TELKOMNIKA Indonesian Journal of Electrical Engineering
Vol. 16, No. 3, December 2015, pp. 401 ~ 408
DOI: 10.11591/telkomnika.v16i3.9067

Optimized Operation-Planning of a Microgrid with Renewable Sources and Vehicle to Grid

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Abstract

The microgrid with renewable sources possesses stability issues. During the grid-connected mode, these issues are taken care by the external grid. However in case of islanding, the distributed generators within the microgrid, have to take care of these issues independently. It needs additional backup like diesel generation or battery storage, which increases the overall capital and operation costs. With the intervention of the V2G storage, these costs can be saved to some extent. However similar to the renewable sources like wind and solar, the power from V2G is also fluctuating which may lead the microgrid towards an uneconomical operation. Therefore an extensive operation-planning is needed to deal with theseuncertainties, for the microgrid to be economically viable. In this context, the stochastic programming has been applied to achievethe optimum results. The stochastic scenarios for wind speed, solar radiation, V2G power and load fluctuation have been generated using the Markov chain Monte Carlo method. The optimized operation-planning aims to minimize the total net present cost, size of the fixed storage and fossil fuel emissions subject to constraints. The simulations have been performed using Matlab/Simulink, HOMER and Excel. The simulation results show that the V2G technology substantially decrease the total net present cost. Moreover for such a microgrid the total net present cost and fossil fuel emissions conflict with each other.

Keywords: *V2G, operation-planning, microgrid, Markov chain Monte Carlo method, optimization*

1. Introduction

In the coming years the traditional power system architecture will be replaced by decentralized dispersed power sources called distributed generators (DGs). This distributed generation will be integrated directly into the medium/low voltage networks and will collectively form a microgrid. The microgrid is then a foot-print power system that will be located at the downstream of the distribution system. The benefit will be the supply of the local load by local generation. It will reduce the line losses and network congestion and hence will improve the reliability of the power system.

The distributed generation (DG) is fueled from distributed energy resources (DERs). The DERs like wind and solar resources are inherently fluctuating in nature. The environmental conditions of wind speed and solar radiation cause the output power to be fluctuating always and create disturbance situations. While in grid-connected mode, these sources are controlled as PQ generators which means that they have to provide whatever power they have. However during the islanding of the microgrid, the Vf mode is activated at certain buses which means that the voltage and frequeccy has to be maintained. During this mode the additional sources like diesel generation or battery energy storage or a combination of both is needed to balance the power system.

The capital cost of the diesel generation is low, however it hashigh operation and maintenance cost. Moreover the diesel generation is too much noisy and it has the problem of carbon emissions. These emissions contribute to be the main source of global warming. On the other hand the battery storage has high investment cost but its operation and maintenance cost is lower than the diesel generation. Also the battery storage responses more quicklyto a disturbance than the diesel generation. The intervention of electric vehicles (EVs) over the last decades has introduced the concept of mobile battery storage. This in turn offers an economically viable solution in the form of V2G storage. The V2G storage is a term that defines

Received September 3, 2015; Revised October 18, 2015; Accepted November 5, 2015

the feeding back of the stored energy into the grid as and when necessary. In most of the countries the EVs have been already in day to day use. According to international energy agency (IEA) in 2010, the EV production target was 50,000 in number. Now in 2015, this production target has been increased to 896,367 number and in 2020, it is expected to grow to 1,523,367 number. This rapid increase of the EV market share can be utilized in the form of V2G storage to balance the power system.

The V2G storage offers a lot of benefits to the power system like distributed storage, off-peak power storage to use it for peak shaving, levelling of fluctuating renewable energy and for spinning reserves [1-3]. The backup provided by the V2G storage can vary from seconds to hours depending upon the situation and the available V2G capacity. The available V2G capacity or in other words available power capacity (APC) of the V2G is also fluctuating due to the random plug-in patterns and hence it is stochastic in nature. However based on the mobility and plug-in pattern, somehow APC can be estimated. According to [4-5], an intermediate body known as an aggregator is needed, which contracts with the EV owner for profit and penalty functions. The vehicle owner also tells the aggregator about his potential driving and plug-in patterns.

