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Backtracking Search Algorithm Based Fuzzy Charging-Discharging Controller for Battery Storage System in Microgrid Applications

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ABSTRACT This paper presents an efficient fuzzy logic control system for charging and discharging of the battery energy storage system in microgrid applications. Energy storage system can store energy during the off-peak hour and supply energy during peak hours in order to maintain the energy balance between the storage and microgrid. However, the integration of battery storage system with microgrid requires a flexible control of charging-discharging technique due to the variable load conditions. Therefore, a comparative evaluation of the developed model is analyzed by considering controllers with fuzzy only and optimized fuzzy algorithms. In this paper, backtracking search algorithm based fuzzy optimization is introduced to evaluate the state of charge of the battery by optimizing the input and output fuzzy membership functions of rate of change of the state of charge and power balance. Backtracking search algorithm is chosen due to its high convergence speed, and it is good for searching and exploration process with exploiting capabilities. To validate the performance of the developed controller, the obtained results are compared to the results obtained with the particle swarm optimization based fuzzy and fuzzy only controllers, respectively. Results show that the backtracking search algorithm based fuzzy optimization outperforms the other control methods in terms of effectively manage the charging-discharging of the battery storage to ensure the desired outcome and reliable microgrid operation.

INDEX TERMS Fuzzy controller, state of charge, battery energy storage, optimization, charging-discharging, microgrid, load.

I. INTRODUCTION

Fossil fuel-based conventional energy sources such as coal, oil, natural gas have strong negative impact on the environment. Moreover, the availability of these fossil fuels is decreasing day by day. Hence, extracting energy from renewable sources such as solar, wind, biomass etc. and their storage systems are becoming the new paradigm to overcome the shortcomings of energy development [1]. These renewable energy technologies have long term benefit of clean and sustainable energy production. Energy Storage Systems (ESS) manages the decent power balance during the power crisis, thus has a significant impact to stabilize the overall power system by mitigating the intermittent nature of renewable generation. ESS can store energy during off-peak hours and release them in peak hours. This trend of integrating renewable sources with ESS and loads is utilizing in microgrid applications. A simplified conceptual framework of this interconnected system is shown in Fig. 1 [2]. Here, the distributed sources, loads and storage are connected to the main grid with point of common coupling (PCC).

Microgrid (MG) is capable of operating in both grid-connected and islanded mode. In grid-tied system, power balance between MG and main grid protect the system from frequency instability. However, in islanded mode MG operates with off-grid network, hence primary frequency control becomes crucial. Different researches have been carried out with the application of the battery storage system in

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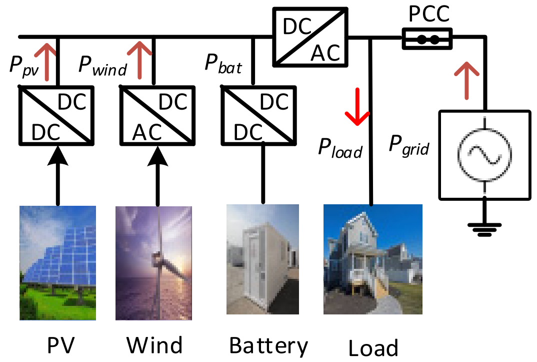

FIGURE 1. Conceptual framework of the interconnected system.

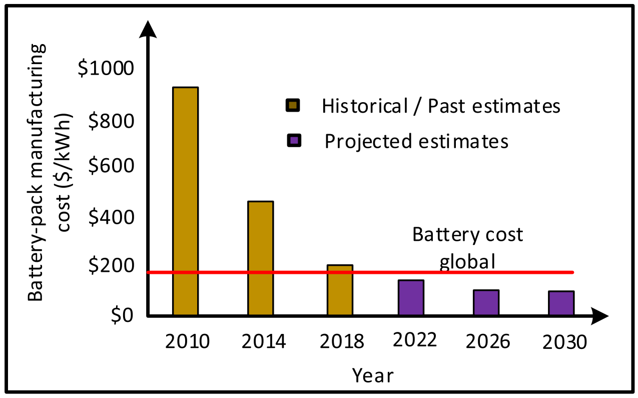

FIGURE 2. Trends of costs of lithium-ion battery [8].

TABLE 1. Specification of different types of ESS [7].

Technologies	Name	Life time (years)	Efficiency (%)	Advantage	Disadvantage
Electrochemical	Lead acid	≤ 20	≤ 85	High recyclable, Low cost	Very heavy, Poor energy density
	Lithium-ion	≤ 15	≥ 90	High storage capacity, Longer life cycle,	Protection is needed for being over charge/discharge, costly
	NaS	≤ 15	≤ 80	High storage capacity, Low cost	Works only with liquid Na and S (290~390^{0}C)
	Vanadium Redox	≤ 10	≤ 80	Possible to use in various RESs	Cost is very high

MG applications. Although there are many storage devices, battery storage has attracted the researchers due to its controlling, maturity and efficiency. The principal advantage of batteries is that, they can be used as the single storage or may be developed as hybrid storage integrating with other batteries or non-batteries storage device [3]. Batteries may be of different kinds such as lead-acid, lithium-ion, sodium sulphur (NaS), redox flow etc. [4]. Table 1 shows the different parameter values of various ESS based on the life time, efficiency and related merits and demerits. From this table, it shows that, lithium-ion battery has high storage capacity with longer life cycle and high efficiency. On the other hand, the non-batteries ESS such as supercapacitors have high power density, low cost and longer life cycle. However, the performance of supercapacitors mostly depends on the improved electrode conductivity with increased accessible area of electrolytes ions. In [5], facile method has been proposed to improve the performance of supercapacitors by one step electrochemical deposition. However, the self-discharge rate of supercapacitors is still very high and needs to be improved for the MG applications. Addressing these issues, in [6], to improve the performance of batteries and supercapacitors, metrics for the evolution of these storages have been extensively described considering the cell voltage, specific energy and operating temperature.

Although the cost of battery was too high initially, the price of the battery is gradually decreasing with the development of technology. Fig. 2 shows the trends of decreasing cost ($/kWh) of lithium-ion battery, starting from the year 2010 to 2018 and the projected cost from 2022 to 2030 [8]. Research shows that the integration of battery energy storage system (BESS) faces the challenges of charging-discharging, efficiency, power system stability, power electronic interfacing, controlling voltage and frequency fluctuations and protection from damages [9]. Moreover, optimal renewable energy penetration and autonomous coordination of multiple PV/battery hybrids technology for isolated MG have gained the attention of the researchers [10].

The aforementioned applications of BESS require the controlling of charging and discharging to ensure the high performance, long life expectancy and high reliability of the storage systems. Numerous researches on charging-discharging control have been carried out by the researchers. Qian et al. in [11] developed a high-efficient grid connected BESS to evaluate the state of charge (SOC) and state of health (SOH) of the storage, respectively. An increase the life expectancy of the battery charge equalization technique was adopted in this research to balance the charge of all the cells from 0% to 100%. Traditional controlling techniques such as constant-current and constant-voltage (CC-CV), pulse charging (PC), reflex charging, trickle charging (TC) and float charging (FC) have been discussed by different researchers. In [12], CC-CV method was used for controlling the battery charging-discharging. However, the efficiency of this technique is comparatively low. Besides, due to the temperature rise, life cycle of the battery decreases. Pulse charging method have been illustrated in [13]. This technique is useful to protect the long-term damage of the battery. Reflex charging for DC microgrid was studied in [14], however, the charging efficiency of this method is low. Trickle charging and float charging [15] methods also were investigated for battery. However, trickle charging method has the overcharging problems and thus can damage the cell. Model predictive control for charging-discharging was used in [16]. Morstyn et al. developed an MPC based *d-q* control model for BESS based MG to describe the optimal power flow in distributed energy system [17]. Voltage and converter current constraints were not considered in this research. PI controller was used to control the charging-discharging of the battery, however, it lacks the feature of fast charging-discharging [18]. Overall, the traditional charging-discharging controller topologies have the limitation of complexity, charging time, efficiency, temperature rise, over-charging or self-discharging problems.

