ANFIS Based DC-Microgrid Voltage Stabilization Considering EV's and Transient Storages

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Abstract: In this paper, a DC-Microgrid is presented considering different elements for voltage stabilization and guaranteeing the battery of electrical vehicle lifetime. Considering a stable unit to procure the voltage of DC-MG, we propose a cost function to minimize the current of the electric vehicle to improve its lifetime. A fuzzy controller optimized using PSO is presented to play the pivotal role of generating a duty cycle for different elements of the stabilized unit such as the battery, the Ultracapacitor, and the Over Voltage security unit. A PV is considered as the main power resource while battery and ultracapacitor are considered as supplementary power sources for long-term and short-term power insufficiency. In this research, some scenarios are presented that showed DC-MG is qualified to make the EV's battery immune and stabilize the bus voltage as well. The proposed methodology is compared with the conventional controller approach, and the effectiveness of the proposed method is investigated by a simulation for different types of energy inequality conditions. Moreover, ultra-capacitor or transient storage is considered to answer the short-term demands of the system and protect the battery of EV against the bad effects of multiple times charging.

Keywords: DC Microgrid, Fuzzy Inference System, Stochastic Power Resource, Particle Swarm Optimization, Battery, Electrical Vehicles, DERs

1. Introduction

With the increasingly development of technology, a microgrid play a pivotal role in the energy management part, due to the advantages of DC MGs such as reduced losses and easy integration with energy storage resources, DC MGs pave the way of expand usage of such a beneficial plants[1, 2]. Power systems are the collection of energy resources, including loads, generation units, power conversion units, and storage devices [3, 4]. EVs gradually increased since a few years ago as a storage part of MGs and as a generation unit during shortage of energy for responding demands [5], furthermore, the centralized generation model is being gradually replaced by a distributed generation model [6]. In addition, not only do microgrids improve flexibility of the grids but also increase system reliability [7, 8]. Although microgrid provides power system with noticeable features, it brings complexity in power system control and increases costs of electricity balance and support services [8]

Maintaining a storage in DC MGs to supply critical loads when MG faced with shortage of produced energy by RESs is one of the great importance in such an isolated MGs, because the presence of battery of EVs during blackouts is directly related to its bus voltage stabilization as there is not any generation units or storages. The variation in MGs have very fatal effects, voltage variation might trigger protection devices and disconnect DERs within the MG.
Centrally controlled MGs (CCMGs) type is dependent on RESs, storage, and controllers. Therefore, it is very important to take care of such storages, DERs, and Control units[9, 10].

The invention of new technologies in renewable energy and distribution generation have resulted in lower cost and emission. The introduction of microgrids in power system facilitates the integration of renewable energy into power grid [11]. Due to the stochastic nature of renewable energy, energy storages are necessary to compensate short- and long-term energy variations [12, 13]. A step change in load demand can be considered as a short-term energy variation, whereas changes in produced energy in a long time can be considered as a long-term energy variation [14, 15].

Renewable energy resources are proposed in many papers for demand response. For example, in [16] a Linear programming method are proposed for optimizing the usage of such resources. This paper proposes an important role of electrical vehicles for energy storage and photovoltaic for energy generation. An MLIP cost function is proposed in this paper, thereby optimizing process is easier.

In this research [17] the author states a MMPC solution for the issue in hand in this paper. The paper is about a biological system and implementing a new control method. In this research they improve the results considering the side effect of different control parameters. In DC-MG it will improve the results if the side-effects of elements has been considered.

Solar systems are a type of cost-efficient energy resources in this area. Using such systems has a great number of pros and cons. In [18] the author investigate different bad condition for a solar system. The structure and characteristics of such system will be considered as a sample to show how using solar systems will be secure.

