OPTIMIZATION OF ELECTRIC VEHICLES ALONG WITH POWER GENERATION UNITS TO IMPROVE MICROGRID RELIABILITY

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Abstract. Microgrids are a new generation of small-scale power systems that can meet the needs of their subscribers independently of the main power grid. One of the features of these systems is the possibility of aggregating scattered products in the field of renewable energy, with probabilistic and oscillating nature, which makes it necessary to check the microgrid reliability and ensure the reliability, and if necessary, Adopts ways to improve it. In this paper, we try to optimize the combination of distributed generation and electric vehicles by using probabilistic methods to improve the microgrid reliability. Optimizing the combination of power generation with electric vehicles to improve microgrid reliability, providing a new way of planning charge and discharge of vehicles, and modeling power injection into microgrids are some of the innovations in this paper.
Keywords: *Monte Carlo algorithm, reliability improvement, optimal combination, electric vehicles*

Introduction

Combining small products and energy storage with low or medium voltage systems forms a new type of power system called microgrids. This system can provide its subscribers' consumption separately from the network and thus prevents the transmission of main network blackouts to subscribers at certain hours, the microgrid will be able to connect to the main network, lacking its power to compensate. More efficient use of renewable distributed generation units, the possibility of meeting the demand for load growth, and improving system performance are other features of the microgrid. Increasing the use of power generation units using renewable energy in microgrids has led to attention to the reliability of these systems. Since such distributed generation sources have a lot of uncertainty, the necessary measures should be considered to provide sustainable power to the consumer. Various researches have been done in this field so far. Asher et al. (2017) presents an analytical method for evaluating the reliability of microgrid subscribers. In Huang et al. (2017), the application of high-reliability distribution systems (HRDS) in the economic operation of microgrids is investigated. In Wang et al. (2013), the authors have introduced a set of standards to better define microgrids. These standards include reliability parameters for microgrids in independent mode, presence of distributed generation index, economic indicators of microgrid, etc. Meanwhile, Arefifar et al. (2012) classifies the distribution network to form microgrids with optimal self-sufficiency. Arefifar and Mohamed (2014) has classified the distribution network within microgrids with high reliability and production security. For this purpose, MAIFI, SAIFI, SAIDI indicators have been used to assess reliability. Arefifar and Mohamed (2014) indicate that the classification of the distribution network within the microgrids is done by considering the probabilistic property of load and distributed generation. The resulting microgrids are obtained from problem optimization to improve the reliability and security of production. What can be further explored is the impact of electric vehicles on microgrid reliability. Electric vehicles are vehicles that can provide many advantages to the power grid while operating in the transportation process due to their energy storage. In the field of electric vehicles has been made to the cost-benefit analysis of network-connected hybrid vehicles (PHEVs) (Rezaei et al., 2017a). The author presents a PHEV charging method by adjusting consumption demand based on price information (Fan 2012). The effect of electric vehicles on the distribution system, especially its effect on network security, has been investigated (Darak and Ferdowsi, 2012; Shao et al. (2012); Pillai and Bak-Jensen, 2010; Kempton and Tomić, 2005). Studies on the optimal charge profile for load intensification during non-peak hours have been performed by Rezaei et al. (2017b). The benefits of participating in PHEV in a variety of power markets are also discussed in Rezaei et al. (2018) research.

The use of electric vehicles in the microgrid, due to the high uncertainty due to the nature of renewable units, reduces the cost of purchasing energy storage devices. In this paper, we try to improve the reliability of microgrids by using electric vehicles along with other power generators. Optimizing the combination of power generation with electric vehicles to improve microgrid reliability, providing a new way to plan vehicle charge and discharge times, and modeling network connectivity in microgrids are innovations that are presented in this article. For this purpose, in the second part, the proposed model for each topic is stated and in the third part, the problem is defined. Then, in the fourth section, the results of the simulation of the models presented in the article and finally, in the fifth section, the conclusion of the paper is stated.