Addressing these issues, fuzzy based controlling system has been proposed by different researchers to control the charging-discharging of battery energy storage device. The main advantage of fuzzy logic controller (FLC) is that, it requires no mathematical calculation, making it easier to be implemented for battery charging-discharging control. A fuzzy based charging and discharging control of lithium-ion battery has been investigated separately considering the different SOC limit [1]. In [2], fuzzy based BESS was introduced to control the battery SOC, where the SOC limit was chosen from 50% to 100%. A similar strategy was followed by Martinez et al. in [19], where 21 fuzzy rules were created to control the SOC of the battery from 5 membership functions (MFs). However, the main limitation of this research is that only charging control method was developed considering the SOC limit from 0% to 100%. Therefore, considering the fuzzy inputs and outputs to control the battery charging-discharging in MG applications is still now a great challenge to limit the SOC within the operating region of 20% to 80%. Table 2 summarizes the different researches on fuzzy-based charging-discharging controlling of BESS in tabular format.

In recent years, optimization algorithms are attracting the researchers to solve different problems of the system. A fuzzy based PSO technique was introduced to optimize the life expectancy of the battery through fuzzy MF optimization [20]. Besides, this algorithm was used to optimize the performance of hybrid PV/Wind battery storage system [21]. However, PSO can converges prematurely and can be trapped into local minimum specially with complex problems. Optimization of charging-discharging current to manage the SOC of lead-acid battery has been investigated in [22]. PSO and nonlinear programming model are used in this study. A novel stochastic genetic algorithm (GA) is proposed to improve the accuracy of the SOC evaluation, where parameters of the model were optimized. However, it requires large population size for accurate results, thus can be complex and may require more computational time. Some other optimization algorithm such as gravitational search algorithm (GSA), firefly algorithm (FA), NARX etc. are available to solve the aforementioned issues [23]. The drawbacks of these techniques are easy trapping in local. Minima [29], [30] and reduce the diversity of the population [31], resulting in missing situations and longer computational time. It means not all these techniques and their variants provide superior solution to some specific problems. Although some of them are efficient, they still need improvement to further enhance their performance. Based on the analysis above, a comparative analysis among the optimization techniques has been depicted in table 3.

TABLE 2. Research on charging-discharging controller of ESS.

Paper	Aim	Features	Battery
Chen et al. [1]	Fuzzy based EMS	• Charging-discharging has been investigated separately	15kW lithium-ion battery
Arcos-Aviles et al. (2018) [2]	Controlling the battery SOC in secure limit	• SOC limits 50%-100% • MF ZE is widely applied to maintain the battery SOC	72kWh lead-acid battery bank
Martinez et al. (2018) [19]	Controlling the charging/ discharging based on FLC	• 21 rules are performed from 5 MF of two inputs	115 Ah, 120V lead-acid battery bank
Cheng et al. (2018) [24]	Fuzzy based charging control of energy storage system	• Only charging condition is fulfilled • SOC input is 0 to 100%	1.2kWh Lithium Iron Phosphate battery
Collotta et al. (2017) [20]	Optimizing MF of FLC to increase the battery life expectancy for the application in industrial wireless sensor networks (IWSNs)	• Sensors sleeping time regulated by FLC, PSO optimization was used in this purpose • 3 MFs are used in this study • Small scale applications	10.8V lithium-ion battery
Abadia et al. (2016) [25]	Fuzzy controlled EMS for standalone application	• SOC shows decreasing trend only • SOC input of FLC is 0 to 100%	12V, 240Ah, 600W lead-acid battery
Teo et al. (2016) [26]	Fuzzy controlled ESS for Charging/ discharging	• Minimum SOC chosen as 5% is not feasible for practical application	90kWh/ 6kW
Moradi et al. (2015) [27]	Minimize the cost, optimal sizing of MG through selecting the operational strategy by FLC	• PSO optimization was used • Maximizing profit by utilizing the renewable sources and reduce the environmental pollution	Not specified
Natasheh et al. (2012) [28]	Managing power flow within standalone hybrid power system	• S-R flip-flop is used for battery storage • Only 3 MFs are used • Input PV power and load demand, output is SOC	200V, 5.8783Ah Li-ion battery

Study shows that the performance of the fuzzy logic controller depends on the parameter values of the membership functions. The best value for these MFs can be derived by using optimization technique. Addressing all these issues, in this research, backtracking search algorithm (BSA) has been studied to optimize the MFs of FLC for the microgrid application. BSA dominates the value of the search on the best population and is good for searching the exploration

TABLE 3. Comparative analysis of various optimization algorithm and their application.

Optimization Technique	Working principal	Features	Application
GA [32]	Metaheuristic approach, inspired by the process of natural selection.	• Large population size, more complex and high computational time.	• Optimal calculation for compressor.
PSO [22]	Stochastic technique, inspired by social behavior of birds flocking or fish schooling.	• Cannot work out the problems of scattering, can converge prematurely and trapped local minima.	• Control the charging-discharging range of lead-acid battery.
BAT [33]	Principal of echolocation, with varying pulse rates of emission and loudness.	• Accuracy may be limited if the number of functions is not high.	• Solving multi-objective optimal power flow problem.
FA [34]	Flashing behavior of firefly considering brightness and attractiveness.	• High probability of being trapped in local optima.	• Determining the optimal switching angle of multilevel inverter, FPGA was used.
LSA [35]	Metaheuristic approach, inspired by the natural phenomenon of lighting and the mechanism of step leader propagation.	• Easy to trap in local minima.	• Photovoltaic inverter controller using eZdsp F28335 kit, reduced the total harmonic distortion of voltage to 2.1%.
BEE [36]	Intelligent behavior of honey bees, food positions are modified by bees with time.	• Premature convergence in the later search period.	• Application in optimal team maintenance capability. • Applied in water tank optimization
GSA [37]	Consider the law of gravity and mass interactions.	• Easy to trap in local minima, weakness in strategy to diversify the population.	• Controlling air pollution and promoting sustainable development
BSA [38]	Good for searching and exploration process with exploiting capabilities.	• Effective for constraint satisfaction problem, can easily detect the global optimal solution.	More stable performance compares to other stochastic algorithm with high convergence speed.

process with exploiting capabilities [39], and it is advantageous in mutation and crossover strategies. Besides, this algorithm was used to design the power system stabilizers [40] and to solve the power flow problems in HVDC systems [41]. Thus, the significant contribution of this research is to develop a new optimized fuzzy logic controller which can effectively control the charging-discharging of the battery. It is also seen that, optimized fuzzy performs better than the non-optimized configuration with the same plant. In this paper, an optimal fuzzy controller has been developed to control the charging and discharging of the battery and SOC evaluation. Initially, fuzzy model for charging-discharging of BESS is developed. Then the input and output membership functions of the fuzzy controller are optimized using BSA to evaluate the performance of the developed controller.

II. FUZZY BASED BATTERY STORAGE SYSTEM IN MG

Simplified topology of the fuzzy-based battery storage system is shown in Fig. 3, which incorporates the microgrid, grid, load, battery storage, buck-boost converter, and fuzzy logic controller. Five distributed sources such as diesel, PV, wind, fuel cell and biomass constitute the microgrid system. Loads are varied from 4 kW to 90kW based on the user demand. A 276V, 400Ah lithium-ion battery is used as the storage. To control the ESS charging-discharging, a bidirectional buck-boost converter is used with the fuzzy controller as shown in Fig. 3, where, S_1 and S_2 are the IGBT switches, L_b and C_b are the inductor and capacitor of the bidirectional converter. Both the switches enable the bidirectional flow of power through the battery. The duty cycle of the IGBT switches are controlled by the command of the Fuzzy controller. Besides, when the grid is ON, it will supply the power to the load and charge the battery. Battery discharges through the load based on the capacity and current SOC of the battery. Thus, the complete charging-discharging of the battery is controlled through the developed FLC considering the available power, load demand and battery SOC.