Distributed generators are integrated with storage facilities and loads to form an autonomous DC microgrid. To overcome the control challenges associated with coordination of multiple batteries within one stand-alone microgrid, control layer is established by an adaptive voltage-droop method aimed to regulate a common bus voltage and to sustain the States of Charge (SOCs) of batteries close to each other during moderate replenishment [15]. In [19] incremental conductance algorithm is used to track maximum power from photovoltaic power plant in a DC microgrid. Mathematical models of fuel cells, photovoltaic, and ultracapacitor converters for the control of power plant are described in [20]. In [21], a parametric programming-based approach for the energy management in microgrids is proposed. A parametric mixed-integer linear programming problem is, in addition, formulated for a grid-connected microgrid with photovoltaic, wind, load demand, and energy storage facilities. It is easy enough to conclude that the proposed method is able to model uncertainties effectively, in wind and solar energy resources.

2. problem definition

In this paper, a DC MG consisting of a stochastic power source—DERs , a stochastic impedance load, a fixed impedance ballast, and a stabilizer unit is considered—consisted of three branches, namely battery of EV, super capacitor, and over voltage discharge—to protect from EV’s battery and super capacitor from overcharge. A central fuzzy inference controller is applied to regulate DC bus voltage, achieving power sharing of batteries and super capacitor, and controlling current stabilizer unit. Fuzzy rules are defined based on researchers’ experience and then Particle Swarm Optimization (PSO) is used to optimize fuzzy rules and fine tune fuzzy
membership functions. It is shown that optimized fuzzy controller in comparison to the conventional PI controller is more capable to regulate DC voltage while increasing operating life of EV’s battery, as a main storage system. Furthermore, fuzzy logic can execute a balancing effect between storage elements and transfer excess energy in one element to another, which having any energy in that of. This feature can easily be introduced, applied, and optimized by fuzzy logic controller while a PI controller, requiring several additional control loops and algorithms for such feature, is not able to do this.

The rest of paper organized as follows: section III presents the DC microgrid case study model. Fuzzy logic inference system and PSO optimization algorithm are introduced in section IV. The results are presented in section V, and section VI concludes the paper.

3. DC Microgrid Configuration

The simplified structure of the DC MG with a variable resource, a variable load, a stabilizer, and a power unit is depicted in Figure 1. The models of a stochastic power source, a stochastic load, a stabilizer, and a ballast load are illustrated in current section[22].

![Figure 1. Simplified microgrid model][22, 23]

3.1. Stochastic Power Source Model

A maximum power point tracking controller is considered in this study. A pseudo-random number generator provides a target power and a boost converter tracks it to model the stochastic characteristic of the power resource, used in this research. A boost converter duty cycle is defined related to the target power. Consisting a boost converter, power resource model is shown in Figure 2.
3.2. Stochastic load model

To model a stochastic load, a pseudo-random number is generated to define power, drawing from the grid. Then, equivalent resistance is calculated and imposed to the grid. The stochastic load model is shown in Figure 3.

3.3. Stabilizer model

Two important sections are considered in stabilizer unit. One section should be considered as power resources to balance the energy, so that of includes battery and ultracapacitor. Also, in the case of excess energy, a dissipating element should be considered to draw the excess power, especially when the battery and ultracapacitor are fully charged. Therefore, stabilizer unit includes a battery, an ultracapacitor, and a dissipating element. Dissipating element is also known as Over Voltage Discharge (OVD). The stabilizer unit structure is drawn in Figure 4.

2.4. Ballast load

Since there exist some boost converters in the DC MG, so it is an appropriate choice to intend a minimum load at all times on DC MG. A boost converter with no load can increase voltage significantly and become unstable and damage itself. Therefore, a large-valued resistor is imposed on the grid.
3. Control Structure

3.1. Conventional PI controller

To control the voltage of the main bus of DC MG, charge, discharge of the battery, charge, discharge of the ultracapacitor, and define the duty cycle of the OVD phase, two cascade PI controllers have been considered for each of phases. In outer control loop, bus voltage error is given to the PI controller and output of the PI controller provides current reference for the battery, the ultracapacitor, and the OVD phases. Another PI controller is used separately to track the current reference by providing the duty cycle of the converter of battery, ultracapacitor, and OVD phases. This structure is shown in Figure 5.