Proposal models

Reliability is one of the most important parameters for evaluating microgrid performance. To improve this parameter, first, indicators should be defined according to the system under study and then evaluation should be done based on these indicators. Among these, there are various indicators for reliability, including the expected energy not supplied (EENS). Since the microgrid must be able to meet the needs of its subscribers, this index examines the ability of the microgrid to supply subscribers. Another feature of the microgrid is to meet this need with the most independence from the main network to prevent unwanted blackouts caused by the upstream network. To check this parameter, you need to use reliability indicators. It is related to the microgrid, which indicates the degree of dependence of the microgrid on the main network. The lower the dependency, the lower the possibility of transmitting blackouts from the main network to the microgrid. In this paper, in addition to the expected energy not supplied, the microgrid connection time index to the main network is also used to evaluate and evaluate reliability. Since the wide integration of distributed generation units with renewable energy is one of the advantages of microgrids, the issue of uncertainty will be one of the issues in this area. Probabilistic methods should be used to evaluate the reliability due to the existing uncertainty. One of these methods is the Monte Carlo method. Monte Carlo methods are a group of computational algorithms that are used to calculate results based on random sampling repetition. Because these methods rely on repetition of calculations and random numbers, these algorithms are suitable for computers. There are different methods for implementing the Monte Carlo algorithm, including sequential Monte Carlo and non-sequential Monte Carlo, the use of each of which depends on the type of study. Since in this article, electric vehicles are present in the microgrid and due to the charging and discharging properties of the vehicles and their dependence on time, the Monte Carlo method is used sequentially to assess the reliability of the microgrid. In the sequential Monte Carlo method, first, the time series related to each of the microgrid components are defined, and then using these series, reliability studies are performed. How to assess reliability is that in the first step, a random time is selected in the study period, and then the network status is determined from time series. Once the network status is determined, the reliability indicators are calculated and the Monte Carlo stop condition is checked sequentially. If the stop condition is not met, go back to the first step, and repeat the above steps. After the algorithm stops, the mathematical expectation of the reliability indices will be obtained from the answers of each iteration.

$$E(ENS) = \frac{1}{N}\left(\sum_i^N P_{NS_i}\right) \times Period \tag{1}$$

$$E(T_{connect}) = \frac{1}{N}\left(\sum_i^N \alpha_{connect_i}\right) \times Period \tag{2}$$

$$\alpha_{connect} = \begin{cases} 0 & if\ microgrid\ disconnected \\ 1 & if\ microgrid\ disconnected \end{cases} \tag{3}$$

Time series of microgrid components

Time series of subscribers load

In order to obtain the subscriber load time series, the IEEE_RTS load model with microgrid peak load is used (Wong et al. 1999).

Wind power generation time series

The wind tone time series is influenced by the wind speed model and the wind turbine model. Since the wind speed per hour depends on the time before it as well as the historical information of the wind speed at the same time on Equation 4 which used to simulate the wind speed per hour (Billinton et al., 1996). It becomes;

$$sw_t = \mu_t + \sigma_t \times y_t \tag{4}$$

where, SW_t is the average wind speed at time σ_t, μ_t, t and the standard deviation of wind speed at time t in previous years. The y_t parameter shows the effect of wind speed at times before *t* on wind speed at time t and can be obtained using the ARMA model.

$$A(q)y_t = C(q)e_t \tag{5}$$

$$A(q) = 1 + a_1 q^{-1} + a_2 q^{-2} + \cdots + a_{n_a} q^{-n^a} \tag{6}$$

$$C(q) = 1 + c_1 q^{-1} + c_2 q^{-2} + \cdots + c_{n_c} q^{-n^c} \tag{7}$$

where, y_t is the output of the model at time e_t, t is normal white noise with a mean of zero and standard deviation σ_n. n_c, n_a. The degrees of freedom of the model and the coefficients ci, ai are also obtained using historical data. The wind turbine model can also be expressed as a relation (8) using the reference (Rezaei et al., 2017a).

$$P_{Wind} = \begin{cases} 0 & V < V_{cut\,in} \\ P_{rated}(aV^2 + bV + c) & V_{cut\,in} \le V < V_{rated} \\ P_{rated} & V_{rated} \le V < V_{cut\,out} \\ 0 & V_{cut\,out} \le V \end{cases} \tag{8}$$

P_{Wind} wind turbine output power, V wind speed $V_{cut\ in}$ low cut-off speed, V_{rated} rated speed, $V_{cut\ out}$ high cut-off speed, Prated rated turbine power and *c, b, a* are turbine dependent specifications. The values of *c, b, a* can be calculated according to the high cut-off speed, low cut-off speed and nominal speed, the relationships of which are given in the reference of Giorsetto and Utsurogi (1983). To calculate the wind power generation time series, first, the wind speed simulation time series in the desired range is determined according to the proposed method, and then according to the wind speed per hour and the turbine model, the wind speed generation time series is determined.

