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Fuzzy Logic for Smart Utilisation of Storage Devices in A Typical Microgrid

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***Abstract*—Efficient utilisation of Storage Devices (SD) among multiple sources of dispatch within a typical microgrid yields reduced economic and environmental generation costs within that particular microgrid. Eventually, managing the multiple sources that supply energy simultaneously is a big engineering challenge. The complexity arises due to the uncertainty of demand, generation cost, availability of renewable energy sources and (charging/discharging) time and price for the installed SD. This paper introduces a utilisation method that makes the SD more efficient in supplying the electricity within a typical medium size enterprise microgrid. The method is simply targeting the dynamic charging price for the SD to achieve a profitable charging, and also to maximise the opportunity of participation during the SD lifetime. A fuzzy logic based adaptive charging price is set for charging the SD based on the microgrid's local generation price at the time of charging, and the amount of the daily SD participation in the microgrid dispatch. By considering the economic and environmental generation costs in 30-minute operation intervals, a multi-objective Particle Swarm Optimisation (PSO) method is applied to optimise the energy dispatch for the managed microgrid. In addition, a switching mechanism based on the SD status is integrated with the proposed PSO to deal with the variable operation scenarios in the managed microgrid. The proposed optimisation technique has been tested on the realistic operation scenarios of the power grid of the Joondalup Campus of Edith Cowan University in Western Australia. The simulation results showed a reasonable amount of efficiency improvement with a range of benefits in cutting the generation cost for the targeted case study.**

***Index Terms*—Energy Management Systems, Fuzzy Logic, Generation Pricing, Microgrid, Particle Swarm Optimisation**

NOMENCLATURE

AP	Achieved profit
T	Charge and discharge time
$Dmnd$	Electricity Demand
G_P	Gas dispatch price
G_G	Gas dispatch
G_{lostG}	Gas generation lost energy
L_P	Local Generation Price
$MoAn$	Maintenance and operating annual fixed cost
MoV	Maintenance and operating variable cost
MxaV	Maximum Average
MnaV	Minimum Average
NOP	Number of participation
Ph_G	Photovoltaics dispatch
RFS	Ready for sale energy
S_P	Storage devices dispatch price
S_G	Storage devices dispatch
SE	Supplied Energy
Up	Utility dispatch price
U_G	Utility Generation
G	Variable gas price
W_G	Wind turbines dispatch

I. INTRODUCTION

The term "$Microgrid$" refers to a low voltage power network that incorporates multiple sources of dispatch including the utility supply. The microgrid can also be disconnected (islanded) from the utility grid to be a self supplied power grid that depends on its local generators. From the economic and environmental prospective, microgrids have been proved to be successful in performing satisfactory amount of generation cost cutting and $CO2$ mitigation [20]. Generally, microgirds are mostly efficient within regional areas, where the cost of transmitting and maintaining the power is effectively higher than the metropolitan areas. However, to run a beneficiary microgird means there is a need to have automation based management strategies that involve smart utilisation of the microgrid resources. Therefore, investigating the importance of the management strategies on improving the microgrid efficiency becomes essential for the investment on upgrading the microgrids. The microgrid operation management has been studied according to the differences and relations between microgrids and large power grids in [20]. In a nutshell, microgrids are expected to contribute to the future economies by being beneficiary projects. Decentralised Storage Devices (SD) can be the biggest players in making economic benefits for the current grid if they are upgraded with the needed infrastructure for the Smartgrid integration [2]. Although power quality issues are still the major problems behind incorporating SD in the grid, decentralised electricity storage devices have been considered in solving power quality problems in microgrids [17], [11]. The SD (electric vehicles) have also been utilised in balancing the microgrids' voltage and frequency. The control and management strategies for unbalanced microgrids voltage that incorporates electrical vehicles have been identified in [16]. Managing the distributed energy systems that incorporates generating units using renewable have been detailed in [15], [7]. Managing the power flow within a power grid that consists of decentralised resources is an optimisation problem in power engineering, especially when the power flow in that particular grid comes with variable cost and intermittent generation in line with highly non-linear demand. Therefore, the utilisation of artificial intelligence is essential in this role to implement efficient Energy Management System (EMS). Computational intelligence methods such as Mesh Adaptive Direct Search (MADS), Fuzzy Logic, Particle Swarm Optimiser and Ant Colony Optimiser have been introduced to minimise the generation cost by considering the environmental issue in [5], [4], [13], [14]. The role of integrating SD in building a reliable microgrid power dispatch has also been discussed in literature. SD have been utilised to manage the power flow in microgrids in [9]. A mixed integer nonlinear cost function has been proposed to minimise the operation cost in [21]. SD (electrical vehicles) have proved that they have a big economic impact on reducing the capital costs of microgrids [12]. The potential financial return for utilising electrical vehicles as a grid resource has been addressed in [22].