So far,not so much research is available on the optimized operation-planning of microgrid with renewable sources and V2G. However some authors have focused on the power capacity estimation of V2G. The authors in [3] used a dynamic scheduling method for charging/discharging of EVs by renewable sources based on the load forecasting model. According to the authors this model-based algorithm ensures the chargeability of the EV to desired SOC before departure and in this way it also improves the accuracy of the V2G power estimation. The authors in [4] have estimated the power capacity by using the probability distribution of the plug-in pattern. The EVs with same plug-in probability have been clustered together. If an aggregator is unable to fulfill the contractual requirement, a penalty is imposed under different penalty categories. In this way the profit function is maximized. The authors in [5] have divided the EV plug-in possibilities by using three types of car parks at offices, recreational places and homes. They have modeled the mobility by trip chains and the driving patterns are profiled based on the surveyed data. According to the authors the car parks at offices and homes have maximum plug-in availability. The authors in [6] have proposed the real time smart charging algorithm for the PEVs from renewable energy with consideration of V2G regulation service. This charging algorithm minimizes the impact of charging by the grid and at the same time regulates the frequency of the grid. However none of the mentioned research has considered the economic implications of the V2G from a microgrid operationpoint of view.

In this paper the authors have formed an optimization model for the operation-planning of microgrid as a multi-objective minimization problem. The multi-objectives include the minimization of the total net present cost, size of the fixed storage and fossil fuel emissions subject to the constraints.The stochastic scenarios for the time series data of wind speed, solar radiation, V2G power and load fluctuation have been generated by using the Markov chain Monte Carlo method. The stochastic chance constrained programming is used to deal with the uncertainties. The confidence level from the chance constraints gives the minimum availability of the fluctuating power from renewable sources and V2G.

The rest of the paper is organized as follows. Section II describes the modified CIGRE benchmark microgrid model. Section III describes the probabilistic estimations of the power from V2G storage and renewable sources. Section IV formulates the stochastic chance constrained model for the operational planning. Section V solves the example problem and discusses the simulation results. Section VI draws the conclusions.

2. Microgrid Model

The microgrid is modelled based on the CIGRE's benchmark distribution system [7] and is shown in Figure 1. It is connected to an external grid via a static switch and a transformer at the point of common coupling (PCC). The DERs comprise of wind turbines (wind), solar PV array (PV), diesel generation (DGEN), fixed energy storage (FS), V2G (V2G) and local loads. The utilized V2G storage is composed of a fleet of 120 EVs. It is assumed that there are five different types of EVs according to the rating of the batteries. The Table 1 shows the technical detail of the generation sources with their possible configurations.

3. Generation of Stochastic Scenarios

To generate the future time series data for the wind speed, solar radiation, V2G power and load fluctuation, the Markov chain Monte Carlo method is used. Within this method, the sampling is performed using the the Metropolis-Hastings algorithmthat draws samples from complex asymmetric probability distributions. According to [8], the algorithm first proposes a possible new state x* in the Markov chain, based on a previous state x(t-1), according to the proposal distribution q(x*|x(t-1)). The algorithm accepts or rejects the proposed state based on the density of the target distribution p(x) evaluated at x*. The Markov chain draws samples such that at any given point in time t, the probability of moving from x(t-1)→x(t) must be equal to the probability of moving from x(t-1)→x(t) and this condition is known as reversibility or detailed balance. The Metropolis-Hastings algorithm deals with asymmetric proposal distributions by implementing an additional correction factor c, defined from the proposal distribution as.

Table 1. Technical Details of Generation Sources

Sr. #	Generation Source	Possible Configurations
1	Wind Turbine (kW)	1500, 3000, 4500, 6000, 7500
2	Solar PV Array (kW)	500, 1000, 1500, 2000
3	Diesel Generation (kW)	500, 600, 700, 800, 900
4	Fixed Storage (kWh)	500, 1000, 1500,…., 6500
5	V2G Type 1 (kWh)	35, 70, 105,………., 735
6	V2G Type 2 (kWh)	32, 64, 96,………..., 672
7	V2G Type 3 (kWh)	24, 48, 72,………..., 504
8	V2G Type 4 (kWh)	56, 112, 158,……..., 1176
9	V2G Type 5 (kWh)	16.5, 31, 49.5,……., 346.5