Photovoltaic power generation time series

To obtain the photovoltaic power generation model, the radiation intensity and the solar panel model are required. The intensity of solar radiation at time t, G_{ht}, can be obtained from the normal distribution function (Moharil and Kulkarni, 2010).

$$G_{h_t} = \frac{1}{\sqrt{2\pi}\sigma_{G_t}} EXP\left(\frac{-(x-\mu_{G_t}^2)}{2\sigma_{G_t}^2}\right) \tag{9}$$

μ_{Gt}, σ_{Gt} are the standard deviations and the mean of the radiation intensity at *t* hour, which is derived from the hourly data of the region at *t* hour from the historical data of previous years at the same time. The value of this distribution function is limited around a minimum and maximum value and therefore the restricted distribution function will be used. Given the intensity of solar radiation (Moharil and Kulkarni, 2009), the production power of each panel is calculated from Equation 10.

$$P_{ph_t} = \begin{cases} -0.0622 \times G_{h_t}^2 + 36.5073 G_{h_t} + 351.2987 & 0 < G_{h_t} < 190 \\ (0.0022 \times G_{h_t} + 4.8821) \times 10^3 & 190 \le G_{h_t} < 1000 \end{cases} \tag{10}$$

In Equation 10, P_{pht} shows the power of the photovoltaic panel at *t*. To obtain the photovoltaic production time series, first, the radiation intensity for a particular hour is calculated based on the normal distribution function of the same hour and then according to the relation 10, the amount of generated power is obtained. By continuing this method, the photovoltaic production time series will be completed.

Charging and discharging time series of electric vehicles

For the use of electric vehicles, in this paper, parking lots have been used where the vehicles are located while charging or injecting power into the network. The central limit theorem has been used to model the behavior of these vehicles (Le Cam, 1986).

Central limit theorem:

If $X_1, \ldots X_n$ are independent random variables with a probability distribution function, their sum, $X_1 + X_2 + \ldots + X_n$ for large n, will have a normal probability distribution function. Now, if we consider the behavior of car owners as the same, we can express the hours of departure and the time of absence in the parking lot according to Equations 8 and Equation 9 (Bioki et al., 2013).

$$T_{h_t} = \frac{1}{\sqrt{2\pi}\sigma_{T_t}} EXP\left(\frac{-\left(x - \mu_{T_t}^2\right)}{2\sigma_{T_t}^2}\right) \tag{11}$$

$$\Delta T_t = \frac{1}{\sqrt{2\pi}\sigma_{\Delta_t}} EXP\left(\frac{-\left(x - \mu_{\Delta_t}^2\right)}{2\sigma_{\Delta_t}^2}\right) \tag{12}$$

T_{exit} the time of departure of vehicles from the parking lot, ΔT the duration of absence of vehicles in the parking lot and σt, μt The standard deviation and the mean of the parameters of exit time and exit time for day t, which is based on historical data of the same day of the year. The past is obtained. Thus, the behavioral parameters of the vehicles are defined for each day - a working day of the week or weekend in different seasons - in proportion to the same day. According to the hours of the presence of cars in the parking lot and the time series of production and consumption of the microgrid, the time series of charging and discharging the microgrid can be calculated. To meet the needs of car owners on day trips, some of the battery charges should remain intact. If this amount of power can be supplied before the car leaves the parking lot, the capacity of the car battery will increase. In this paper, using a control signal, the car recharge status is calculated until the exit and if the battery is recharged, it is discharged to the maximum possible level. Of course, it should be noted that there is always another minimum level to prevent a reduction in battery life, which is called the depth of discharge (DOD) and must be observed in the car discharge. By obtaining a control signal from the time of entry and exit of vehicles and according to the situation of power shortage, the car battery can be injected into the network according to the maximum discharge rate, discharge, and the resulting power. The management of this power injection is designed to prevent vehicles from connecting the microgrid to the main network as much as possible. If it is not possible to prevent the connection of the microgrid - the necessary capacity to provide the microgrid consumption is not provided with the vehicles - charging or discharging the vehicle will depend on the new situation - shortage or surplus production in the main network and microgrid.