Minimising the cost of generation can be more complicated when the energy demand in that particular grid is subject to a highly non-linear load profile that comes from large number of consumers. Therefore, the concept of demand management or load shedding is also needed to enhance the overall management performance in such kind of microgrids. A smart charging method with load control tool management module has been presented in[18]. Also, to deal with the non-linearity that comes from large number of consumers' behaviour, managing the daily electricity for organizations with large number of employees using a mixed integer linear program to include on-site energy generation facilities has been modelled and implemented in [6]. From on the research findings in this area, we found that enhancing the microgrid operation with large number of employees can have an impact among the energy systems developers. Therefore, we are targeting the utilisation of SD to propose demand and price change sensitive optimisation for the energy dispatch of such kind of microgrids. Hence the main challenging investigation in this problem will be the SD charging/discharging time and price uncertainties. In this paper, section II illustrates the case study with it possible operation scenarios and the proposed generation capacities. Sections IV shows the design details for the proposed PSO, and shows the operation constrains for the managed case study. V andVI details the simulated scenarios data with the obtained results and conclusions with future recommendations respectively.

II. Case Study

In this work, we will target a university type power grid to test our proposed optimisation method. Edith Cowan University's power grid in Joondalup, Western Australia, has been utilised to test our design assumptions. On this power grid, several design and upgrade assumptions have been applied to create virtual power grid operation scenarios for testing. The most important factor that will be used as the backbone of our upgrade assumptions is the demand within the microgrid. Based on our studies for the last 4 years of demand patterns within the microgrid, we built our own demand prediction model to estimate the monthly demand levels. Hence the predicted demand values have a range of accuracy, which will be considered in the design considerations. The second major assumption factor is the ability of integrating renewable energy sources within the microgrid. For this issue, we have made strategic planning and installation studies to estimate the possible amount of installation for the renewable energy sources on the campus. Assuming that there are no financial and political restrictions, we have evaluated the campus capacity for installing renewable energy sources. Thereby, we found that we can supply up to 350 kWh from solar panels [10], 250 kWh from wind turbines [8] and up to 350 kWh from storage devices [3]. The other major concerns come from the gas gen-sets installation considerations. To ensure reliability and security in the installation specifications, we have refered to the installation standards of installing generation units that cover the maximum demand plus the safety and emergency margin amount. To relate this method to our case study, we realised that we can integrate seven gen-sets, each with 500 kWh, to cover six lots of the demand. Another unit of 500 kWh will be used for emergency cases.

Although we have created our virtual simulation environment, we still lack the simulation data. Based on our demand change patterns and the weather conditions around the case study, we could generate the required simulation data based on simple engineering calculations. The first source of data was the Australian Energy Market Operator (AEMO) [1] to obtain the electricity market trends, which will reflect the utility price changes. Accordingly, we have scaled the obtained values to suit our case study, thus we can have our own semi-realistic operation data. For the gas prices, we have sticked to the fixed prices at this stage and we have utilised the available prices from [19]. However, to use the collected data into the local generation price analyses, we have converted the obtained units of gas supply into Nm^3/hr by:

$$1Nm3/h = 0.031736GJ \tag{1}$$

Therefore, we expect to have 137.6 $Nm3/h$ of natural gas for each unit, which will be considered in the instantaneous cost in the microgrid.