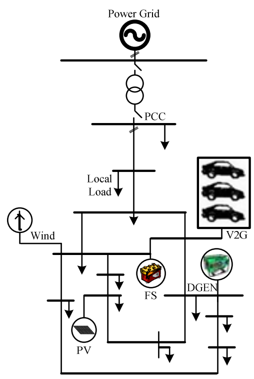

Figure 1. Microgrid model

$$c=\frac{q\left(x^{(t-1)}|x^{*}\right)}{q\left(x^{*}|x^{(t-1)}\right)} \quad (1)$$

The correction factor adjusts the transition operator to ensure that the probability of moving from $x^{(t-1)}\rightarrow x^{(t)}$ is equal to the probability of moving from $x^{(t-1)}\rightarrow x^{(t)}$, no matter the how the proposal distribution is.

Using this algorithm, the future time series data for each year is generated for wind speed, clearness index (solar readiation), V2G power (plug-in pattern) and load fluctuation.The expected values are then estimated by using the probability distributions. The two parameter Weibull distribution is used for wind speed, Beta distribution is used for clearness index and the Normal distribution is used for V2G plug-in pattern and load fluctuation.

The output wind power can be calculated from following equations [9].

$$P_W^t=\frac{1}{2}\rho A v_t^3 C_p \quad (2)$$

$$P_W^t=\begin{cases} 0 & v\leq v_{ci} \\ P_w\frac{(v-v_{ci})}{(v_r-v_{ci})} & v_{ci}\leq v\leq v_r \\ P_w & v_r\leq v\leq v_{co} \\ 0 & v>v_{co} \end{cases} \quad (3)$$

Where P_W^t is the output power of wind turbine at time t, ρ is the air density in kg/m3, A is the sweap area in m2, v_t is the wind speed in m/s at time t and C_p is the power coefficient. The power curve in Equation (3) further explains the output power of wind turbine at different speeds. In Equation (3) v is the mean wind speed, v_r is the rated wind speed, v_{ci} is the cut in wind speed and v_{co} is the cut out wind speed.

The two parameter Weibull probability distribution is the most appropriate and recommended distribution for wind speed data analysis [10]. This is because it gives a better fit for measured monthly probability density distributions than other statistical functions. The Weibull probability density function is given as:

$$f(v_t)=\left(\frac{k}{c}\right)\left(\frac{v}{c}\right)^{k-1}\exp\left[-(\frac{v}{c})^k\right] \quad (4)$$

Where $f(v_t)$ is the probability density function of wind speed v_t, k is a dimensionless Weibull parameter and c is the Weibull scale parameter in m/s. The values of k and c can be computed from Equation (5) and (6).

$$k=\left(\frac{\sigma}{\mu}\right)^{-1.086} \quad (5)$$

$$c=\frac{\mu}{\Gamma\left(1+k^{-1}\right)} \quad (6)$$

Where μ is the mean value and σ is the standard deviation.

The output solar PV power strongly depends upon solar radiation [10-11] and can be calculated from following equations.

$$P_{PV}^t=G_tP_{PV}^{max} \quad (7)$$

$$G_t=K_tG_t^{ex} \quad (8)$$

$$G_t^{ex}=I_{sc}\left(1+0.033\cos\frac{360n}{365}\right)\sin_{\alpha t} \quad (9)$$

$$\sin_{\alpha t}=\sin_{\phi}\sin_{\delta}+\cos_{\phi}\cos_{\delta}\cos_{\omega t} \quad (10)$$

Where P_{PV}^t, P_{PV}^{max}, G_t, K_t, G_t^{ex} represent output PV power at time t, maximum PV power, horizontal radiation at time t, clearness index and extraterrestrial radiation respectively. I_{sc} is the solar constant, n is the day of a year, α is the altitude of the sun, δ is the declination of the sun and ω is the hour angle.

The clearness index represents an index that the G_t^{ex} suffers by factors such as clouds and temperature. The clearness index follows a beta distribution and is given as:

$$f(K_t)=\frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)}(K_t)^{a-1}\left(1-K_t\right)^{b-1} \quad (11)$$

$$a=\frac{(\mu)^2(1-\mu)}{\sigma^2}-\mu \quad (12)$$

$$b=\frac{a(1-\mu)}{\mu} \quad (13)$$

Where μ is the mean value and σ is the standard deviation.