Time series of power injected into the microgrid in the case of connection to the main network

The model presented for injector power to the microgrid in this paper is based on the maximum load that can be transferred to the microgrid by the main network. To obtain this maximum load, the amount of load received by the junction of the microgrid connection must be increased to the point where the system constraints are violated. There are different methods for determining the maximum transferable power to a microgrid. One of these methods, which is used in this article, is the maximum power optimization method. The process of this method includes determining the objective function, determining the constraints and solving the optimization problem using a valid and efficient algorithm. In this method, the computation time is less than the classical load distribution and continuous load distribution.

The formulation of this problem includes the definition of the objective function and the constraints of the problem, which can be expressed according to relations 13 and 14.

$$Max\ P_{micto} \tag{13}$$

$$S.T. \begin{cases} P_G^{main} = P_D^{main} + P_{micro} + P_L^{main} \\ P_{G\ main}^{min} \leq P_G^{main} \leq P_{G\ main}^{max} \\ V_i^{min} \leq V \leq V_i^{max} \\ I_{ij}^{min} \leq I \leq I_{ij}^{max} \end{cases} \tag{14}$$

In the above relation P_{micro} is the maximum power injected into the microgrid, P_G^{main} is the output power of the main network P_L^{main} are the main network losses and I, V are the bus voltages, and currents passing through the lines in the main network. There are different methods to solve the above optimization problem, which can be generally divided into two categories of intelligent methods, including genetic algorithms, particle clustering, ant colony, and metal annealing. Be. To solve the problem, these methods use the classical load distribution for evaluation, and since the Jacobin matrix has a convergence problem near the point of voltage breakdown, these methods provide a suitable answer in a They are not efficient in a reasonable time. In addition, intelligent methods require a long time to perform calculations. Classical algorithms include linear programming, nonlinear programming, and offshore algorithms. In these algorithms, second-order derivatives of power equations are usually used. Also, these algorithms require less time to perform calculations. In this section, the far-edge algorithm, which is based on nonlinear programming, is briefly described. The problem of maximum power transmission to the microgrid can be written in general terms in relations 15 and 16. These relationships represent the general form of relationships 13 and 14.

$$max: F(x) \tag{15}$$

$$S.T. \begin{cases} G(x) = 0 \\ h_{min} \leq H(x) \leq h_{max}(x) \end{cases} \tag{16}$$

Where *x* is the state variable including the size and angle of the bus voltage, *G(x)* represents the equal constraint including the power balance equations, *H(x)* the unequal constraint includes the bus voltage limit, and the power generation of the generators and line current. *F(x)* also includes the objective function of maximizing the transmission power to the microgrid. h_{max}, h_{min} represent the upper and lower limits of unequal constraints. Initially, unequal constraints are converted to equal constraints in the form of relation 17 through floating variables.

$$\begin{cases} H(x) - s_l - h_{min} = 0 \\ H(x) - s_u - h_{max} = 0 \\ s_u, s_l \geq 0 \end{cases} \tag{17}$$

In the above relation, s_u and s_l are the floating-point variables of low and high, respectively. After converting unequal constraints to equals, Lagrangian functions are formed using logarithmic boundary functions and Lagrangian coefficients in the form of Equation 18.

$$\begin{aligned} &L(x, \lambda, s_u, s_l, \pi_u, \pi_l, \mu) = F(x) - \lambda^T G(x) \\ &-\pi_l^T (H(x) - s_l - h_{min}) \\ &-\pi_u^T (H(x) - s_u - h_{max}) \\ &-\mu \left(\sum_i 1ns_{li} + \sum_i 1ns_{ui} \right) \end{aligned} \tag{18}$$

Next, the Karush-Cohan-Tucker condition is used to minimize or maximize the Lagrange function. In this paper, to calculate the maximum transmission power to the microgrid, the main network consumption is first determined using the IEEE_RTS load pattern for the peak load of the main network. Having the consumption of the main network at time t and consequently the load of the subscribers of each bus, and also using the maximum output at the same time for the main network, the maximum power that can be transferred to the microgrid using the model provided by hand. The maximum output for time t in the main network is obtained from the maximum power of the upstream substations and the maximum power of the wind unit in the main network at time t - the maximum wind power output is due to the wind intensity at time t. This power is available for the microgrid when the microgrid input key is not in the fault state. To model the key failure using the failure rate and equipment repair rate, the time series in the key circuit is obtained. To do this, the time series starts from the beginning of the desired period and the duration of the state of health is determined from Equation 19. At this point, the value of series 1 is set, which means that the key is in the circuit. After this time, the value of the time series will be zero for the duration of the failure specified in Equation 20. This process continues until the end of the time series interval.