III. Storage Devices Charging Decision

In this work, a method for monitoring the microgrid's operation is applied to build a rule base for charging the SD. Based on evaluating the economic and environmental cost factors in the most recent seven days of operation, and adaptable rule base can be obtained to tackle the non-linearity of the operation conditions. Basically, the SD charging price is set to the difference between the mean of the maximum daily prices and the mean of minimum daily prices for U_p or G_P. Basically, these values are updated every 24 hours to follow the most recent daily price change trends based on monitoring the recent seven days of operation. Figure 1 shows a sample of seven days of price changes, which helps identifying the minimum and maximum price values, thus finding G_{ChP} and

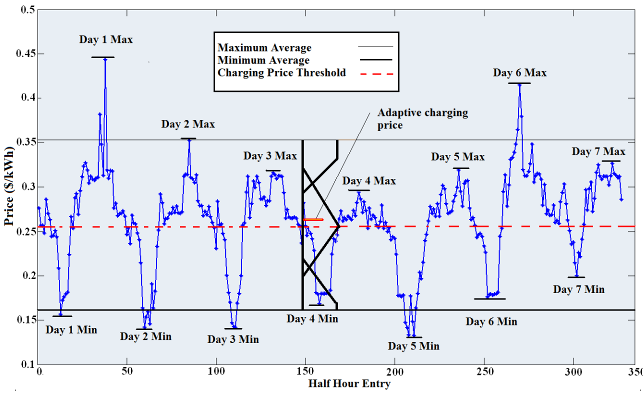

Figure 1. A sample of seven days generation price change for G_P

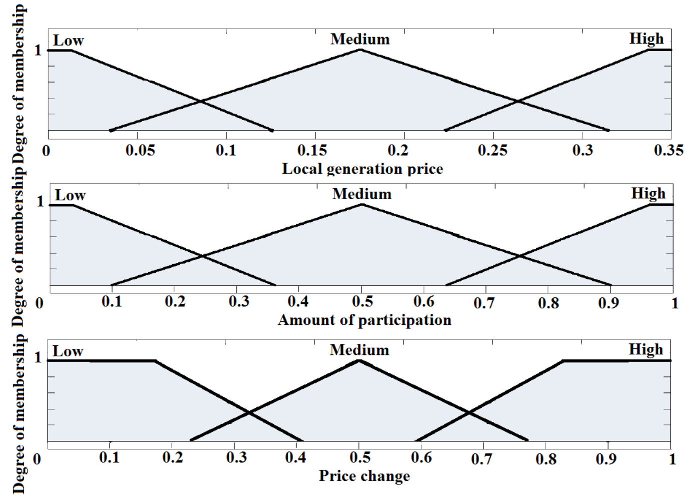

Figure 2. Charging price generator fuzzy system membership functions design

U_{ChP}, which will accordingly set the discharging price for the storage devices.

In case of discharging, the decisions are made by the PSO based on comparing the storage devices dispatch cost with other dispatch parameters cost, such as the gas and utility dynamic generation price. To implement the smart involvement for the storage devices in dispatching the electricity for the managed microgrid, we have developed a fuzzy system that has two inputs: the local generation price, which is evaluated based on studying every operation scenario in the microgrid as illustrated in Table I, and the actual daily accumulated amount of SD participation in the micrgrid dispatch. We believe that local generation price will effect on the operation status for the ST in the microgrid dispatch. Therefore, we have considered creating an adaptive charging price to follow the operation conditions, and maximise the chance of participation in the microgrid's electricity dispatch. For the best amount of SD participation within the microgrid, we believe that half of the total operation time will be the ideal target for the SD, when the other half will be ideal time for charging. As per optimum operation, we expect the storage devices to work continuously between charging and discharging, which might divide the operation time between 50% of charging and other 50% of discharging.