Charging-discharging of the battery is controlled by FLC which consists of two inputs and one output. Five membership functions for each input and output variables were graded for this FLC. They are: VS (very small), MS (Medium small), N (normal), ML (medium large), and VL (very large) as shown in Fig. 4. Fuzzy rules have been created based on these MFs. All the boundaries of the MFs are arranged such that, no one can overlap each other. All input and output MFs are normalized within the range $[-1, 1]$. Thus, MFs of output current (I) are selected as VS $[-1\ -0.4]$, MS $[-0.8\ 0]$, N $[-0.4\ 0.4]$, ML $[0\ 0.8]$, and VL $[0.4\ 1]$. In the fuzzification step, the crisp value is transformed into fuzzy value by means of the membership function of the FLC makes a decision for the system by means of the fuzzy rules. Finally, in the defuzzification step, the output MF is shown which will further control the duty cycle of the bidirectional converter for charging or discharging. In this research, $P_{balance}$ and ΔSOC are chosen as the inputs as shown in Fig. 3 and Fig. 4. $P_{balance}$ is the power difference between available power and the load demand. ΔSOC is evaluated from the current battery SOC and reference SOC ($SOC_{reference}$). $SOC_{reference}$ is used to limit the battery SOC beyond the certain limit and thus prevents the battery from over-discharging. $P_{balance}$ and ΔSOC are selected as the parameters. Then, the fuzzy inference system describes how battery charging-discharging are directly related and can be clearly evaluated by using these parameters. Thus, to develop the fuzzy rules, the minimum

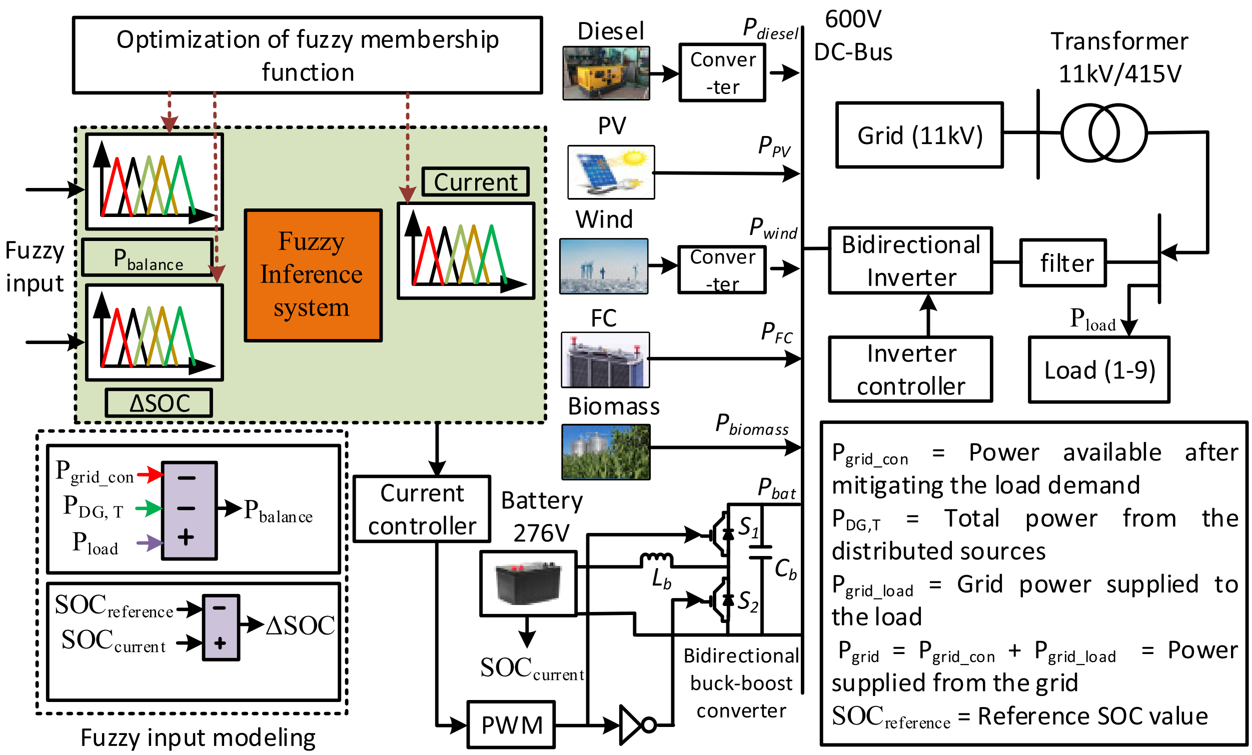

FIGURE 3. Simplified topology for the proposed Fuzzy based battery charging-discharging model.

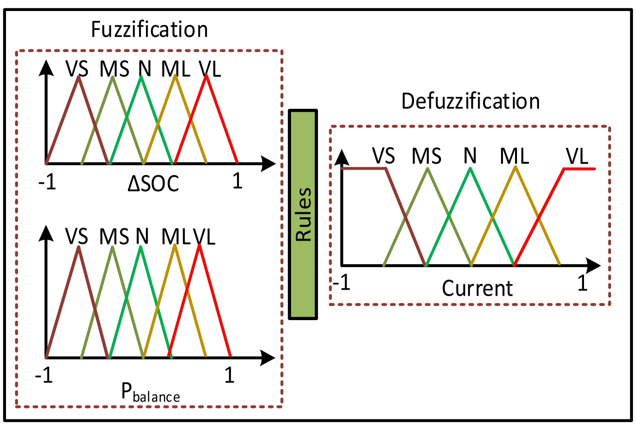

FIGURE 4. Input and output membership functions of FLC.

and maximum SOC of the storage are chosen as 20% and 80% respectively, while the $SOC_{reference}$ is chosen as 20% to extend the life of storage batteries [1]. Moreover, the available DG powers from the sources are varied from 12kW to 21kW. Finally, optimization has been introduced to optimize the membership functions of the fuzzy logic controller to get the optimal charging-discharging output.

III. FUZZY BASED CHARGING-DISCHARGING MODEL OF THE BATTERY

The methodological framework for the proposed charging-discharging controller is illustrated in Fig. 5. Firstly, the lithium-ion battery is selected based on the capacity, efficiency (>90%), size, cost, charging time, and life cycle of the storage. high energy density and rapid response time [42], [43].

The complete charging-discharging characteristics considering the battery SOC and $P_{balance}$ can be designed as shown in Fig. 6. According to this figure, within the safe operating region of 20% to 80%, the battery will be charged or discharged based on the difference of current SOC and reference SOC, load demand and availability of power of grid and distributed sources. When SOC is equal to 20%, it will definitely charge whatever the load demand and the SOC will not exceed the maximum threshold of 80%.

Fuzzy theory allows more flexible space in logic formulation to create conceptual ideas and experience. It creates a set of qualitative rules and thus differs from the traditional controller. In this research, mamdani-type fuzzy inference system (FIS) is used with two input and one output parameters. Fuzzy controller has three steps of operation. The first step is called fuzzification process where the real scalar value is transformed into fuzzy value by means of the fuzzy membership functions. Secondly, fuzzy rules are created with some if-then statement to achieve the result from the control system. The if-then statement is generated with both input and output MFs. Finally, the controller operation ends with the defuzzification process to recover the crisp or actual output as it needs to be transmitting to operate the controller. As stated, input parameters of the proposed fuzzy logic controller are ΔSOC and $P_{balance}$. The output parameter is current, I.