![Figure 5. Conventional PI controller structure](image)

3.2. Fuzzy inference system

A Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. It was introduced by Lotfi Zadeh in 1973 [24]. A fuzzy inference system includes fuzzification, membership function, if-then rules, fuzzy logic operators, and defuzzification. There exist two type of fuzzy inference systems, namely a Mamdani’s fuzzy inference method [25] and a Sugeno-type fuzzy inference system [26]. The Mamdani’s method is among the first control systems, built using fuzzy set theory. It was proposed in 1975 by Ebrahim Mamdani as an attempt to control a steam engine and a boiler combination by synthesizing the set of linguistic control rules obtained from some experienced human operators[27].

In this paper, an expert knowledge has been used to build the initial fuzzy and then, the PSO has been applied to optimized fuzzy membership functions.

3.2.1. Membership Functions

Four inputs and three outputs have been considered for fuzzy inference system. This fuzzy controller is going to be used instead of outer PI controllers. These four inputs are bus voltage error, integrated the error of bus voltage, the SOC of battery, and the SOC of ultracapacitor. Also, three outputs are current reference for the battery, the ultracapacitor, and the OVD phase. This structure is shown in Figure 6.
The membership function of bus voltage error and the integrated bus voltage error are shown in Fig 7 and 8, respectively. For each input, two membership functions are considered as Negative—NEG—and Positive—POS. It should be noted that the currents/voltages are normalized, per unit, when given to the fuzzy inference system.

The membership functions for SOC of battery and ultracapacitor are shown in Fig 9 and 10 [22], respectively. Two membership functions are considered for battery and ultracapacitor SOC namely “Low” and “High.” It might seem that these membership functions do not cover some parts of axis. But, in rule basis, “NOT” of each membership functions are used to cover the whole section between 0 and 1. Also it should be mentioned that 0.3 is assigned as an end of “Low SOC” condition and 0.7 is assigned as a begin of “high SOC”. Researchers’
experiences have been used to define these boundaries. These boundaries are a bit larger in ultracapacitor since ultracapacitor is less sensitive to the charging and discharging stress[22, 23].

The membership function for the output current of battery, ultracapacitor, and OVD are displayed in Figure 11, Figure 12, and Figure 13, respectively. A normalized output boundary is between -1 and 1. Positive value means current injected into the grid and negative value means vice versa. The number of membership function of the battery is defined five, and their types are chosen Gaussian. Also, the number of membership functions for ultracapacitor are chosen four. A zero-membership function is defined for battery since it is more sensitive to current stress[22, 23].
3.2.2. Fuzzy rules
The input and output of fuzzy inference system are shown in Table 1. It should be noted that voltage error is defined as (1) and when this value is positive, it means bus voltage is less than nominal value.

\[ \text{Voltage Error} = V_{\text{nominal}} - V_{MG} \]  

Table 1: Fuzzy Input/Outputs

| Input / Output                        | Term       |
|--------------------------------------|------------|
| Bus Voltage Error (V)                | \( e \)    |
| Integrated Bus Voltage Error (V.sec) | \( e \)    |
| Battery Voltage (V)                  | \( v_b \)  |
| Ultracapacitor Voltage (V)           | \( v_u \)  |
| Battery Current (V)                  | \( i_b \)  |
| Ultracapacitor Current (A)           | \( i_u \)  |
| Overvoltage Discharge Current (A)    | \( i_o \)  |

20 rules have been defined to map the inputs to the outputs. Rules 1 through 6 show relationships between battery voltage and bus voltage. Rule 1, for example, shows when \( v_b \) is “Not high” and \( V_u \) is “High” and \( e \) and \( \int e \) are “Negative” then \( i_b \) “should be “very Negative”, that is the bus voltage is higher than nominal value and battery is not full, so it can store the excess energy. Rules 7 to 10 define the relations of the ultracapacitor and the bus voltage. The OVD phase rules are presented by rules 11 to 16, and finally rules 17 to 20 determine transferring energy between battery and ultracapacitor.

