	20.00	25.00
$t=5$	361.60	360.00	240.00	42.68	143.00	60.00	30.00	53.18	20.00	25.00
$t=6$	370.00	360.00	240.00	92.68	143.00	60.00	30.00	83.18	28.78	55.00
$t=7$	370.00	360.00	240.00	142.68	143.00	60.00	30.00	107.72	21.47	55.00
$t=8$	370.00	360.00	240.00	192.68	143.00	60.00	30.00	103.73	41.42	55.00
$t=9$	370.00	360.00	240.00	200.00	143.00	60.00	30.00	120.00	71.42	55.00
$t=10$	370.00	360.00	240.00	200.00	143.00	60.00	30.00	120.00	80.00	55.00
$t=11$	370.00	360.00	240.00	200.00	143.00	60.00	30.00	120.00	80.00	55.00
$t=12$	370.00	360.00	240.00	200.00	143.00	60.00	30.00	120.00	80.00	55.00
$t=13$	370.00	360.00	240.00	200.00	143.00	60.00	30.00	120.00	80.00	55.00
$t=14$	370.00	360.00	240.00	200.00	143.00	60.00	30.00	120.00	80.00	55.00
$t=15$	370.00	360.00	240.00	187.30	143.00	60.00	30.00	108.46	50.00	55.00
$t=16$	299.02	360.00	240.00	137.30	143.00	60.00	30.00	78.46	20.00	25.00
$t=17$	289.49	360.00	240.00	100.00	143.00	60.00	30.00	60.00	20.00	25.00
$t=18$	362.49	360.00	240.00	150.00	143.00	60.00	30.00	90.00	23.75	25.00
$t=19$	370.00	360.00	240.00	200.00	143.00	60.00	30.00	120.00	53.75	55.00
$t=20$	370.00	360.00	240.00	200.00	143.00	60.00	30.00	120.00	80.00	55.00
$t=21$	320.00	320.00	240.00	200.00	143.00	60.00	30.00	120.00	69.86	55.00
$t=22$	240.00	240.00	240.00	150.00	143.00	60.00	30.00	90.00	80.00	55.00
$t=23$	160.00	160.00	160.00	100.00	100.00	60.00	30.00	60.00	60.00	55.00
$t=24$	80.00	80.00	80.00	50.00	50.00	50.00	30.00	30.00	30.00	30.00

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