The output V2G storage power strongly depends upon the state of charge of the plugged-in EVs and can be calculated by modified Coulomb counting method [12] using the following equation.

$$P_{V2G_t}=\frac{W_{V2G_t}}{t}=SOC(t)=SOC\left(t\text{-}1\right)+\frac{I_c(t)}{Q_n}\Delta t \tag{14}$$

Where I_c, SOC and Q_n represent the corrected current, state of charge and the charge stored in the battery respectively.

The V2G plug-in pattern and load fluctuation follow a Normal distribution and is given as:

$$f(V2G_t)=\frac{1}{\sigma_{V2G}\sqrt{2\pi}}e^{\frac{-(V2G-\mu_{V2G})^2}{2\sigma_{V2G}^2}} \tag{15}$$

$$f(P_{Lt})=\frac{1}{\sigma_L\sqrt{2\pi}}e^{\frac{-(P_L-\mu_L)^2}{2\sigma_L^2}} \tag{16}$$

Where μ is the mean and σ is the standard deviation.

4. Chance Constrained Programming

Stochastic chance constrained programming was introduced by Charnes and Coopers [13] and it contains the stochastic variables in the constraints. The stochastic variables in the constraints should be met with some confidence level.

In current problem the multiple objectives include the minimization of the total net present cost (NPC), size of the fixed storage and fossil fuel emissions [15]. They can be expressed as

$$\min f_1 = ß\left(k_w+k_{pv}+k_{fs}+k_{V2G}+k_G+k_{DGEN}\right) \tag{17}$$

$$\min f_2=\sum_{t=1}^{T}(E_G+E_{DGEN}) \tag{18}$$

$$\min f_3=\sum_{t=1}^{T} fs \tag{19}$$

s.t.

$$Pr\left\{\sum_{i=1}^{N}\cdot\sum_{t=1}^{T}\cdot\left(P_{L_t}-P_{G_t}-P_{w_{it}}-P_{pv_{it}}-P_{DGEN_{it}}-P_{V2G_{it}}\right)\le\square 1\right\}\ge\alpha 1 \tag{20}$$

$$Pr\left\{\sum_{i=1}^{N}\cdot\sum_{t=1}^{T}\left(P_{w_{it}}+P_{pv_{it}}\right)\le\square 2\right\}\ge\alpha 2 \tag{21}$$

$$\sum_{i=1}^{N}\cdot\sum_{t=1}^{T}\cdot\left(P_{w_{it}}+P_{pv_{it}}+P_{DGEN_{it}}+P_{V2G_{it}}+P_{G_t}\right)\ge P_{L_t}+P_{RES} \tag{22}$$

$$SOC_{min}\le SOC\le SOC_{max} \tag{23}$$

$$P_{DGEN_{min}}\le P_{DGEN}\le P_{DGEN_{max}} \tag{24}$$

$$DS_{(wind+pv+DGEN+fs+V2G)}\le DS_{max} \tag{25}$$

Where the Equation (17), (18) and (19) represent the three objective functions. k is the total cost in $ and ß is the net present cost factor. The subscripts w, pv, fs, V2G and G represent wind, solar, fixed storage, vehicle to grid and grid respectively. The total costs include the capital, replacement, operation and maintenance, fuel, energy not served and emission costs. These costs can be calculated according to the mathematical formulations of [14]. E_G and E_{DGEN} are the emissions from the external grid and the diesel generation.

The Equation (20) and (21) show the chance constraints. The chance constraint in Equation (20) states that the power provided by the V2G storage must be enough to mitigate the difference of power between the generation and load. So the difference between the load and all generation sources must be at least equal to the Ɛ1 limit/error with a confidence level equal to α1. Similarly the chance constraint in Equation (21) states that output power of the wind and solar generation must be at-least equal to limit Ɛ2 with a confidence level equal to α2. The constraint in Equation (22) shows the power balance equation in which the total generation by all the sources must be at most equal to the load and reserve power. The constraint in Equation (23) ensures that all the storage devices are operated within the limits instructed by the manufacturer. The constraint in Equation (24) ensures that the diesel generation is operated within the limits instructed by the manufacturer. Similarly the constraint in Equation (25) ensures that the operational planning is carried out within the deployment space.