3.3. Optimization method

The PSO is chosen as an optimization algorithm, since its results are so accurate and does not need complex calculation [28, 29]. Also, based on previous works on fuzzy optimization, the PSO can optimize fuzzy membership functions more accurately and quickly in comparison to other algorithms [30]. Differnt literature is explained PSO in detail [31, 32], avoiding to repeat here. Flow chart of optimization is shown in Fig 14. In this part after implementing the PSO algorithm the results of [22, 23] has been improved because by reducing the current, spending by battery of EV's. The cost function which is implemented had something to do with battery life-time. Considering the minimum current spending by EV's these results has been showed in this paper.
The flowchart works as follows:

1. PSO parameters are determined
2. Boundaries of the expectation and the standard-deviation of each membership functions are defined.
3. The Fuzzy Inference System (FIS) is initialized.
4. PSO updates its positions and velocities of each population.
5. PSO runs MATLAB/Simulink and provide it with a new FIS. After simulation, PSO calculates the objective function value.
6. If this new FIS results in a better answer, it is considered as a best FIS up to now.
7. If stop condition is not met, go to step 4.
8. Print the results.

4. Fuzzy Training and Numerical Study

As mentioned in the previous sections the DC MG in issue is made of four parts, namely stochastic power resource, stochastic load, stabilizer unit, and ballast resistor[22, 23]. The system is simulated in MATLAB/Simulink. Battery bank are made by connecting four 12 V, 10 Ah unit in series form[33]. Battery voltage changes from 47.2 V to 50.8 V. The voltage “47.2 V” is considered as exhausted resource (0% of SOC) and “50.8” is considered as full charge (100% SOC). As shown in Figure 4. Stabilizer unit is modeled by a fixed DC resource in series with a 3kF capacitor. The capacity of ultracapacitor is considered as 150F and 54 V, presented in the following two sections. In the first, the initial fuzzy system is optimized based on objective function. In the next section, system is simulated, and results are compared and discussed

4.1. Cost function considering EVs' battery lifetime
The optimization objective function consists of two terms. The first term is DC bus voltage error and the second term in absolute value of the battery current of EV. The first term is essential, since the main goal of fuzzy controller is control of DC bus Voltage. The second term is also important because ultracapacitor is less sensitive to charge and discharge stress in transient time in comparison to the EV’s battery, and it has been tried to impose this transient stress to the ultracapacitor. A piece of information that should bear in mind is that, in this study, the membership functions of the outputs have been tuned, since they play more important role in DC microgrid control. Also, the membership functions of inputs do not need essential modifications, because the real condition fuzzification process have been tried to map here. The training objective function is as follows: This objective function will minimize the voltage ripple and the number of charge and discharge of batter as well. The penalty will define a new constraint that help the system to show a higher level of control for battery lifetime.

\[
OF = \int_0^T (v_{bus} - 100)^2 dt + 0.1 \int_0^T I_{battery}^2 dt
\]  

The PSO iteration is chosen 100 and population is chosen 60. The simulation time is considered 150 second, in MATLAB scale, producing a change in power 10 second and load changes every 3 seconds. The objective function values during optimization process are shown in Figure 15. Objective values during optimization process.

![Figure 15. Objective values during optimization process](image)

Figures 16 to 18 shows changes in values of sigma (standard deviation) and center of Gaussian membership function for battery current, ultracapacitor current, and OVD phase.
Figure 16. Changes in values of Sigma and center for battery current during optimization process

Figure 17. Changes in values of Standard-deviation and expectation for the ultracapacitor current’s MFs during optimization process
Figure 18. Changes in values of Standard-deviation and expectation for the OVD phase during optimization process

Modified membership functions are shown in Fig 19 to 21.

