A Microgrid Energy Management System for Inducing Optimal Demand Response

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Abstract—**This paper focuses on optimal operation schedule of a Microgrid that is interconnected to the power grid. We develop a mathematical model to compute the optimal operation schedule that embodies *demand response*. Integer Programming optimization is used to this end. Our model incorporates the electricity load into three types: fixed, transferable, and user-action loads. The transferable load plays a key role in molding demand response. Experimental results show that the proposed model exploits the demand elasticity and significantly reduces the total operation cost. Also observed from the experiments are the impact of the uncertainty in renewable distributed generators on operation schedule and total cost and the role of power storages for enhancing the demand elasticity with respect to user-action loads and for reserving power against high price.**

Keywords— microgrid; optimization; demand response; storage planning; smartgrid.

I. INTRODUCTION

As the electric power system evolves into Smart Grid, the centralized energy management by utility grid is no longer adequate to the new operation environment with new system components such as renewable energy sources, distributed generators, electric vehicles, etc. In this context, Microgrid is a key concept to transform the current power system to Smart Grid and realize the distributed control scheme on the power system operation.

Studies on Microgrid are largely classified into two groups: system integration and operation. Research on system integration deals with building a Microgrid system as a test-bed or as a real application focused on the aspects of power-electronics and power system engineering technologies. Research on Microgrid operation focuses on computing the most economic scheduling of electricity supply and demand. This study belongs to the latter group. We propose a model for the optimized operation of a Microgrid that considers renewable energy sources, storage devices and elastic demand response.

This paper is organized as follows. Section II reviews relevant studies. Section III introduces the Microgrid under consideration and describes the importance of demand response in Microgrid. Section IV explains the operation of various components in Microgrid, and Section V shows the mathematical formulation. Section VI presents the experiment results and analyzes the effect of demand response and storage capacity. Section VII concludes the paper.

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II. RELATED WORKS ON MICROGRID OPERATION

The scheduling aspect of Microgrid operation has recently received a great deal of attentions. Sinha *et al.* analyzed pricing mechanism and bidding process for Microgrid in the competitive electricity market [1]. The economic optimization analysis was carried out in simulation considering the reliability issues of Microgrid operation in [2].

Zhe *et al.* compared Microgrid with prior distributed generation with respect to the configuration, principle and operation [3]. Wencong *et al.* studied planning and operation jointly to accommodate the high demand of renewable energy and the environment policy [4]. Yen-Haw *et al.* examined optimal operation of Microgrid system that includes many components, such as solar power, wind power, biomass power, gas turbine, fuel cell generators, power generators, power storage, heat storage device [5]. In this work, such factors as electricity demand and heat demand were considered. Bagherian and Tafreshi presented Microgrid Management System (MMS) that generates an optimum operation plan for Microgrid on next day based on operation cost and power trade [6].

Due to the complexity and uncertainties of Microgrid operation, the scheduling is often decomposed into multiple steps. A three-step method was proposed for optimal generation scheduling to set up an initial feasible solution of the thermal unit commitment problem in a Microgrid [7]. Optimization was used as a preferred tool for scheduling a Microgrid, but heuristic methods were introduced for reflecting uncertainties caused by renewable energy sources and consumer demands in this work.

Chakraborty *et al*. introduced a Distributed Intelligent Energy Management System (DIEMS) based on a neural forecasting method for the optimization of Microgrid operation to consider the uncertainties especially from photovoltaic energy sources [8].

Most previous studies have modeled new system components like renewable energy sources and storage devices and their interactions in simple decision-making procedures. In comparison, this paper proposes a more sophisticated and realistic formulation, which is able to produce practically-

meaningful optimal scheduling for Microgrid operation in a single step.

III. DEMAND RESPONSE IN MICROGIRD

A. Microgrid Architecture

The Microgrid system considered in this paper is composed of three components: generation sources, storage devices, and price-elastic demands. Generation sources include various small and modular generators such as micro-turbines, fuel cells, PVs, wind-turbines, etc. Note that renewable energy sources have much stronger impacts on the operation of Microgrid system than that of a bulk power system. Therefore it is necessary for storage devices to buffer the uncertainties and variations caused by renewable energy sources. For storage devices on Microgrid, flywheels, capacitors and batteries are mainly used. Price-elastic demands also take a critical role in balancing the supply and demand of power to avoid a waste of resources. Microgrid may be interconnected to the power grid or operated as an islanded mode [9]. In this paper, we consider the former case. Figure 1 shows the general configuration of Microgrid.