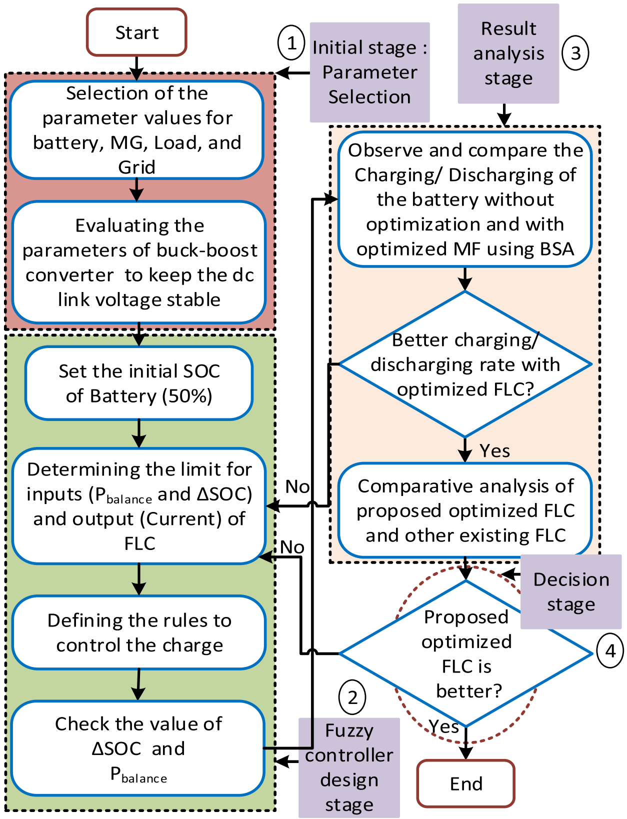

FIGURE 5. **Methodological framework for the proposed model.**

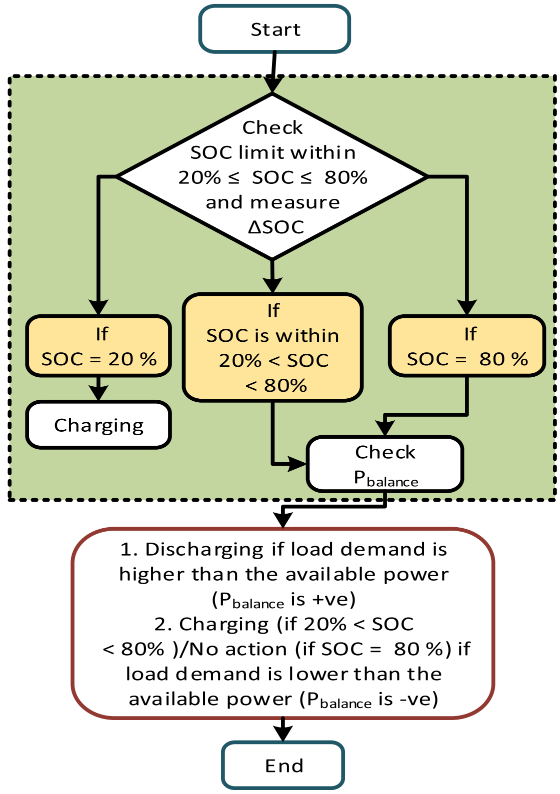

FIGURE 6. **Complete charging-discharging architecture of battery considering the SOC and $P_{balance}$.**

Now, the FLC input, $P_{balance}$, which is the power difference between the load demand and total available power from the distributed sources and grid (if grid is OFF, then no power will be generated from grid). Thus, the equation for $P_{balance}$ can be expressed as,

$$P_{balance} = P_{load} - P_{DG,T} - P_{grid\_con}. \tag{1}$$

where, P_{load} is the power consumed by the load, P_{grid_con} is the power available after mitigating the load demand and $P_{DG,T}$ is the total power from distributed sources. $P_{DG,T}$ can be calculated as given below,

$$P_{DG,T} = P_{diesel} + P_{pv} + P_{wind} + P_{FC} + P_{biomass}. \tag{2}$$

where, P_{diesel}, P_{pv}, P_{wind}, P_{FC} and $P_{biomass}$ denote the power from diesel generator, photovoltaic power, wind power, power from fuel cell and biomass respectively. Therefore, finding the total generated power ($P_{Gen,T}$), from the battery power (P_{bat}), and distributed sources it can be written as,

$$P_{Gen,T} = P_{bat} + P_{DG,T}. \tag{3}$$

Now, the total required grid power $P_{grid,T}$ can be deduced from the following equation,

$$P_{grid,\,T} = P_{load,\,T} - P_{DG,T} - P_{bat,\,T}. \tag{4}$$

Other input of FLC is ΔSOC which denotes the state of charge difference between the current SOC and reference SOC. Power variables involved in Fig. 1 are considered as positive when power flows according to the direction.

Now, the input variable ΔSOC of the FLC can be expressed as follow,

$$\Delta SOC = SOC_{current} - SOC_{reference}. \tag{5}$$

P_{bat} depends on the battery SOC, which is limited between a minimum (SOC_{min}) and maximum (SOC_{max}) value. It is needed to preserve or extend the battery lifetime [26]. Therefore, the overall SOC can be measured by the following constraints,

$$\begin{aligned} SOC_{\min} &\leq SOC_{(n)} \leq SOC_{\max}, \\ P_{balance,\min} &\leq P_{balance} \leq P_{balance,\max}. \end{aligned} \tag{6}$$

The objective of this proposed controller is to control the SOC of the battery. General equation for SOC of the battery can be expressed as,

$$SOC = 100\left(1 - \frac{\int_0^t I dt}{Q}\right). \tag{7}$$

where, I is the current and Q is the nominal capacity of the battery. Now, considering the inputs of fuzzy, $P_{balance}$ and ΔSOC, from equation (7), the equation of current I can

TABLE 4. Fuzzy rules for charging-discharging of BESS.

I		$P_{balance}$				
		VS	MS	N	ML	VL
ΔSOC	VS	VS	VS	VS	VS	VS
	MS	VS	VS	N	ML	ML
	N	MS	MS	N	ML	ML
	ML	MS	MS	N	ML	VL
	VL	N	N	N	ML	VL

further be derived as follows,

$$I = \left(\frac{P_{balance}}{E_0}\left(1 - \frac{\Delta SOC}{100}\right)\right). \tag{8}$$

where, E_0 is the battery constant voltage.

To accomplish the overall charging-discharging controller strategy, 25 rules are set to concurrently smooth the current for controlling the battery charging-discharging. The rules are set with the expert knowledge considering the impacts of the inputs to control the charging-discharging behaviour of the battery. Table 4 represents the conditions for the controller.

From the analysis, if the total power from the renewable sources is not enough for supplying power to the load, therefore, the battery should operate in discharging mode. If, load demand becomes lower than the available power, then the battery can operate in charging mode. Thus, the fuzzy rules in the tabular format can be explained as,

Rule 1: If ΔSOC is VS, $P_{balance}$ is VS then the output current I is VS.

It means, if the ΔSOC is low (when the current SOC of the battery is low) and the load demand is high, so the battery charges.

....

Rule 8: If ΔSOC is MS, $P_{balance}$ is N then the output current I is N.

This rule states that, if the ΔSOC is enough high to discharge (when the current SOC is higher than the reference high), and the demand of load also high, then, the battery can operate in both charge or discharge mode.

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Rule 25: If ΔSOC is VL, $P_{balance}$ is VL then the output current I is VL.

The rule illustrates that, if ΔSOC is very large (when the battery current SOC is high), with the less load demand, the battery will be discharged. The rules stated that, if the SOC comes below the set range, it will surely charge whatever the load demand and protect the over-discharging. In contrast, if the battery reaches at maximum limit, then it will not accept the charge to protect the overcharging. Fig. 7 demonstrates the surface of the fuzzy inference systems which shows that current changes with the variation of $P_{balance}$ and ΔSOC. If SOC is low enough whatever the demand, battery will absorb the current, and if SOC is high, then based on the demand it can be discharged.

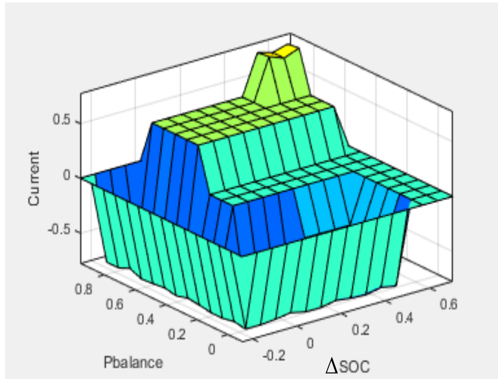

FIGURE 7. FIS current with variation of ΔSOC and $P_{balance}$.