To normalise these values for the fuzzy system input, we multiply the actual accumulated amount of SD participation value by two to establish an input membership functions universe of discourse with range of one, which resulted from combining the charging and discharging times in the microgrid's operation participation. The optimum accumulated amount of the SD for the most recent seven days of operation is evaluated as follows:

$$The\ Amount\ of\ Participation = \frac{1}{h}\sum_{h=0}^{336} 2 * \frac{S_G(t)}{S_Gmax} \quad (2)$$

where h is the half hour operation interval in the seven days of operation.

In case of the output of the proposed fuzzy system, it is proposed that it carries the amount of the charging price

Table II
CHARGING PRICE FUZZY RULE-BASE SYSTEM

L_P\Amount of Participation	Low	Medium	High
Low	Low	Low	Medium
Medium	Medium	Medium	Medium
High	Medium	High	High

change ΔG_{ChP}, which updates the charging price value as follows:

$$G_{ChP} = MnaV + \Delta G_{ChP}(MxaV - MnaV) \quad (3)$$

Figure 2 illustrates the proposed membership functions design for the proposed charging price adaptation fuzzy system.

The relationship between the two fuzzy inputs and their output is detailed in Table III, which illustrates the rules that adapt the charging price for the SD in the managed microgrid.

IV. MULTI-OBJECTIVE OPTIMISATION PROBLEM

The Particle Swarm Optimisation (PSO) method is applied to solve the multi-objective optimisation problem in the managed microgrid, by considering the dynamic variables change and the solution constraints in the economic and environmental generation costs. In this work, we will discuss the switching mechanism that has been integrated with the PSO to control the storage device behaviour. We have developed a signal indicator that indicates the storage devices status (charging, discharging or standby). The indicator compares the storage devices instantaneous capacity with the full practical storage devices capacity, and generates a signal whenever the capacity goes below 100% of the capacity. This signal will be treated under other pricing conditions:

1) when the local generation price is below the adaptive pricing threshold, a charging signal will be activated.

2) when the storage device charging price is less than other generation sources price, a discharging signal is activated to dispatch the electricity to the microgrid's loads.

Table I
LOCAL GENERATION PRICE BASED ON THE DEMAND, AVAILABILITY OF THE SOURCES AND THE DYNAMIC GENERATION PRICE WITHIN THE MANAGED MICROGRID

Price \ $Dmnd$ (scenarios)	$Ph_G + W_G \geqslant Dmnd$	$Ph_G + W_G < Dmnd < Ph_G + W_G + S_G$	$Dmnd \geqslant Ph_G + W_G + S_G$
$G_P < U_P < S_P$	0	$G_P * (\frac{G_{SG}}{Dmnd})$	$G_P * (\frac{Dmnd-(Ph_G+W_G)}{Dmnd})$
$G_P < S_P < U_P$	0	$G_P * \frac{G_{SG}}{G_G+Ph_G+W_G}$	$G_P * \frac{G_{SG}}{Dmnd}$
$S_P < G_P < U_P$	0	$\frac{S_P*S_G}{Dmnd}$	$G_P - (\frac{S_G(G_P-S_P)}{Dmnd})$
$U_P < G_P < S_P$	0	$\frac{U_P*U_G}{Dmnd}$	$U_P * (\frac{U_G}{Dmnd})$
$U_P < S_P < G_P$	0	$\frac{U_P*U_G}{Dmnd}$	$U_P * (\frac{U_G}{Dmnd})$
$S_P < U_P < G_P$	0	$S_P * (\frac{Dmnd-(Ph_G+W_G)}{Dmnd})$	$U_P * (\frac{Dmnd-(Ph_G+W_G)}{Dmnd})$

3) when the adaptive charging price is above the local generation price or when they have initially been charged with higher price than other generation units generation price at time of comparison, a standby signal is activated.