5. Example Problem and Simulation Results

In the example problem, a microgrid has to be integrated to a community distribution system which is supplied by an external grid. The estimated peak value of the load is 1057 kW and its average value is 454 kW. The external grid has capacity shortage problem due to known as well as random outages. The tariff of buying electricity from the external grid is 0.2 $/kWh and selling electricity to external grid is 0.19 $/kWh. The same tariff also applies to energy exchange with V2G storage. The penalty for capacity shortage is 0.2 $/kWh. Numerous simulations have been performed using Matlab/Simulink, HOMER and Excel, and following are the observations:

1) When the load demand is supplied by the external grid with no capacity shortage, the total NPC is 10788040 $. However with a known capacity shortage of 49.2 %, the total NPC reaches to 10543499 $. Similarly with a known capacity shortage of 60.3 %, the total NPC decreases to 10491614 $.

2) An 1100 kW of diesel generation is required to fulfill the capacity shortage of 100 %. Similarly a 900 kW of diesel generation is required to fulfill the capacity shortage of 49.2 %. When this diesel generation is utilized, the total NPC reaches to 17129770 $ and operating hours of diesel generation count to 4379 hrs. In the current example problem the capacity shortage of 49.2% is used for all scenarios.

3) With the addition of a fixed storage of 1000 kWh, the total NPC reaches to 18377890 $ and the operating hours of diesel generation count to 4376 hrs. By increasing the size of fixed storage to 6000 kWh the total NPC reaches to 24464850 $ and the operating hours of diesel generation count to 4367 hrs. This minimal decrease is because of the reason that fixed storage is also getting charge power by the diesel generation.

4) With the addition of 1500 kW of wind and 1500 kW of solar generation, the total NPC decreases to 16678530 $ and the operating hours of diesel generation count to 2755 hrs. In this case the size of the fixed storage is 2000 kWh. As the percentage of the renewable fraction is increases, the count of the operating hours of the diesel generation decrease. With 7500 kW of wind and 2000 kW of the solar generation, the total NPC increases to 25766520 $ and the operating hours of the diesel generation count to 1421 hrs. In this case the size of the fixed storage is kept constant at 2000 kWh. For the same situation if the size of the fixed storage is increased to 6000 kWh, the total NPC increases to 29299760 $ and the operating hours of the diesel generation further decrease to 1286 hrs.

5) For the same model, the diesel generation has been eliminated and the minimum capacity shortage of 9.3% is found. This is the case when the load is fulfilled by the 7500 kW of wind and 2000 kW of the solar generation in parallel to the external grid. A fixed storage of 9000 kWh is utilized for this case. Also the total NPC for current case is increased to 27122368 $ and the operating hours of the diesel generation count to zero. On the other hand if the size of the renewable fraction and fixed storage is decreased, the total NPC also decrease but it will increase the capacity shortage.

6) The capacity shortage problem will persist until and unless the generation capacity is increased. But because of the constraint of the deployment space any further increase in the

renewable fraction is not possible so the turned off diesel generation has to be turned on to overcome the capacity shortage problem.

7) With the addition of the 1000 kWh V2G storage along with 2000 kW of solar, 7500 kW of wind and 600 kW of diesel generation, the total NPC decreases to 20887310 $ and the operating hours of the diesel generation count to 1607 hrs. In this case the fixed storage is kept zero. As the capacity of V2G storage is increased to 2000 kWh with same capacity of generation, the total NPC further decreases to 15558450 $ and the operating hours of diesel generation further decrease to 1473. With same capacity of generation, if the size of the V2G storage is further increased, the total NPC will decrease further and same is true for operating hours of the diesel generation.

From the synthesized SOC time series data for the V2G storage based on the plug-in patterns, it is found that the value of limit Ɛ1 is minimal and equal to 0.00001. It is assumed that the EVs of same category have same plug-in pattern to simplify the simulations. The graph in Figure 2 shows relationship between the confidence level α1 and the V2G capacity. The graph shows that there is always a confidence level of 19 % of supplying power by the V2G storage and as V2G capacity increases this confidence level will also increase. The graph in Figure 3 shows the relationship between the confidence level α1 and the total NPC. The graph shows that as the confidence level α1 increases, the total NPC decreases and at a level of 24 %, the total NPC stabilizes. The reason is that as more and more EVs are plugged in to provide power, the utilization of the other generation sources decreases, so the total NPC also decreases. However for the case of fixed storage, the total NPC continuously increases.