IV. FUZZY BASED BSA OPTIMIZATION

As stated earlier, BSA is used to optimize the fuzzy MF to get the optimal charging-discharging of the battery. BSA has five steps of operation, initialization, selection - I, mutation, crossover, and selection-II. Initialization is the primitive configuration for the numerical values of population which can be expressed as,

$$X_{ij} = rand \cdot \left(up_j - low_j\right) + low_j. \tag{9}$$

where, $i = 1, 2, \ldots\ldots, N$, and $j = 1, 2, \ldots\ldots, D.N$ and D, are the population size and problem dimension, respectively. In selection-I, the search direction can be obtained from the historical population $\left(oldX_{ij}\right)$. Therefore,

$$oldX_{ij} = rand \cdot \left(up_j - low_j\right) + low_j. \tag{10}$$

Historical population randomly choose the population from previous generation; thus, a new trial population is generated. Now, conditions between the random values can be written as,

$$\begin{aligned} &if\ a < b\ then\ oldX_{ij} := X_{ij} \\ &oldX_{ij} = permuting\left(oldX_{ij}\right). \end{aligned} \tag{11}$$

Mutation is the process of generating new population of the initial and history population and thus can be derived by,

$$Mu\tan t = X_{ij} + F \cdot \left(oldX_{ij} - X_{ij}\right). \tag{12}$$

where, F determines the amplitude of search direction matrix and can be obtained as follows,

$$F = 3 \cdot randn. \tag{13}$$

BSA generates a trial population and then takes a partial advantage of its experiences from previous generations. The initial of trial population is taken from mutation as shown in equation (12). The next step of BSA is crossover where a binary matrix called map_{ij} is generated and comparison between initial and trial population takes place. This step gives the update map_{ij}. Besides, it controls the boundaries for the trial population. Finally, in selection-II, objective function is determined from the comparison of initial and trial population. Optimisation process runs to obtain the best population as well as the objective value. An objective function is the required target of optimization techniques to obtain the best output. Thus, the objective function searches for the best value of the FLC output to control the battery charging-discharging effectively. In this research, the objective is the optimal control of battery SOC which could ensure the smooth operation of the battery throughout the time and could minimize the storage overcharging and over-discharging. Therefore, the equation for the objective function can be expressed as,

$$\text{Objective function} = \min\left[\sum_{i=1}^{N} U(t_i)/t_i\right] = \min\left[\sum_{i=1}^{N} I(t_i)\right] \tag{14}$$

where, $I(t_i)$ and $U(t_i)$ denote the current (A) and capacity (Ah) of the battery at time t_i. Here, $I(t_i) = (I_{est} - I_{actual})^2 / N$ is the function that used to determine the optimal solution by obtaining the minimum value of the objective function through iteration. Thus, the objective function is calculated based on the estimated value (I_{est}), actual value (I_{actual}) and number of observations (N). The estimated value can be monitored following the equation (7). Moreover, the storage charging and discharging condition can be seen from the battery SOC. If the current SOC goes below or above the safe operating region, then it can be called as over-discharging or over-charging.

Table 5 illustrates the pseudo code for BSA optimization. From the table, BSA starts with the initialization of the population size and problem dimension. Then, to determine the search direction, historical population is determined according to the equation (10).

BSA can be redefined by if-then rule and update the operation. The order of the individual historical population can be rearranged by using the permuting function. Later, the search direction matrix is generated to complete the mutation process. The search direction matrix is controlled by F, as shown in (13). Mutant is the initial trial population value, while crossover is the final set of trial population (T). Crossover starts with the formation of binary integer-valued matrix (map) of size N. The value of mixrate determines the exact number of elements of individuals that will take part in mutation in a trial. If the best individual of $X(X_{best})$ has the better objective value then the global minimum value obtained by BSA, then the global minimizer and global minimum value both are updated to X_{best} accordingly.

To achieve the desired fuzzy output, center of gravity (COG) method is used in this study. Therefore, equation for crisp output can be written as,

$$Output_{crisp} = \frac{\sum_{i=1}^{n} I_i \cdot \mu_{\bar{I}}(I_i)}{\sum_{i=1}^{n} \mu_{\bar{I}}(I_i)} \tag{15}$$

where, $output_{crisp}$ represents the controller output, $\mu_T(I_i)$ is the degree of membership of the aggregated fuzzy set for output *I*, I_i is the output value of MFs for the corresponding rule and n signifies the rule number. Hence, the

TABLE 5. Pseudo code for BSA optimization.

Setting the parameters:
Input: iteration (i), population size (N), Problem dimension (D),
Output: *globalminimum*, *globalminimizer*

for i=1 to N **do**
for j=1 to D **do**
$X_{i,j} = rand\ .\ (up_j - low_j) + low_j$
$oldX_{i,j} = rand\ .\ (up_j - low_j) + low_j$
end
$ObjectiveX_i = ObjFun(X_i)$ **end**
for *iteration*=1 to N **do**
if $(a < b \mid a, b \sim U(0, 1))$ **then** $oldX_{ij} := X_{ij}$ **end**
$oldX_{ij} := permuting\ (oldX_{ij})$
$Mutant = X_{ij} + 3.\ randn.\ (oldX_{ij} - X_{ij})$
$map_{1:N,\ 1:D} = 1$
if $(c < d \mid c, d \sim U(0, 1))$ **then**
for i=1 to N **do**
$map_{i,u\ (1:[mixrate\ .\ rnd\ .\ D])} = 0 \mid u = permuting\ (1, 2, 3, \ldots, D)$
end
else
for i=1 to N **do**, $map_{i,\ randi(D)} = 0$,
end; end
$T: = mutant$
for i=1 to N **do**
for j=1 to D **do**
if $map_{i,j} = 1$ **then** $T_{i,j} : = P_{i,j}$
end; end
for i=1 to N **do**
for j=1 to D **do**
if $(T_{i,j} < low_j)$ or $(T_{i,j} < up_j)$ **then** $T_{i,j} = rand.\ (up_j - low_j) + low_j$
end; end; end; end
$ObjectiveT = ObjFnc(T)$
for i=1 to N **do**
if $(ObjectiveT_i < ObjectiveX_i)$ **then** $ObjectiveX_i := ObjectiveT_i$
$X_i := T_i$
end; end
$ObjectiveX_{best} = \min\ (ObjectiveX) \mid best\ \epsilon\ \{1, 2, 3, \ldots, \ldots, N\}$
if $ObjectiveX_{best} < globalminimum$ **then**
$globalminimum : = ObjectiveX_{best}$
$globalminimizer : = X_{best}$
end; end

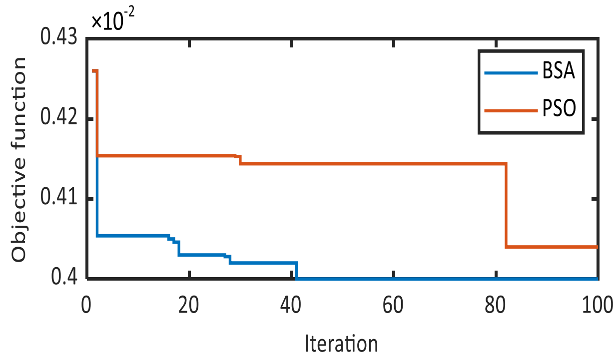

FIGURE 8. Objective function for BSA and PSO.

charging-discharging constraints can further be expressed as,

$$\sum_{t=1}^{T}\left(P_{DG,\,T}(t)+P_{grid\_con}(t)-P_{load}(t)\right) \geq \sum_{t=1}^{T} P_{bat}(t), \quad (16)$$

for charging,

$$\sum_{t=1}^{T}\left(P_{DG,\,T}(t)+P_{grid\_con}(t)-P_{load}(t)\right) \leq \sum_{t=1}^{T} P_{bat}(t), \quad (17)$$

for discharging.

Optimal solution is thus determined by choosing the best value of the objective function. The objective function with 100 iterations using the BSA algorithm is shown in Fig. 8. To prove the effectiveness, the optimization process is compared with the particle swarm optimization (PSO) algorithm of same population size and problem dimensions. Details of the PSO algorithm has been illustrated in [24]. It shows that, the objective reaches its minimum value faster in BSA optimization (after 42 iterations) compare to PSO (81 iterations). Thus, the optimal operation of FLC through opting the MFs is accomplished as shown in Fig. 9 which is distributed with the same fuzzy subsets VS, MS, N, ML and VL, for each input and output. Optimal range of MFs for the output current (I) with BSA optimization is VS[−1 −0.3132], MS[−0.3734 0], N[-0.3132 0.3531], ML[0 0.5327] and VL[0.3531 1], while for PSO the values are VS[−1 −0.4519], MS[−0.7120 0], N[−0.4519 0.7362], ML[0 0.8191] and VL[0.7362 1]. Besides, Fig. 10 shows the dc-link voltage which is maintained within the permissible range of 600V during the operating conditions.