This paper presents an optimal algorithm for Microgrid scheduling and operation. For the operation mode of Microgrid, two approaches are possible which are centralized and decentralized. In the decentralized approach, Multi-Agent System (MAS) is often used to model the interaction between the system components [9-13]. While the primary focus of MAS studies is given to the 'interaction' among components, the scheduling and operation aspects are typically overlooked and tend to be overly simplified. We focus on the optimal scheduling problem. Storage scheduling and price-responsive loads are critical to maximize the economic efficiency of the operation. It is necessary to capture the incentives or penalties applied to demand response, which is the key contribution of this paper.

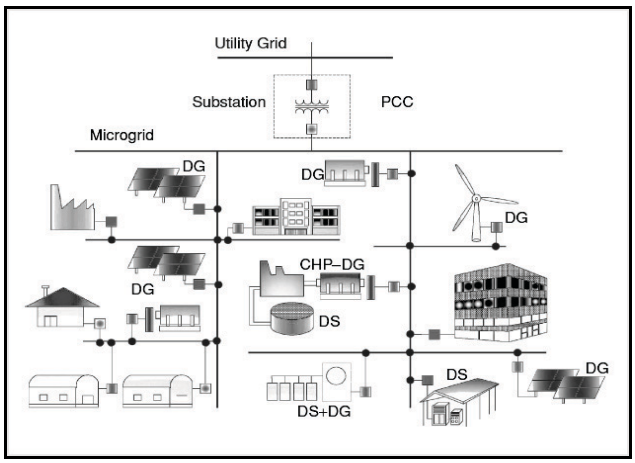

Figure 1. A typical Microgrid configuration (adapted from [14]).

B. Demand Response

We define Demand Response (DR) as the change in electric usage by the end-use customers. The customers change their normal electricity consumption patterns according to the change in price from the power market or according to the additional incentives to reduce electricity usage at the peak load.

DR is critical to maintain the stability of the overall electricity system. In the short term, the difference between the marginal cost and retail rate results in inefficient usage of resources. Inelasticity of DR enables generators to exercise their market power and raise prices. In the long term, excessive investments may be needed to meet the peak load for just a few days in a year. To induce DR, two different types of DR programs have been implemented by US Department of Energy: Incentive-Based Programs (IBP) and Priced Based Programs (PBP). They aim at reducing the power demand at peak time as giving customers incentives or time-varying rates [15].

The demand in electricity system is the sum of loads in multiple Microgrids. Thus, it is important to manage the load in each Microgrid to increase the demand elasticity. To apply the DR programs in the lower-level units such as Microgrid, it is imperative to embody the load change in the operation schedule.

IV. MICROGRID OPERATION SCHEDULE

In this section, we describe the requirements for a day-ahead operation schedule of the three components (i.e., generators, storage devices, price-elastic loads) of the Microgrid system considered in this paper. We assume that the buy and sell prices for each time interval are announced by PG on a day-ahead basis. Using these prices, we plan the operation schedule for the next day. The Microgrid Energy Management System (EMS) decides the amount of power to be purchased, sold, transferred, and stored for each time period to minimize the total operation cost.

A. Operation schedule of Distributed Generators

Distributed generators are divided into the Controllable Distributed Generators (CDGs) such as micro-turbines and the Renewable Distributed Generators (RDGs) that generates unstable output using renewable sources such as wind and sun. Note that among diverse energy sources such as hear, gas, electricity, etc., we focus on electricity. The CDG produces power as long as the buy price is higher than the production cost constrained on its capacity to meet the customers' load. The CDG incurs the startup cost when the power generation of the CDG starts. The production cost is the sum of the setup cost and the variable cost. We assume that the weather forecast can be used to predict the power produced by renewable sources and that the RDG incurs no operation cost such that the RDG continues to produce power at their maximum.

B. Operation schedule of Loads

We consider three types of demand: fixed, transferable, and user-action load [16].We assume that the amount of expected power for each type of load is gained from various electronic devices.

The Fixed Load (FL) indicates the minimum amount of power needed by customers at each time period and is predicted by historical usage data.