Similarly from the synthesized wind speed and clearness index time series data for wind and solar generation, it is found that the value of the limit Ɛ2 is 0.499. It means that always 50% of the total renewable power is always available. The graph in Figure 4 shows the relationship between the confidence level α2 and the total NPC. The graph shows that there is always a 35 % confidence level of supplying the renewable power to the grid and as this level increases, the total NPC increases because of the high investment costs of renewable sources.

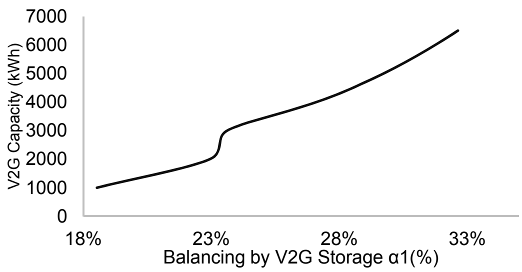

Figure 2. Confidence level α1 vs V2G capacity

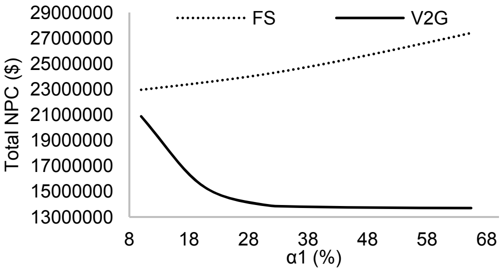

Figure 3. Confidence level α1 vs total NPC

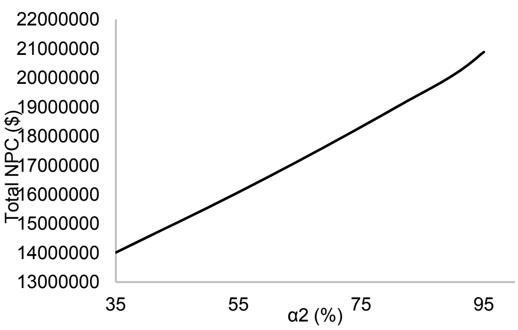

Figure 4. Confidence level α2 vs total NPC

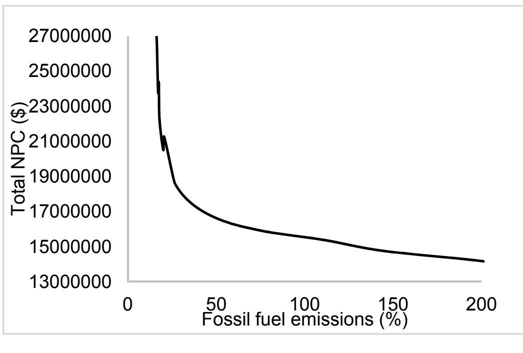

Figure 5. Pareto front “objective functions”

The observations discussed above, show that objective functions total NPC and fossil fuel emissions are conflicting with each other. It means that if the total NPC increases, the fossil fuel emissions decrease. For such a situation there is no single optimal solution available and Pareto fronts are utilized to find the most near to the optimal solutions. These most near to the optimal solutions are the non-dominant solutions which means that they are the best solutions from the solution space. The selection of the most favorable solution from the Pareto front is a trade-off and it depends upon the utility operator and the state policies. The Pareto front in Figure 5 shows the most near to the optimal solutions.

6. Conclusion

In this paper the optimized operation-planning of a microgrid with renewable sources and V2G is carried-out. The results have shown that V2G integration substantially decreases the total net present cost of the microgrid. Also along with the integration of renewable sources, the utilization of the diesel generation is minimized and hence the emissions are reduced. Using the stochastic chance constrained programming the confidence level of integrating the random sources to the microgrid has been determined. It is seen that there is always a confidence level of 19 % of supplying power by V2G and this confidence level increases as the V2G capacity increases. It is also seen that as this confidence level increases the total NPC decreases and at a level of 24 % it almost stabilizes. It is also seen that there is always a 35 % confidence level of supplying power by the renewable sources and as this confidence level increases the total NPC also increases. So in a nutshell this operation-planning model using the stochastic chance constrained programmingdetermines the availability of the power from the fluctuating renewable sources and V2G with least net present cost, which provides the firm basis for the robust operation-planning of microgrid.

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