Therefore, the PSO will consider the storage devices as loads, sources or not counted based on the generated signals at time of processing. Hence the proposed PSO aims at finding optimum solution for minimising the economic and environmental costs by introducing a general multi-objective cost function, which is described as follows:

$$F_{min} = [Cost1, Cost2, ..., Costn] \tag{4}$$

where F_{min} is a multi-objective cost function, and n is the number of the tested cost functions. Here, we have used environmental and economic cost functions, which are initially subject to the following constraints:

a) The storage devices charging/discharging time is evaluated through:

$$T = \frac{C}{I^{Pn}} \tag{5}$$

where C is the theoretical capacity, I is current, and Pn is Peukert number.

b) All updated velocities of the selected initial values of each generation unit must not exceed the capacity of the source itself:

$$\begin{gathered} U_{Gmin} \leqslant U \\ S_{Gmin} \leqslant S \leqslant S_{Gmax} \\ G_{Gmin} \leqslant G_G \leqslant G_{Gmax} \end{gathered} \tag{6}$$

c) When each gen-set is covering 500kWh, we always look to nominate the dispatch values that maximising the spinning reserve utilisation from the running gen-sets. Therefore, the gas gen-sets dispatch cost is formulated as follows:

$$G_{lostG} = (\frac{(int(\frac{G_G}{500}) + 1) * 500 - G_G}{500}) \tag{7}$$

d) Summing all the initialised values should always be greater or equal to the demand in the managed microgrid:

$$G_G(t) + S_G(t) + U_G(t) + W_G(t) + Ph_G(t) \geq Demand(t) \tag{8}$$

e) The cost function must consider storage devices operation status ($StorageisOn$), which is represented by environmental and economic cost functions indicators, to switch the searching mechanism to prioritise the utilisation of the storage devices when they are ready for dispatch. We would also like to slot another cost indicator "$Charging$" in the economic and the environmental cost functions, which indicates the charging/discharging status for the storage devices. This cost indicator is decided by the adaptive charging price fuzzy system. The environmental cost function can be formulated in the following equation:

$$\begin{gathered} Cost1 = (G_G + G_{lostG}) * (StorageisOn + G_E) \\ + \\ S_G * (S_E) * Charging \\ + \\ U_G * (U_E + StorageisOn) \end{gathered} \tag{9}$$

In the economic cost function, there are variable and fixed costs for each dispatch source, added to the main cost function: (MoV) variable maintenance and starting and shutting down cost, and (MoA) fixed annual insurance, inspection and operating cost. Therefore, the following equation details the proposed economic cost function:

$$\begin{gathered} Cost2 = (StorageisOn + G_P + MoV_G + MoAn_G) \\ * \\ (G_G + G_{lostG}) \\ + \\ S_G * (MoV_S + S_P) * Charging \\ + \\ U_G * (MoA_U + U_P + StorageisOn) \end{gathered} \tag{10}$$

f) All velocity updates will result in positive values:

$$\begin{gathered} V_{i,j}^{k+1} = w.V_{i,j}^{k} + (P_{best.i,j}^{k} - X_{i,j}^{k})C_1.rand_1() + \\ (G_{best.i,j}^{k} - X_{i,j}^{k})C_2.rand_2() \end{gathered} \tag{11}$$

$$X_{i,j}^{k+1} = abs(X_{i,j}^{k} + V_{i,j}^{k+1}) \tag{12}$$

g) The update process is repeated based on a predefined number of iterations i as shown in the flow diagram illustrated in Figure 3.