The Transferable Load (TL) is defined as the load that can be transferred from its original time interval to another interval. It is desirable to shift the power demand to a cheaper time interval to minimize the cost. A typical example is the washing machine. Of course, the shift of demand should be allowed within certain limits, which reflects an individual's preference and/or time constraints. For example, it may not be advisable for a washing machine to operate in the middle of night

because of noise. The preferences and constraints on the shift of TL are modeled as penalty. Each TL also has inflow and outflow capacity constraints. The former constrains the shift of demand not to exceed the given line capacity; the latter indicates that at each time interval the total amount of transferred power demand should be within the maximum amount of the TL allowed.

The User-action load (UL) is the direct result of a user's action. As it is hard to predict the amount of the power the customer needs in advance, it is needed to keep a certain level of power suggested by historical data. We assume that the UL is covered by distributed storages.

C. Operation schedule of Distributed Storages

The Distributed Storage (DS) can store leftover power from the available power minus the amount of power needed by FLs and TLs at each time interval. The DS can sell to and buy from the power grid depending on the State of Charge (SOC) of the batteries. The DS can also hold the power needed for the UL. When it charges or discharges power, the DS incurs charge loss or discharge loss, respectively.

V. MATHEMATICAL FORMULATION

In the following, we propose an EMS model for the Microgrid operation in Section Ⅳ. The optimal scheduling of Microgrid is formulated as a mixed Integer Programming (IP) model, where the integer variables are restricted to be binary.

A. Model parameters and variables

We use the following notations in our optimization model.

Model parameters

I : set of Controllable Distributed Generators (CDGs)
J : set of Renewable Distributed Generators (RDGs)
N : set of loads
T : time period ($t = 1, 2, \ldots, t_n$)
$b_i(t)$: variable cost of the ith CDG at time t
$c_i(t)$: startup cost of the ith CDG at time t
$CDG_i^{\min}$: minimum production capacity of the ith CDG
$CDG_i^{\max}$: maximum production capacity of the ith CDG
$r_j(t)$: the amount of power produced by the jth RDG at time t
$\rho_n^{t,t'}$: penalty of transferring the nth TL from time t to t'

$$= \begin{cases} a \le t \le b, & \rho_n^{t,t'} = \infty \\ otherwise, & \rho_n^{t,t'} = 0 \end{cases}$$

$\mathrm{IF}_n^{\max}(t)$: maximum inflow power capacity of the nth TL at time t
$\mathrm{OF}_n^{\max}(t)$: maximum outflow power capacity of the nth TL at time t
$D_n^{FL}(t)$: the amount of power consumed by the nth FL at time t
$D_n^{TL}(t)$: the amount of power consumed by the nth TL at time t
$D_n^{TL'}(t)$: the amount of *modified* power consumed by the nth TL after the load transfer at time t
$D_n^{UL}(t)$: the amount of power consumed by the nth UL at time t
$A_r(t)$: the amount of left-over power after considering fixed and modified TL at time t
$A_s(t)$: the state of charge (SOC) of the DS at time t
$A'_s(t)$: the final SOC of the DS after considering ULs at time t
$A_s^{\max}$: maximum power capacity of the DS
L^D, L^C : loss rate of power when the DS discharges / charges $(0 \le L^D, L^C \le 1)$
$P_B(t)$: buy price from power grid at time t
$P_S(t)$: sell price to power grid at time t

Variables

$X_i(t)$: the amount of power produced by the ith CDG at time t
$Y_i(t)$: on or off mode of the ith CDG at time t
$B(t)$: the amount of power purchased from the PG at time t
$S(t)$: the amount of power sold to the PG at time t
$U_n^{t,t'}$: the amount of the nth TL transferred from time t to t'

B. Mixed Integer Programming Model.

$$\begin{aligned} \text{Minimize } V = & \sum_{t\in T}\sum_{i\in I}\{b_i(t)X_i(t) + c_i(t)Y_i(t)\} \\ & + \sum_{t\in T}\{p_B(t)B(t) - p_S(t)S(t)\} \\ & + \sum_{n\in N}\sum_{t\in T}\sum_{t'\in T}\left(\rho_n^{t,t'} \cdot U_n^{t,t'}\right) \end{aligned} \tag{1}$$

Subject to:

Minimum and maximum production constraint:

$$CDG_i^{\min} \cdot Y_i(t) \le X_i(t) \le CDG_i^{\max} \cdot Y_i(t) \tag{2}$$

On-off mode binary constraint:

$$Y_i(t) = binary \tag{3}$$

Minimum load constraint:

$$\begin{aligned} & \sum_{j\in J} \mathrm{r}_j(\mathrm{t}) + \mathrm{A}_\mathrm{s}^{'}(\mathrm{t}-1)\cdot\left(1-\mathrm{L}^D\right) + X_i(\mathrm{t}) + B(\mathrm{t}) - S(\mathrm{t}) \\ & \ge \sum_{n\in N}\left(\mathrm{D}_n^{FL}(\mathrm{t}) + \mathrm{D}_n^{TL'}(\mathrm{t})\right) \end{aligned} \tag{4}$$

TL inflow constraint:

$$\sum_{t'\in T} U_n^{t,t'} \le \mathrm{IF}_\mathrm{n}^{\max}(t) \tag{5}$$

TL outflow constraint:

$$\sum_{t\in T} U_n^{t,t'} \le \mathrm{OF}_\mathrm{n}^{\max}(\mathrm{t}) = \mathrm{D}_n^{TL}(\mathrm{t}) \tag{6}$$

TL flow balance constraint:

$$\sum_{t'\in T} U_n^{t,t'} = \sum_{t\in T} U_n^{t,t'} \tag{7}$$

Modified TL constraint:

$$\mathrm{D}_n^{TL'}(\mathrm{t}) = \mathrm{D}_n^{TL}(\mathrm{t}) + \sum_{t'\in T}\left(U_n^{t',t} - U_n^{t,t'}\right) \tag{8}$$

Leftover power constraint:

$$\begin{aligned} \mathrm{A}_\mathrm{r}(\mathrm{t}) = & \sum_{j\in J} \mathrm{r}_j(\mathrm{t}) + \mathrm{A}_\mathrm{s}^{'}(\mathrm{t}-1)\cdot\left(1-\mathrm{L}^D\right) + X_i(\mathrm{t}) \\ & + B(\mathrm{t}) - S(\mathrm{t}) - \sum_{n\in N}\left(\mathrm{D}_n^{FL}(\mathrm{t}) + \mathrm{D}_n^{TL'}(\mathrm{t})\right) \end{aligned} \tag{9}$$

State of charge constraint:

$$\mathrm{A}_\mathrm{r}(\mathrm{t})\cdot\left(1-\mathrm{L}^C\right) = \mathrm{A}_\mathrm{s}(\mathrm{t}) \tag{10}$$

Upper and lower bounds of DS constraint:

$$\sum_{n\in N}\left\{\mathrm{D}_n^{UL}(\mathrm{t})\cdot\left(1+\mathrm{L}^D\right)\right\} \le \mathrm{A}_\mathrm{s}(\mathrm{t}) \le \mathrm{A}_\mathrm{s}^{\max} \tag{11}$$

Final SOC of DS constraint:

$$\mathrm{A}_\mathrm{s}^{'}(\mathrm{t}) = \mathrm{A}_\mathrm{s}(\mathrm{t}) - \sum_{n\in N}\left\{\mathrm{D}_n^{UL}(\mathrm{t})\cdot\left(1+\mathrm{L}^D\right)\right\} \tag{12}$$

Nonnegative constraint:

$$X_i(t), Y_i(t), B(t), S(t), U_n^{t,t'} \ge 0 \tag{13}$$

The first term in objective function (1) defines the production cost by CDGs, where $b_i(t)X_i(t) + c_i(t)Y_i(t)$ estimates the variable and startup costs of production. The second term represents the cost of the transaction with power grid, where $p_B(t)B(t) - p_S(t)S(t)$ defines the cost of purchasing power at buy price minus the revenue of selling power at sell price. The third

term $\rho_n^{t,t'} \cdot U_n^{t,t'}$ denotes the penalty incurred when transferring power demand from *t* to *t'*.

Constraint (2) ensures the production capacity by CDGs, and Constraint (3) reflects on or off mode of CDGs. Note that Constraint (2) together with (3) ensures that the startup cost is always incurred when the CDG produces power.

The total available power at *t* is comprised of the output by RDGs, the final SOC of the storage at *t-1*, the output by CDGs, the power purchased from power grid minus the power sold to power grid. Constraint (4) ensures that the total available power at *t* satisfies the demand from FLs and modified TLs.