V. RESULT AND ANALYSIS

Matlab/Simulink software (Matlab 2017a with windows 10, 16GB RAM, 64-bit operating system, 3.4GHz processor) is used to simulate and verify the performance of the proposed controller. In this research, comparative analysis of with fuzzy and with optimized fuzzy based charging-discharging control of BESS has been investigated under various load variation. Fig. 11 reflects the load variation and power from the distributed sources at different time.

Battery output current and the SOC variation in both fuzzy and optimized fuzzy control are depicted in Fig. 12 and

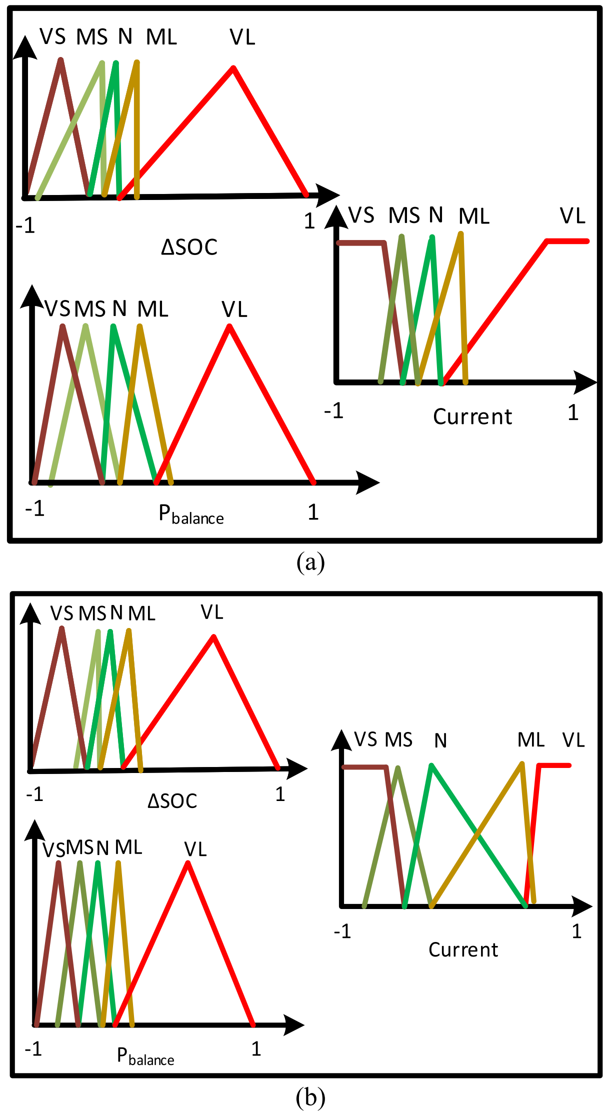

FIGURE 9. (a) BSA Optimized MFs for both input and output parameters. (b) PSO Optimized MFs for both input and output parameters.

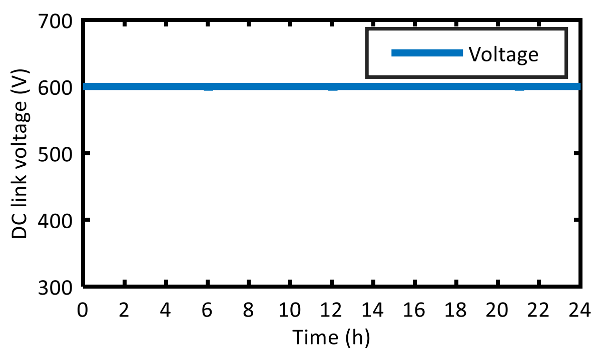

FIGURE 10. Waveshape for dc link voltage response.

Fig. 13, respectively. From Fig. 11 – Fig. 13, initially, the grid was stopped and the grid is in operation within 17-22h. Obtained results show that when the grid is OFF, from 0 to 6h, battery operates in discharging mode as the load demand

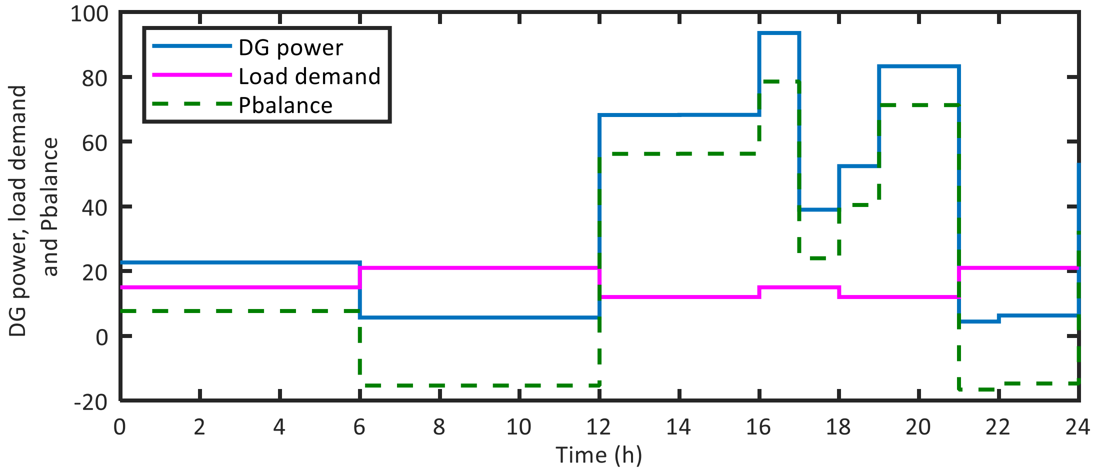

FIGURE 11. Load demand, power from DGs and difference between load and DG power ($P_{balance}$).

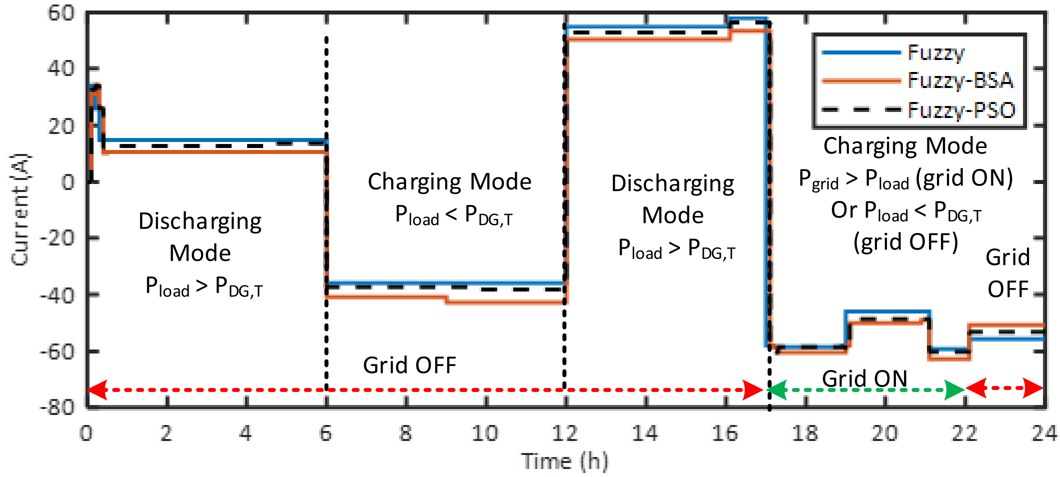

FIGURE 12. Comparative analysis of battery current output in both fuzzy and optimized fuzzy mode.

is higher than the available distributed power. From, 6 – 12h, power from the distributed sources exceeds the load demand and hence operates in charging mode. Between 12 – 17h, the load demand is higher and thus battery discharges more current in both fuzzy and optimized fuzzy mode. However, when the grid is turned ON at 17 – 22h, the grid supplies the required power to the grid and the rest power will go to charge the battery. Between, 22 – 24h, the grid remains OFF, but power from distributed sources is higher than the load demand. Hence, the battery operates in charging mode. SOC of battery varies starting from its initial level of 50%, which is plotted in Fig. 13. Overall Fig. 12 and Fig. 13 demonstrate that the fuzzy based BSA optimization outperforms the fuzzy only controller and fuzzy-PSO controller in term of efficient charging and discharging battery storage system as well as their SOC performance, respectively. The segmental analysis of grid position, load demand, battery charging and discharging mode and SOC performance of based on Fig. 11 - Fig. 13 is shown in Table 6.