Figure 19. Optimized membership functions for battery current
Figure 20. Optimized membership functions for ultracapacitor current

Figure 21. Optimized membership functions for OVD current

4.2. Numerical study and results comparison

To evaluate the proposed fuzzy-PSO controller, this controller has been applied to the abovementioned system in 150 second in which loads changes every 3 second and stochastic power changes every 10 second, each of these times is in MATLAB time scale and these mean second in that of not means second in real, so this assumption had been intended only to simulate this plant in MATLAB. To compare the results, PI controller suggested in [34] has been implemented as well. Also, to show how well the training process has been done, the initial fuzzy controller has been simulated too.

Stochastic power and load have been defined as the same for these three scenarios. The produced power, the load, and the ballast are shown in Figure 22 As can be seen in Figure 22,
in 150 second almost all conditions that can be occurred are considered. There are times that produced power is more than, equal, or less than demand and ballast power. Source and load power are as the same in the three scenarios. DC bus Voltage is depicted in Figure 23. As can be seen, in all time absolute value of the voltage error is less than 1% in all scenarios.

![Figure 22. Load and power source](image)

![Figure 23. Voltage regulation in three scenarios](image)

Figure 24 shows the current of stabilizer unit, power source, and demand load. It is obvious that the current of load and power source are the same in all scenarios, since their power have been exposed equally. There is a little difference between stabilizer current, but it cannot be seen in figure so just the current of PI controller has been shown. The current of battery and ultracapacitor are shown in Figure 25, Figure 26, respectively.

![Figure 24. Current of stabilizer unit, power source, and demand load](image)
4.3 Discussion

Integral of Absolut value of voltage error is less than 0.2% in both PI controller and PSO fuzzy controller. It is about 0.4% for initial fuzzy as well. There exist several criteria to evaluate these three controls, but two criteria, i.e. “Battery charge, discharge stress” as well as “transferring energy capability between battery and ultracapacitor” are the main ones. As there is not a big difference in voltage regulation for these three controllers, we use these two criteria to determine the better controller. Battery lifetime highly depends on charge and discharge stress and in this stress decrease, lifetime of battery increases. The absolute of integral time value of the current of battery is used as a first index. It is showing the amount of energy which battery stores and discharges from battery. This Energy is calculating as follows:

\[ Q = \int |I| \, dt \] (3)

This index for PI controller is 110.6 J, for initial Fuzzy is 97.43 J, and for the PSO Fuzzy is 78.69 J. It shows that PSO fuzzy imposes less stress to the battery while keeps the bus voltage in its normal value. Also, another index is “capability of transferring energy between battery and ultracapacitor”. This is not possible to do with control structure defined in section 2 and it needs at least two more controllers to transfer energy between battery and ultracapacitor when
one of them is fully charged and another is fully depleted. Moreover, initial fuzzy has this ability based on the defined rules, but trained fuzzy do a better operation in this area. Figure 27. Transferring energy between storages shows a condition in which ultracapacitor is fully charged and battery is almost empty. In 20 second, PSO fuzzy transfers energy from ultracapacitor to battery faster in comparison to initial fuzzy.

![Figure 27. Transferring energy between storages](image)

V. Conclusion

This paper represents a new control methodology for DC Microgrid control. The inputs of proposed fuzzy controller get four variables, that is the error of bus voltage, the integrated error of bus voltage, the SOC of the battery, and the SOC of the ultracapacitor to define currents of stabilizer units. The simulation has shown the proposed controller is successful in bus voltage regulation. The main contribution of the proposed method in comparison to the others is lower stress on the battery and also proper energy transmission between different storages when one of them is almost full charged and another is completely depleted. Also, the initial fuzzy controller has been tuned by PSO to even improve the results.
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