Constraints (5)-(7) express inflow, outflow, and flow balance constraints, respectively, when transferring power from *t* to *t'*. Constraint (8) represents modified TL at *t*, which is the original TL at *t* plus the inflow from time *t'* and minus outflow to time *t'*. Constraint (9) shows the amount of leftover power after meeting the demand from FLs and modified TLs. Note that the amount of leftover power defined in Constraint (9) is used in Constraint (4). Constraint (10) defines the SOC of the DS, which is the leftover power in (9) at charge loss L^C. Constraint (11) ensures that the SOC of the DS after considering discharge loss should meet ULs and that the SOC cannot exceed the maximum capacity of DS. Constraint (12) expresses the final SOC of the DS after ULs are consumed at *t*. Finally, all variables should be nonnegative by Constraint (13).

VI. EXPERIMENTAL EVALUATION

A. Parameter setting

To verify the operation of the proposed model, we have implemented the model with two CDGs and three RDGs with different cost coefficients and capacities.

Table Ⅰ presents the variable and startup costs and the minimum and maximum capacities of CDGs. Since RDGs are assumed to operate with no additional cost, they have maximum capacities only

For experiments, six time intervals are used. Table II shows the market prices from the power grid. Generally, the sell price is set lower than the buy price. For experimental purposes, the prices are set to fluctuate wildly on purpose.

The forecasted outputs of RDGs, the predicted load data and the penalties for transferring loads are given in Table III. Since the market price and the demand tend to be positively correlated, we set the load to be higher when the market price is higher. We intentionally set a huge penalty to avoid power to be shifted to undesirable time.

TABLE I. FIXED COST, VARIABLE COST, AND CAPACITY OF DGS

DGs	Cost (¢/kWh)		Capacity (kw)	
	Variable	Startup	Minimum	Maximum
CDG1	50	100	6	30
CDG2	30	150	3	30
RDG1	0	0	0	15
RDG2	0	0	0	3
RDG3	0	0	0	2.5

TABLE II. DAY-AHEAD MARKET PRICES FROM POWER GRID

(¢)	Time interval (t=1,2,..,6)					
	1	2	3	4	5	6
P_buy	20	30	90	120	80	40
P-sell	18	27	81	108	72	36

TABLE III. OUTPUT OF RDGS, LOAD, AND PENALTLY

	(Unit)	t=1	t=2	t=3	t=4	t=5	t=6
RDG1	Generator (kWh)	0	7	12	15	8	0
RDG2	Generator (kWh)	0	2	3	3	3	0
RDG3	Generator (kWh)	0	2.5	2.5	2.5	2	0
FL1	Load (kWh)	5	10	15	20	24	18
FL2	Load (kWh)	10	20	30	40	48	36
TL1	Load (kWh)	2	5	12	14	8	5
TL2	Load (kWh)	4	10	24	28	16	10
UL1	Load (kWh)	2	2	5	7	3	3
UL2	Load (kWh)	2	2	7	10	5	4
Penalty_TL1	Penalty ($)	∞	0	0	0	0	0
Penalty_TL2	Penalty ($)	∞	0	0	0	0	∞

B. The results

Figure 2 shows the optimization result. 'TotalSupply' represents the total available power which is the sum of 'buy', 'CDGs', 'RDSs', and 'FinalSOC' at each time interval. 'TotalDemand' line represents the total amount of loads after the shift of TLs. 'Buy' represents the amount of power purchased from power grid. 'CDGs' and 'RDGs' represent the amount of power produced by CDGs and RDGs, respectively. 'FinalSOC' indicates the final state of charge of the storage.

As shown in Figure 2, although the market price is the highest at time 4, the total power demand is not higher than other time intervals. This is because the loads at time 4 are shifted to other times with cheaper price. When the buy price is high (*t*=3,4,5), CDGs produce maximum power and Microgrid purchases relatively little power from power grid. It is clear from the graph that the output of CDGs is inversely related to the purchase of power from PG.

At time intervals 1 and 2, total power supply exceeds total demand. This is because Microgrid is saving the excess powers in the storage to use it at t=3 when the buy price soars.