TABLE 6. Segmental representation of charging-discharging of BESS.

Paramete r	Time				
	0-6h	6-12h	12-17h	17-22h	22-24h
Grid	OFF	OFF	OFF	ON	OFF
MG	ON	ON	ON	ON	ON
Load and MG diff.	$P_{load} > P_{DG,T}$	$P_{load} < P_{DG,T}$	$P_{load} > P_{DG,T}$	$P_{load} > P_{DG,T}$	$P_{load} < P_{DG,T}$
Grid, load and MG	-	-	-	$P_{DG,T} + P_{grid\_con} > P_{load}$	-
Battery mode	Disc harg- ing	Chargin g	Dischar ging	Charging	Chargi ng

Besides, BSA requires less time (4628.4 minutes) for 42 iterations to reach the optimal solution compare to PSO (6415.2 minutes) for 81 iterations. However, the optimization time per iteration for BSA and PSO are 110.2 minutes and 79.2 minutes, respectively.

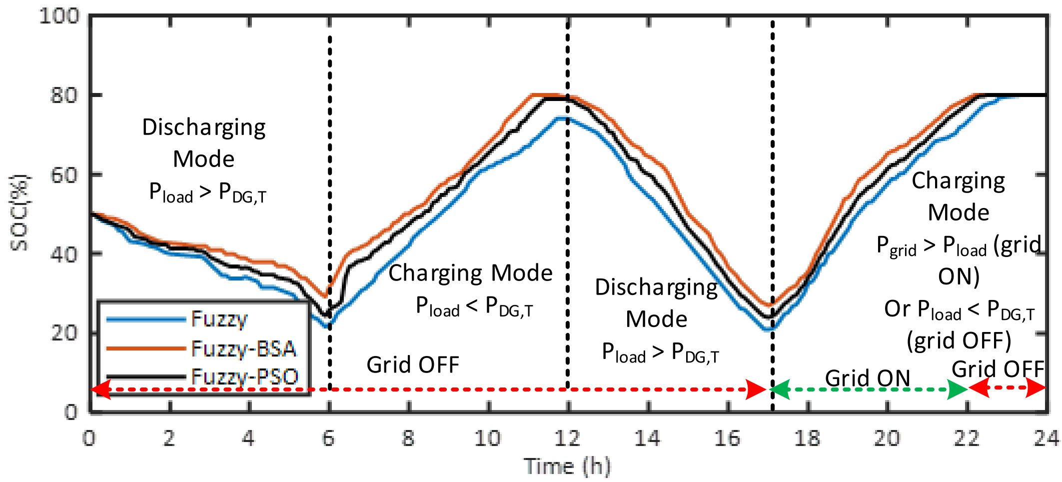

FIGURE 13. Comparative analysis of SOC output with fuzzy and optimized fuzzy controller in grid connected mode of operation.

VI. CONCLUSION

In this research, a low complexity fuzzy logic controlling system for charging and discharging of lithium-ion battery has been investigated. It is observed that battery gets charged when there is available power and it gets discharged if the load demand exceeds the generated power. The main purpose of this research is to improve the performance of the battery storage system and hence, ensure the reliable MG operation through proper controlling of the SOC of the battery. The optimized fuzzy model is used to control the charging-discharging of the battery which have 25 rules with two inputs (ΔSOC and $P_{balance}$) and one output (current). The obtained results show that, the controller performs according to the desire mechanisms to get the battery charged or discharged. Furthermore, proposed controller has been investigated with BSA optimization techniques. The MFs of the fuzzy controller have been optimized to get the best controlling output. The results demonstrate that the BSA technique performs well to control the SOC of the battery and the outcome is comparatively better than the fuzzy only and fuzzy-PSO system, respectively. It implies that the proposed optimized fuzzy gives accurate output to control the charging-discharging of the battery. Furthermore, the intended future scope of this research is to implement the system for real time application which is still in laboratory stage.

REFERENCES

[1] Y.-K. Chen, Y.-C. Wu, C.-C. Song, and Y.-S. Chen, "Design and implementation of energy management system with fuzzy control for DC microgrid systems," *IEEE Trans. Power Electron.*, vol. 28, no. 4, pp. 1563–1570, Apr. 2013.

[2] D. Arcos-Aviles, J. Pascual, L. Marroyo, P. Sanchis, and F. Guinjoan, "Fuzzy logic-based energy management system design for residential grid-connected microgrids," *IEEE Trans. Smart Grid*, vol. 9, no. 2, pp. 530–543, Mar. 2018.

[3] J. Li, M. Zhang, Q. Yang, Z. Zhang, and W. Yuan, "SMES/battery hybrid energy storage system for electric buses," *IEEE Trans. Appl. Supercond.*, vol. 26, no. 4, Jun. 2016, Art. no. 5700305.

[4] M. Faisal, M. A. Hannan, P. J. Ker, A. Hussain, M. Mansur, and F. Blaabjerg, "Review of energy storage system technologies in microgrid applications: Issues and challenges," *IEEE Access*, vol. 6, pp. 35143–35164, 2018.

[5] J. Cui, "A facile synthesis of mesoporous Co_3O_4/CeO_2 hybrid nanowire arrays for high performance supercapacitors," *J. Mater. Chem. A,*, vol. 3, no. 19, pp. 10425–10431, Apr. 2015.

[6] A. Noori, M. F. El-Kady, M. S. Rahmanifar, R. B. Kaner, and M. F. Mousavi, "Towards establishing standard performance metrics for batteries, supercapacitors and beyond," *Chem. Soc. Rev.*, vol. 48, no. 5, pp. 1272–1341, Feb. 2019.

[7] O. Palizban and K. Kauhaniemi, "Energy storage systems in modern grids—Matrix of technologies and applications," *J. Energy Storage*, vol. 6, pp. 248–259, May 2016.

[8] D. Reichmuth and J. Goldman, "Accelerating US leadership in electric vehicles," Union Concerned Sci., Cambridge, MA, USA, Tech. Rep., 2017. [Online]. Available: https://www.ucsusa.org/EV-incentives

[9] M. Farrokhabadi, S. König, C. A. Cañizares, K. Bhattacharya, and T. Leibfried, "Battery energy storage system models for microgrid stability analysis and dynamic simulation," *IEEE Trans. Power Syst.*, vol. 33, no. 2, pp. 2301–2312, Mar. 2018.

[10] H. Mahmood and J. Jiang, "Autonomous coordination of multiple PV/battery hybrid units in islanded microgrids," *IEEE Trans. Smart Grid*, vol. 9, no. 6, pp. 6359–6368, Nov. 2018.

[11] H. Qian, J. Zhang, J.-S. Lai, and W. Yu, "A high-efficiency grid-tie battery energy storage system," *IEEE Trans. Power Electron.*, vol. 26, no. 3, pp. 886–896, Mar. 2011.

[12] L. Patnaik, A. V. J. S. Praneeth, and S. S. Williamson, "A closed-loop constant-temperature constant-voltage charging technique to reduce charge time of lithium-ion batteries," *IEEE Trans. Ind. Electron.*, vol. 66, no. 2, pp. 1059–1067, Feb. 2019.

[13] J. M. Amanor-Boadu, A. Guiseppi-Elie, and E. Sanchez-Sinencio, "Search for optimal pulse charging parameters for Li-ion polymer batteries using Taguchi orthogonal arrays," *IEEE Trans. Ind. Electron.*, vol. 65, no. 11, pp. 8982–8992, Nov. 2018.