$$T_h = \frac{-1n(x)}{\lambda} \tag{19}$$

$$T_{uh} = \frac{-1n(x)}{\mu} \tag{20}$$

In Equations 19 and Equations 20, *x* is a random number with a uniform distribution function, λ is key failure rate, and μ is repair rate. Thus, if the production units and electric vehicles of the microgrid cannot provide the required power of the microgrid, the required shortage will be compensated by the power transmission from the main network to the microgrid (P_{micro}). The amount of deficit compensated according to the maximum transferable power and depending on the time series in the circuit of the microgrid input key, production time series, consumption time series, and charging and discharging time series of electric vehicles, the microgrid power injection time series is obtained.

Problem definition

The present study aims to optimize the presence of electric vehicles along with other power generation units to improve microgrid reliability. The installation capacity of wind and solar units, the number of diesel units required to compensate for part of the microgrid uncertainty, as well as the installation capacity of electric vehicle parking, are microgrid generation variables that must be optimally selected to achieve the project objectives. For this purpose, first, the objective functions are determined, and then, using search algorithms, the optimal response is determined from among the possible scenarios. Since the problem space has uncertainties, the probabilistic evaluation presented in the second section has been used to evaluate each candidate case.

Objective functions

In this section, the objectives of the problem are introduced.

A: Improving microgrid reliability

To assess the reliability, the microgrid non-power supply index and the microgrid connection time index to the main network are used. The higher the microgrid is able to supply its load, the better it will perform in the field of reliability. On the other hand, independence from the main network prevents the main network blackouts from being transferred to the microgrid, thus improving the reliability of the microgrid. Due to the uncertainty in the system components, probabilistic reliability indicators have been used in the objective functions.

$$E(ENS) = \frac{1}{N}\left(\sum_i^N P_{NS_I}\right) \times Period \tag{21}$$

$$E(T_{conect}) = \frac{1}{N}\left(\sum_i^N \alpha_{concet_I}\right) \times Period \tag{22}$$

$$\alpha_{conect} = \begin{cases} 0 & if\ microgrid\ disconected \\ 1 & if\ microgrid\ disconected \end{cases} \tag{23}$$

B: Reducing project costs

One of the most important factors in the success of a project is the economic review of the project costs. These costs must meet the objectives of the issue and be able to pursue economic benefits. To this end, this paper aims to reduce project costs as a goal. There are different costs in the implementation of this plan, in which only a few initial costs per unit are sufficient.

$$\text{Cost} = \text{wind cost} + \text{solar cost} + \text{parking cost} \tag{24}$$

Where the design cost, wind cost of wind units, solar cost of photovoltaic units and parking cost are the cost of construction of parking for electric vehicles.

C: Reducing the use of diesel units

Since renewable energy distribution units have high uncertainty, diesel units are used to compensate for some of this uncertainty. These units have high operating costs and high pollution, which aims to reduce their use as much as possible.

Optimization method

Different methods can be used to search among possible answers. In the present study, particle swarm search methods, genetic algorithm and gravitational search algorithm have been used to investigate the different values of installation capacity of wind and solar units, diesel units and parking capacity of electric vehicles in the microgrid. In this method, a code is first defined for each of the search variables - number of wind units, number of solar panels, number of diesel units and capacity of electric parking vehicles. Then, for each combination of these units and using the probabilistic models presented in this paper, time series, microgrid consumption, wind generation, photovoltaic generation, vehicle charging and discharging and injection of main network power into the microgrid, Is formed. From these series, the Monte Carlo algorithm is executed sequentially and the probability indices of reliability are obtained. Using these indicators and other defined objectives, the value of each response is determined. The problem-solving flowchart is shown in *Figure 1*.