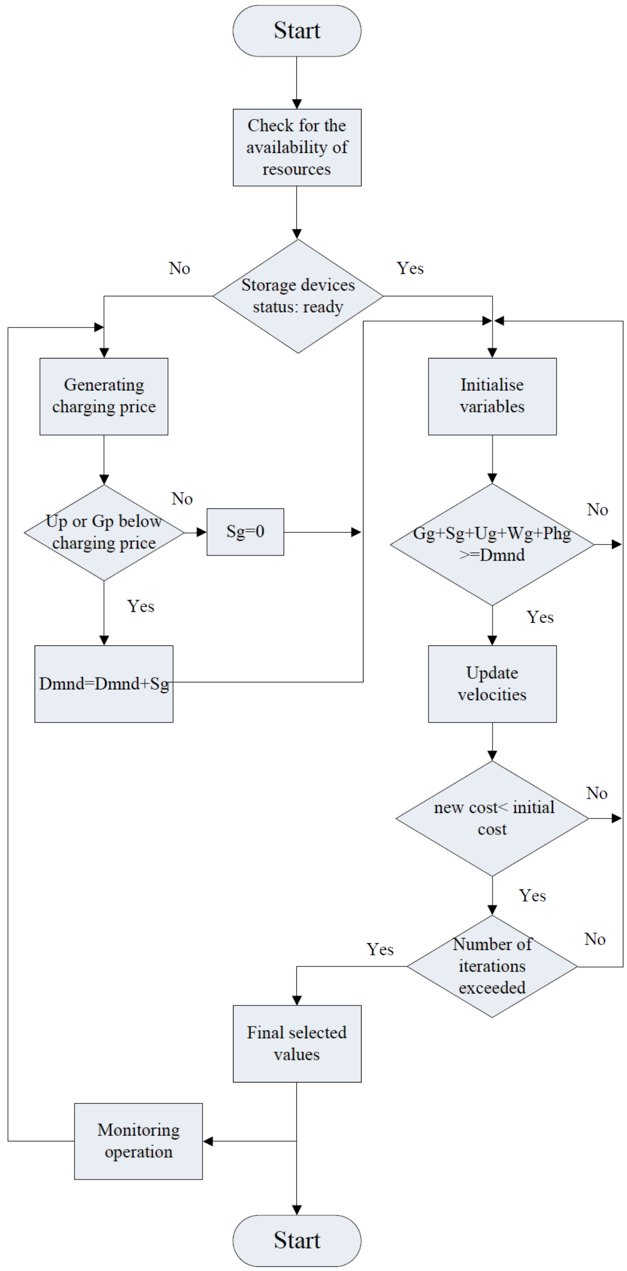

Figure 3. The Proposed Particle Swarm Optimisation Update Process

V. Results

In details, we show the microgird overall management performance with the proposed method. Accordingly, we test the integrated optimisation roles by simulating the system with the operation scenarios data. It is shown from the results that the initial proposed PSO was successful in maximising the utilisation of the spinning reserve of the installed gas gen-sets. It is also shown that the method could control the dynamic generation cost dispatch with the intermittent generation from the renewable sources. Table III illustrates the performance of the proposed optimisation method for a typical 12-hours daily operation.

Among the results, we identify the robustness of the proposed adaptive PSO in switching its calculation mechanism based on the encountered operation scenarios. Figure 4 shows the control for the SD generation capacity during their charging and discharging times.

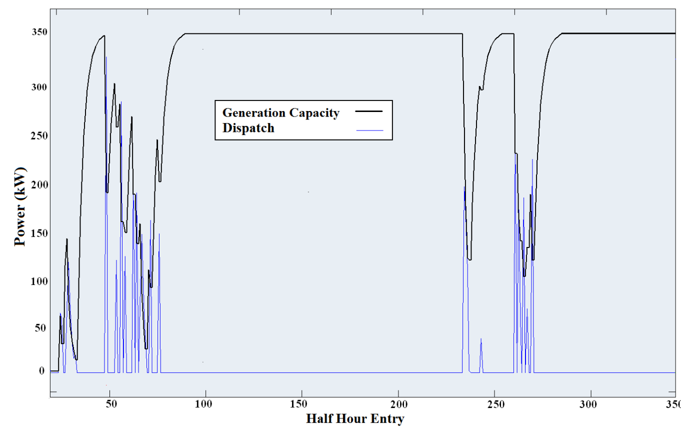

Figure 4. Storage devices charging/discharging status for a typical one week of operation in the managed microgrid