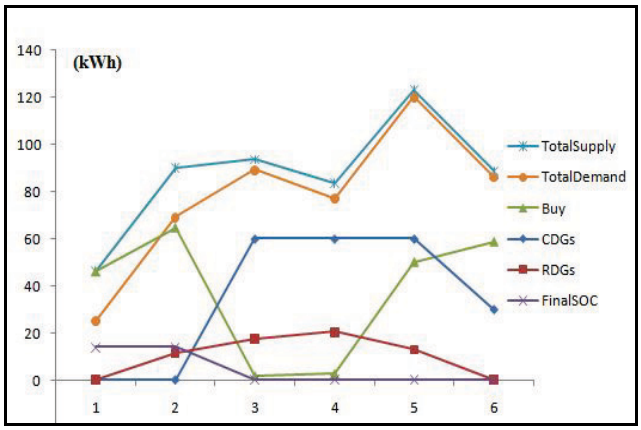

Figure 2. Total supply and demand at each time interval.

C. Demand response

To confirm the proper behavior of demand response, we conduct sensitivity analysis with three scenarios. The first scenario optimizes total cost using the original TLs without shifting the loads. The second scenario optimizes total cost by shifting TLs with penalty. The third scenario optimizes total cost where TLs are able to shift power demand to any time

interval (i.e., without penalty). The result is shown in Figure 3. The demand response of each scenario is represented as white, gray, and black bars, respectively. As a reference, the buy price is marked as a solid line.

In Figure 3, the original TLs are the white bars and do not change in scenario 1. In scenario 2, the modified TLs with penalty (gray) shift the original TLs from the time periods when the buy price is high (t=3,4) to time intervals when the buy price is relatively cheap (t=2,5,6). In scenario 3, the modified TLs without penalty (black) behave similarly.

The difference between scenarios 2 and 3 are clearly shown at t=1 when the buy price is the cheapest and the penalty is the highest. The TL with penalty does not shift the load to t=1, while the TL without penalty shifts a significant amount of load to t=1 to take advantage of the cheap buy price. Also note that at t=4, the original TL is the highest, but the modified TLs with or without penalty (in scenarios 2 and 3, respectively) are shifted to the other cheaper time intervals.

Table IV summarizes the total cost of scenarios 1, 2, and 3 and the rate of cost changes of scenarios 2 & 3 compared to scenario 1. As expected, the performance is the best in scenario 3 (without penalty) than in scenario 2 (load shift with penalty). The experiment confirms that one may have the optimal schedule having highest demand response like scenario 3 as well as reflecting an individual preference or time constraints with penalty such as scenario 2.

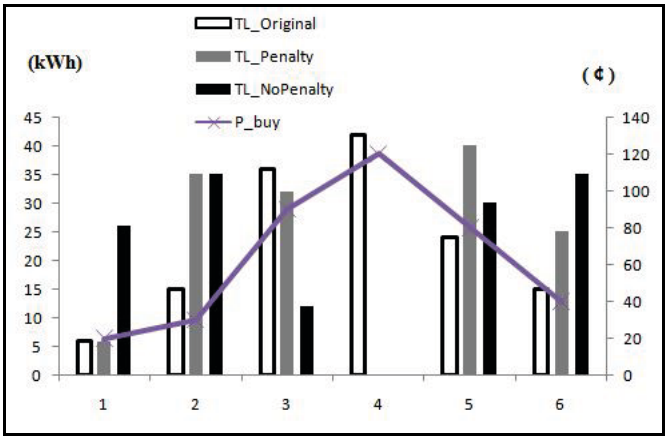

Figure 3. Original TLs, modefied TLs with penalty, and modefied TLs without penealty, and the buy price at each time interval .

TABLE IV. TOTAL COSTS AND DIFFERENCES OF THERE SCENARIOS

	Total cost (¢)	*Difference (%)*
TL_Original (Senario 1)	21,840	0
TL-Penalty (Senario 2)	18,720	-14%
TL-NoPenalty (Senario 3)	17,061	-22%

D. *Uncertainty of the Renewable Distributed Generator*

Since a Renewable Distributed Generator (RDG) has inherent uncertainty, it is important to know the effects of the change of the amount of power produced by RDGs on operation schedule and total cost. In this experiment, we vary the amount of power produced by RDG 1 at time 4, the largest amount of power among time intervals of the RDGs. The varied amount of power by RDG 1 at time 4 would have the biggest influence on the Microgrid operation schedule.