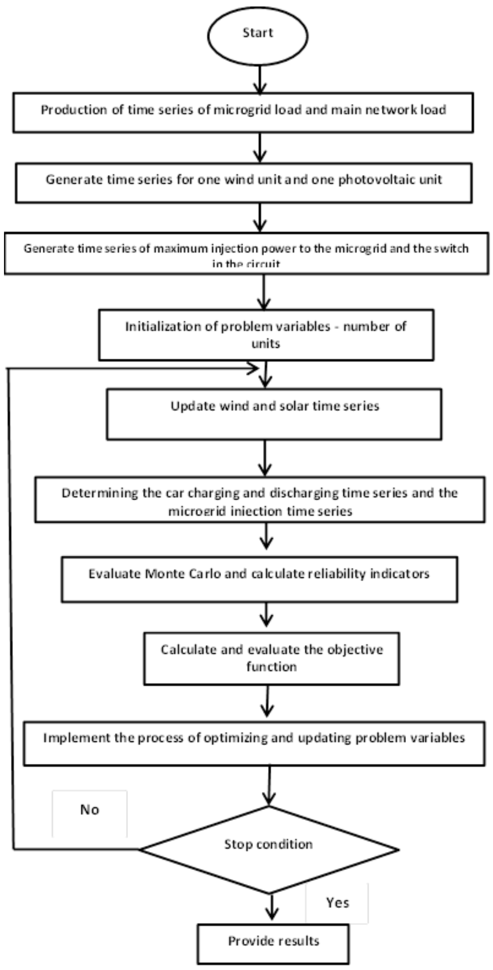

Figure 1. *Problem solving flowchart.*

Since the proposed objective functions are varied, it is not possible to combine these values. Therefore, the fuzzy theory method is used to aggregate the value of the objectives. In this method, using membership functions, the value of each goal is measured with a maximum and minimum value, and a value between zero and one is assigned to it. In this way, the value obtained for all targets can be combined.

$$Min \;\; Fitness = \sum_{i}^{n} \alpha_i \mu_i (G_i) \tag{25}$$

$$G_1 = E(ENS) \tag{26}$$

$$G_2 = E(T_{conect}) \tag{27}$$

$$G_3 = cost \tag{28}$$

$$G_4 = number\ of\ Diesel\ Generator \tag{29}$$

Results and Discussion

To validate the models presented in this paper, they are simulated on a sample network and the results are presented. For this purpose, CIVANLAR 16-bus distribution test network has been used to power the microgrid (*Figure 2*). The information of the network lines is given in the reference of Nojavan et al. (2014). In this network, the total load of the subscribers follows the IEEE_RTS load pattern for the peak load of 28.7 MW and is divided according to the load of each bus mentioned in the reference of Nojavan et al. (2014).

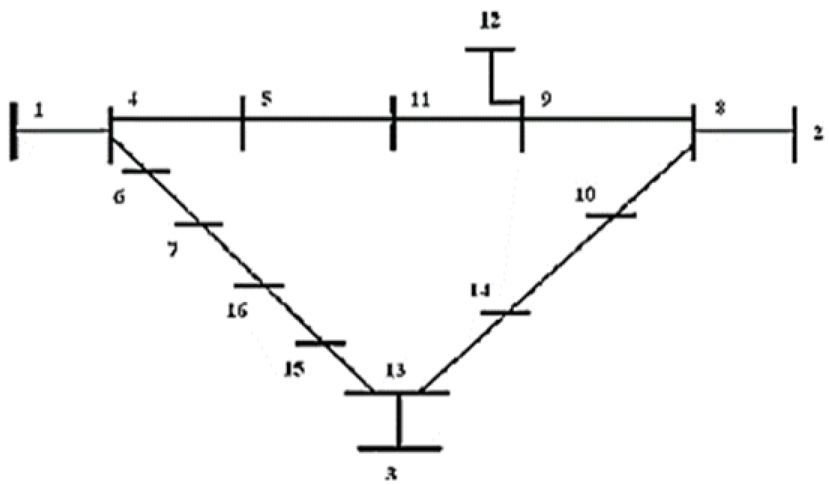

Figure 2. *CIVANLAR test network.*
Source: Darabi and Ferdowsi (2012).

The main network is supplied through two substations with a maximum capacity of 15 MW at bus 1 and 2 and a wind unit with a capacity of 2 MW at bus 3. The installed turbine was of type V=100 (Vertas Company Official Portal, 2021) (*Table 1*). The wind turbine data for this turbine belongs to the McHenry section of North Dakota over a period of 20 years, from August 14, 1995 to August 14, 2015 (NDAWN Center, 2021).