Table IV
Storage Devices Performance Comparison

Performance	PSO	Fuzzy-PSO
NOP	227	246
SDSE kWh	94402	98918
Money $	2478	2686
AP	885	959
Microgrid Total Energy kWh	2367000	2359300

The results have also proved that the SD can play a substantial role in balancing the operation within a remote self-supplied microgrid. However, the role can be utilised to enhance the SD efficiency. Here, we test the proposed artificial intelligence method to control the charging/discharging of the SD based on monitoring their operation performance. At this stage, we would like to discuss our simulation results. The method is evaluated based on its ability to increase the amount of SD participation in the microgrid power dispatch with the lowest possible generation cost. The method was found to bring a range of benefits to the system in terms of Number of Participation (NOP), Supplied Energy (SE), Achieved Profit (AP) and generation Cost. Table IV illustrates the difference in the values incurred by adding the proposed fuzzy pricing method to the typical PSO.

The results in Table IV showed that the proposed fuzzy pricing method was successful in performing smart switching within the PSO to cope with the dynamic generation cost. This has eventually increased the amount of NOP by 8.3%, SE by 4.7% and AP by 8.3%. These increments have resulted from following the weekly prices pattern around the microgrid's operation. Hence investigating the best time domain for the prices change can be an optimisation problem, which has been left as an investigation topic for future research.

VI. Conclusion

In this paper, we have presented a smart energy management method that aims at performing smart use of the SD to

Table III
MICROGRID GENERATION PERFORMANCE EVALUATION

H	$Dmnd$	U_P	Ph_G	W_G	G_P	G_G	$GNo.$	S_P	S_G	U_G	G_G	$GNo.$	S_P	S_G	U_G
	Operation parameters					PSO					FPSO				
1	1537	0.2394	0	0	0.2147	1476	4	0.192	/	99	487	2	0.208	/	1101
2	1647	0.2694	300	0	0.2485	1463	4	0.192	/	0	0	0	0.208	/	1194
3	2191	0.2912	561	0	0.2479	1970	4	0.192	/	0	2416	6	0.208	/	0
4	2365	0.3173	325	0	0.2485	2469	6	0.192	/	0	2435	6	0.208	/	0
5	2328	0.3208	364	0	0.2809	0	0	0.192	+240	1792	2424	6	0.204	+249	0
6	2516	0.318	389	0	0.2343	2459	6	0.204	-80	0	1952	5	0.188	-84	0
7	2454	0.3349	543	0	0.2552	2441	6	0.2	-46	124	2473	6	0.192	-46	0
8	2495	0.3445	232	0	0.2924	2455	6	0.204	-24	0	1985	5	0.196	-26	0
9	2382	0.3644	509	0	0.2485	1972	5	0.208	-14	0	1922	5	0.196	-14	141
10	2357	0.3373	498	0	0.2349	2448	6	0.208	-8	0	1949	5	0.196	-8	0
11	2265	0.3543	243	34	0.2485	1976	5	0.208	-4	0	1974	5	0.196	-4	53
12	1767	0.3394	481	0	0.2343	1857	5	0.208	-4	0	1461	4	0.196	-4	0

reduce the generation costs in a typical autonomous microgrid. The proposed method is applied by controlling the charging process of the SD through a fuzzy charging price threshold system. The proposed system is designed to work based on monitoring the microgrid's local generation price and the total amount of SD dispatch in the most recent seven days of operation. The generated charging prices aim at maximising the chance of charging the SD with low prices, thus maximising the chance of having cheaper dispatch throughout the SD lifetime. After evaluating the charging price, a switchable Particle Swarm Optimisation is applied to control the electricity dispatch based on the dynamic generation cost of the generation within the microgrid. The results have shown higher amount of SD participation, and higher amount of profit with the proposed system, which reduce the overall generation cost in the managed microgrid. As future extended works, we recommend adding the demand response and the ancillary services trade considerations under competitive prices environment to the investigated optimisation method.

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