The effects on the operation schedule differ depending on the values of RDG. When the amount of power produced by RDGs increases, the amount of power purchased by PG or produced by CDGs decreases. Due to the reduction in the amount of purchased or produced power, total cost will decrease. In the given parameter settings, the varied amount of RDG 1 at time 4 affects the amount of power purchased by PG at time 4 and total cost as shown in Figure 4.

As the uncertainty in RDG's power generation impacts the operation schedule and total cost, we can use them to predict the proper bidding price for the next day in a day-ahead pricing market. If we know the difference in the total cost with respect to the amount of power by RDGs, we can plan a bidding price strategy that let us profit.

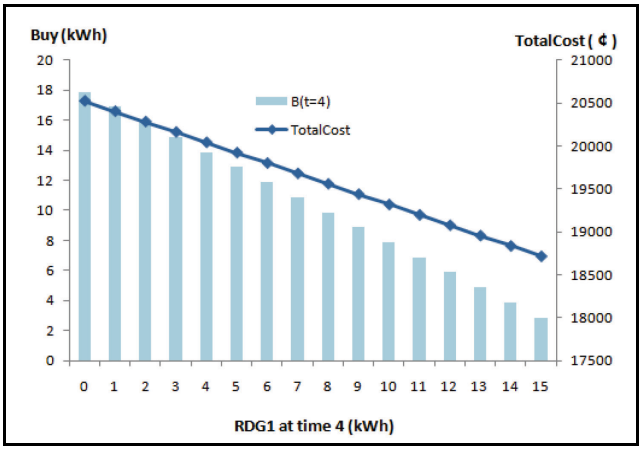

Figure 4. Sensitivity of the amount power purchased by PG at time 4 and total cost to the amount of power produced by RDG 1 at time 4

E. *Storage capacity*

We conduct sensitivity analysis on storage capacity as well. When the storage capacity increases, Microgrid is able to store power at a cheaper price and then sells one at a higher price. This would result in higher sales revenue and lower total cost. Figure 5 shows the increase in total sales revenue and the decrease in total cost according to the increase of storage capacity. Note that if the storage capacity is too small, Microgrid may not cover the user-action load and cannot produce a solution. In Figure 5, no feasible solution exists below 20 kWh. In a practical point of view, this means the model allows us to estimate the storage capacity, based on the size of a Microgrid, appropriate for reliable operation.

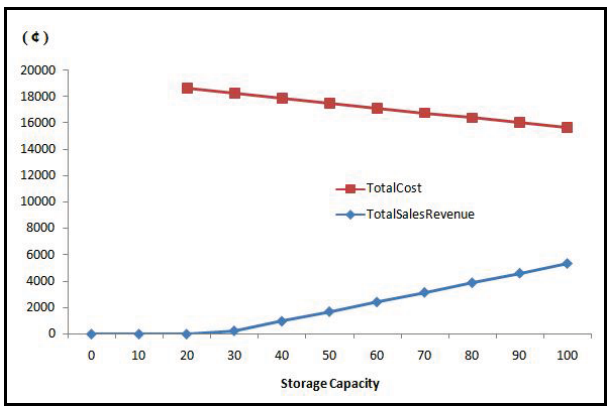

Figure 5. Sensitivity of total sales revenue and total cost to storage capacity

VII. CONCLUSION

This paper proposes a model for the optimized operation of a Microgrid. Compared to previous studies, our model treats the scheduling problem in more depth to obtain practically-meaning results. Specifically, we focus on price-elastic demand response. We also verify the impact in renewable power generation on the operation schedule and total cost. In addition, we capture the roles of storages for supporting the demand flexibility caused by user-action loads and for reserving power against high price.

Experimental results show that the proposed model exploits the demand elasticity and significantly reduces the total operation cost. Two key implications are as follows. First, one may reflect individual preference or time constraint in modeling demand response. Second, the optimization model can be used to estimate the storage capacity according to the size of a Microgrid.

As a future work, we are currently extending our model to capture both the uncertainties of renewable energy sources and loads. The new model will reschedule the operation plan using the updated information of the renewable energy source and loads while considering real limits such as fixing the amount of power sold to PG. We are also investigating the method of incorporating energy sources other than electricity, such as heat and gas, into the model.

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