Table 1*. Technical information of V-100 turbine.*

High cut-off speed	Low cut-off speed	Nominal speed	Nominal power

Vcut out	Vcut in	Vr	Pr
200 m/s	3 m/s	12 m/s	2MW

The microgrid is connected to the CIVANLAR network via bus 12. The peak load of the microgrid is 3.8 MW. The meteorological data for McDenray, North Dakota, and reference data for a period of 20 years, from August 14, 1995 to August 14, 2015, were used for the hourly data required by the microgrid for solar radiation intensity. Since the main network and the microgrid are in the same geographical area, the main network information is also used in this microgrid for the required wind data. The cost per unit of 2 MW wind turbine is 3$ million (Wind Industry Official Portal, 2021) and for each 2.5 kW photovoltaic panel is 61.3 cents per watt (CleanTechnica Official Portal, 2021). The cost of building an electric car parking lot and the cost of installing equipment needed for cars such as converters (Esmaeilian et al., 2012), is estimated at 300$ per square meter and 400,000$ per MW, respectively. The required area of each car is 6 square meters. The electric vehicles used in this paper are Chevrolet, the parameters of which are given in *Table 2* (He et al., 2012).

Table 2. *Parameters of electric vehicles (Chrevolet).*

Battery capacity	Electric mode range	Maximum charging power
16 KWh	64 Km	5 Kw

The maximum charge and discharge rates of cars in this article are assumed to be the same and are selected using Table 2, 5 kW. For probabilistic modeling of electric vehicles, the model parameters for different working days and weekends are assumed. Also, the two seasons of spring and summer have the same procedure but different from the other two seasons of the year - autumn and winter. In this article, each diesel unit has a nominal power of 250 kW. The time series are defined according to the IEEE_RTS load consumption pattern in the range of 8736 hours. To further investigate and analyze the issues expressed in this paper, three scenarios are proposed and the simulation results of each of them are presented.

Scenario 1: Micro-network optimization without considering electric vehicles

In this scenario, the combination of microgrid power output is simulated in order to improve reliability, without considering electric vehicles. *Tables 3* and *Table 4* show the simulation results using the particle swarm algorithm.

Table 3. *Optimal composition of microgrid production.*

Category	PSO
Number of wind turbines	1
Number of photovoltaic panels	2789
Number of diesel units	8

Table 4. *Optimal response information.*

Category	PSO
Fuzzy value	0.7375
Index E (ENS)	19.71 MW per year
Index E ($T_{connect}$)	1339.2 hours per year

Scenario 2: Micro-network optimization in the presence of electric vehicles without considering the recharge signal

This scenario involves the presence of electric vehicles in combination with distributed power generation units in the microgrid. In this scenario, to provide the energy needed by cars for daily travel, one level of car battery charge will remain intact at all times. *Tables 5* and *Table 6* show the simulation results using the particle swarm algorithm.

Table 5. *Optimal composition of microgrid production.*

Category	PSO
Number of wind turbines	2
Number of photovoltaic panels	3068
Vehicle parking capacity	1044
Number of diesel units	5

Table 6. *Optimal response information.*

Category	PSO
Fuzzy value	0.3786
Index E (ENS)	23/41 MW per year
Index E ($T_{connect}$)	398 hours per year

Scenario 3: Micro-network optimization in the presence of electric vehicles according to the recharge signal

This scenario is the most complete model for the problem of optimizing the composition of power generation units among the previous scenarios. In this case, the charge and discharge management of the vehicles is done according to the recharge control signal. This signal indicates the possibility of charging the vehicle before leaving the parking lot. Thus, it is not necessary to lock the charge level at all hours of the vehicle in the parking lot, but the cars will receive the energy needed for daily travel before the time of leaving the parking lot, according to the recharge signal. By simulating the problem using a particle swarm search algorithm, genetic algorithm, and gravitational search algorithm, the optimal capacity of each unit to improve the goals set according to *Table 7* is obtained. The optimal composition presented in *Table 7* depends on the meteorological information of the microgrid region and the main network and will generally change depending on their geographical location.