[14] C.-M. Lai, J. Teh, Y.-H. Cheng, and Y.-H. Li, "A reflex-charging based bidirectional DC charger for light electric vehicle and dc-microgrids," in *Proc. IEEE Region Conf. (TENCON)*, Penang, Malaysia, Nov. 2017, pp. 280–284.

[15] A.-H. Hussein and I. Batarseh, "A review of charging algorithms for nickel and lithium battery chargers," *IEEE Trans. Veh. Technol.*, vol. 60, no. 3, pp. 830–838, Mar. 2011.

[16] T. I. Bø and T. A. Johansen, "Battery power smoothing control in a marine electric power plant using nonlinear model predictive control," *IEEE Trans. Control Syst. Technol.*, vol. 25, no. 4, pp. 1449–1456, Jul. 2017.

[17] T. Morstyn, B. Hredzak, R. P. Aguilera, and V. G. Agelidis, "Model predictive control for distributed microgrid battery energy storage systems," *IEEE Trans. Control Syst. Technol.*, vol. 26, no. 3, pp. 1107–1114, May 2018.

[18] C.-L. Nguyen and H.-H. Lee, "Power management approach to minimize battery capacity in wind energy conversion systems," *IEEE Trans. Ind. Appl.*, vol. 53, no. 5, pp. 4843–4854, Sep./Oct. 2017.

[19] J. J. Martínez, J. A. Padilla-Medina, S. Cano-Andrade, A. Sancen, J. Prado, and A. I. Barranco, "Development and application of a fuzzy control system for a lead-acid battery bank connected to a DC microgrid," *Int. J. Photoenergy*, vol. 2018, Feb. 2018, Art. no. 2487173.

[20] M. Collotta, G. Pau, and V. Maniscalco, "A fuzzy logic approach by using particle swarm optimization for effective energy management in IWSNs," *IEEE Trans. Ind. Electron.*, vol. 64, no. 12, pp. 9496–9506, Dec. 2017.

[21] H. Lan, S. Wen, Y.-Y. Hong, D. C. Yu, and L. Zhang, "Optimal sizing of hybrid PV/diesel/battery in ship power system," *Appl. Energy*, vol. 158, pp. 26–34, Nov. 2015.

[22] I. A. Azzollini, V. Di Felice, F. Fraboni, L. Cavallucci, M. Breschi, A. D. Rosa, and G. Zini, "Lead-acid battery modeling over full state of charge and discharge range," *IEEE Trans. Power Syst.*, vol. 33, no. 6, pp. 6422–6429, Nov. 2018.

[23] M. A. Hannan, M. G. M. Abdolrasol, M. Faisal, P. J. Ker, R. A. Begum, and A. Hussain, "Binary particle swarm optimization for scheduling MG integrated virtual power plant toward energy saving," *IEEE Access*, vol. 7, pp. 107937–107951, 2019.

[24] Y. Cheng, Y. Liu, and H. C. Hesse, "A PSO-optimized fuzzy logic control-based charging method for individual household battery," *Energies*, vol. 11, no. 469, p. 469, Feb. 2018.

[25] I. Abadlia, T. Bahi, and H. Bouzeria, "Energy management strategy based on fuzzy logic for compound RES/ESS used in stand-alone application," *Int. J. Hydrogen Energy*, vol. 41, no. 38, pp. 16705–16717, Oct. 2016.

[26] T. T. Teo, T. Logenthiran, W. L. Woo, and K. Abidi, "Fuzzy logic control of energy storage system in microgrid operation," in *Proc. IEEE Innov. Smart Grid Technol.-Asia (ISGT-Asia)*, Nov./Dec. 2016, pp. 65–70.

[27] M. H. Moradi, M. Eskandari, and S. M. Hosseinian, "Operational strategy optimization in an optimal sized smart microgrid," *IEEE Trans. Smart Grid*, vol. 6, no. 3, pp. 1087–1095, May 2015.

[28] E. M. Natsheh, A. R. Natsheh, and A. Albarbar, "Intelligent controller for managing power flow within standalone hybrid power systems," *IET Sci., Meas. Technol.*, vol. 7, no. 4, pp. 191–200, Jul. 2013.

[29] R. García-Ródenas, L. J. Linares, and, J. A. López-Gómez, "A memetic chaotic gravitational search algorithm for unconstrained global optimization problems," *Appl. Soft Comput.*, vol. 79, pp. 14–29, Jun. 2019.

[30] L. Zhang, L. Liu, X.-S. Yang, and Y. Dai, "A novel hybrid firefly algorithm for global optimization," *PLoS ONE*, vol. 11, no. 9, Sep. 2016, Art. no. e0163230.

[31] G. Sun, A. Zhang, X. Jia, X. Li, S. Ji, and Z. Wang, "DMMOGSA: Diversity-enhanced and memory-based multi-objective gravitational search algorithm," *Inf. Sci.*, vol. 363, pp. 52–71, Oct. 2016.

[32] Z. Wang, J. Li, K. Fan, W. Ma, and H. Lei, "Prediction method for low speed characteristics of compressor based on modified similarity theory with genetic algorithm," *IEEE Access*, vol. 6, pp. 36834–36839, 2018.

[33] G. Chen, J. Qian, Z. Zhang, and Z. Sun, "Applications of novel hybrid bat algorithm with constrained Pareto fuzzy dominant rule on multi-objective optimal power flow problems," *IEEE Access*, vol. 7, pp. 52060–52084, 2019.

[34] M. Gnana Sundari, M. Rajaram, and S. Balaraman, "Application of improved firefly algorithm for programmed PWM in multilevel inverter with adjustable DC sources," *Appl. Soft Comput.*, vol. 41, pp. 169–179, Apr. 2016.

[35] A. H. Mutlag, A. Mohamed, and H. Shareef, "A nature-inspired optimization-based optimum fuzzy logic photovoltaic inverter controller utilizing an eZdsp F28335 board," *Energies*, vol. 9, no. 3, p. 120, Feb. 2016.

[36] L. Zhang, L. Zhang, H. Shan, and H. Shan, "Selective maintenance planning considering team capability based on fuzzy integral and dynamic artificial bee colony algorithm," *IEEE Access*, vol. 7, pp. 66553–66566, 2019.

[37] H. Xue, Y. Bai, H. Hu, T. Xu, and H. Liang, "A novel hybrid model based on TVIW-PSO-GSA algorithm and support vector machine for classification problems," *IEEE Access*, vol. 7, pp. 27789–27801, 2019.

[38] H. C. Tsai, "Improving backtracking search algorithm with variable search strategies for continuous optimization," *Appl. Soft Comput.*, vol. 80, pp. 567–578, Jul. 2019.

[39] J. A. Ali, M. A. Hannan, A. Mohamed, and M. G. M. Abdolrasol, "Fuzzy logic speed controller optimization approach for induction motor drive using backtracking search algorithm," *Measurement*, vol. 78, pp. 49–62, Jan. 2016.

[40] N. Niamul, M. A. Hannan, H. Shareef, and A. Mohamed, "An application of backtracking search algorithm in designing power system stabilizers for large multi-machine system," *Neurocomputing*, vol. 237, pp. 175–184, May 2017.

[41] M. G. M. Abdolrasol, M. A. Hannan, A. Mohamed, U. A. U. Amiruldin, I. B. Z. Abidin, and M. N. Uddin, "An optimal scheduling controller for virtual power plant and microgrid integration using the binary backtracking search algorithm," *IEEE Trans. Ind Appl.*, vol. 54, no. 3, pp. 2834–2844, May/Jun. 2018.

[42] G. Graditi, M. G. Ippolito, E. Telaretti, and G. Zizzo, "Technical and economical assessment of distributed electrochemical storages for load shifting applications: An Italian case study," *Renew. Sustain. Energy Rev.*, vol. 57, pp. 515–523, May 2016.

[43] M. A. Hannan, M. Hoque, S. E. Peng, and M. N. Uddin, "Lithium-ion battery charge equalization algorithm for electric vehicle applications," *IEEE Trans. Ind Appl.*, vol. 53, no. 3, pp. 2541–2549, May/Jun. 2017.