Table 7. *Optimal composition of microgrid production.*

Category	Number of wind turbines	Number of photovoltaic panels	Vehicle parking capacity	Number of diesel units
PSO	1	4522	1096	5
GA	1	451	1092	5
GSA	1	3697	1147	5

As can be seen from *Table 8*, among the algorithms implemented on the problem, the final answer of the PSO algorithm is more accurate than the genetic algorithm and gravitational search. On the other hand, in terms of convergence speed of algorithms, if the number of iterations until the final answer is considered as the definition of velocity, the gravitational search method has a better velocity than the genetic algorithm and particle swarm and then the particle swarm algorithm is faster than the genetic algorithm. The first rank of the accuracy of the particle swarm algorithm along with the second rank of speed, among the three proposed algorithms, shows the better performance of the particle swarm algorithm than the genetic algorithm and the gravitational search algorithm in this issue. The convergence diagrams of the particle swarm algorithm, the genetic algorithm, and the gravitational search algorithm are shown in *Figure 3*.

Table 8. *Optimal response information*.

Category	Fuzzy value	Repeat convergence	Index E (ENS)	Index E ($T_{connect}$)
PSO	0.3281	43	11.8 MW per year	240/83 hours per year
GA	0.3282	49	11.9 MW per year	242/2 hours per year
GSA	0.3742	2	5/26 MW per year	318/3 hours per year

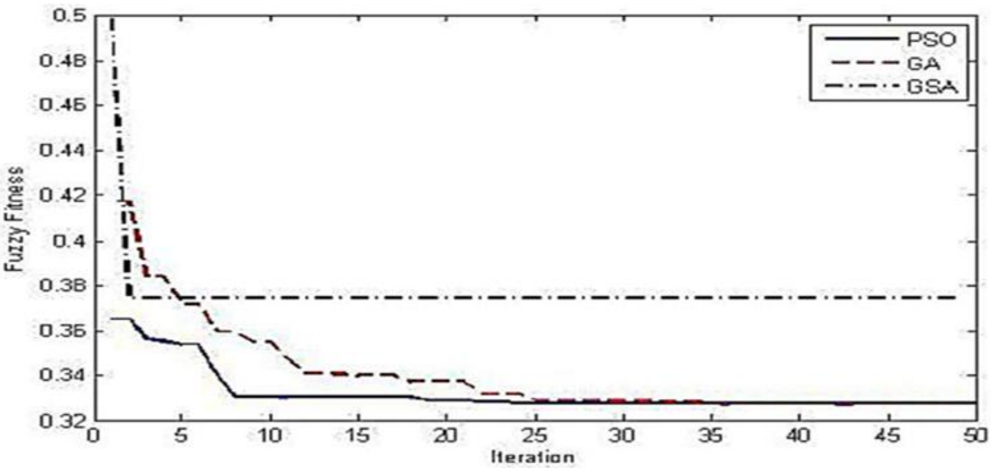

Figure 3. *Convergence diagram.*

As shown in *Tables 4*, *Table 6*, and *Table 8* for the particle swarm algorithm, the fuzzy value of the third scenario is more preferable, given all the objectives - cost reduction, improved reliability indices, and reduced need for diesel units. The result is a more favorable response than other scenarios. This means that the use of electric vehicles, using the recharge control signal, has favorable effects on the optimization problem. In this answer, if the average value of consumption in the microgrid in the time series definition period is considered as a basis, the percentage of reliability for the energy index lost in the same period is 0.002%. And for the microgrid connection index to the main network will be 2.75%. In other words, during the definition of time series, with this combination of production units, the microgrid will maintain its independence in 99.998% of the power supply capacity in 97.25% of the time.

Conclusion

Combining small generation and energy storage in low or medium voltage systems is a new type of power system called microgrids. One of the features of this system is the possibility of integrating scattered products in the field of renewable energy, which highlights the reliability of the microgrid. The optimal combination of power generation units with electric vehicles can play an important role in sustainable energy supply. As the dependence of the microgrid on the main network decreases, along with the provision of subscribers' consumption, the reliability of the microgrid will increase. In this paper, the presence of electric vehicles, in combination with other power generation units, is optimized to improve load supply and reduce microgrid dependence on the main network. Using the probabilistic models provided for the system components and for different modes of combining power generation units, the reliability assessment was performed by probabilistic methods and the best response was determined using particle swarm algorithm, genetic algorithm, and gravitational search algorithm. In this paper, it was shown that the use of electric vehicles in microgrids, using the recharge control signal, will improve the ultimate goal, including the fuzzy combination of objectives to improve reliability indicators, reduce costs and reduce the number of diesel units required in microgrids.

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Conflict of interest

Author confirm there are no conflict of interest with any parties involce in this research study.

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