Int. J. Nonlinear Anal. Appl.
Volume 12, Special Issue, Winter and Spring 2021, 161-172
ISSN: 2008-6822 (electronic)
http://dx.doi.org/10.22075/IJNAA.2021.5009

Using Not-Dominated Sorting Backtracking Search Algorithm for Optimal Power System Planning in the vicinity of the Electric Vehicle Charging Station and Scattered Generation Sources under Uncertainty Conditions

Seyed Masoud Alizadeh Masoumian[a*], Alireza Alfi[b], Ahmad Rezaee Jordehi[c]

[a,b]Faculty of Electrical Engineering, Shahrood University of Technology, Shahrood, 36199-95161, Iran.
[c]Department of Electrical Engineering, Rasht Branch, Islamic Azad University, Rasht, Iran.

(Communicated by Dr. Ehsan Kozegar)

Abstract

The cost of electricity generation depends on different parameters and characteristics. These parameters and characteristics are regional characteristics, fuel costs of fossil fuel power plants, government policies, and technological capabilities, which lead to fluctuations in the cost of electricity generation. The production cost has gradually decreased with the rapid progress of technology and gaining more experience in using wind and solar energy. Therefore, the cost of electricity generation per kilowatt-hour has declined significantly in recent years. On the other hand, the cost of fuel for gas and thermal power plants is increasing with the reduction of oil and gas reserves and the elimination of subsidies for petroleum products. Therefore, it is necessary to replace gas and thermal power plants with wind and photovoltaic power plants in the future. Moreover, using charging stations for electric vehicles as a source of energy exchange in the form of V2G and G2V greatly helps to manage the costs involved. Using electric vehicles reduces fuel costs, maintenance costs, and air pollution allows protecting the environment and reducing respiratory, heart, and lung diseases. In this paper, the optimal planning in the location of the photovoltaic power plant, wind, and charging station in the presence of load uncertainty and electricity price uncertainty are examined using the crowding-based distance index in the edited Not-Dominated Sorting Backtracking Search Algorithm. Examining the results in MATLAB software on the 33-bus IEEE network indicated the high accuracy, speed, and control of the algorithm.

Keywords: Photovoltaic power plant, Wind power plant, Charging station, NSBSA, Optimization

*Corresponding Author: Seyed Masoud Alizadeh Masoumian
Email address: sma.masoumian@gmail.com (Seyed Masoud Alizadeh Masoumian[a*], Alireza Alfi[b], Ahmad Rezaee Jordehi[c])

Received: June 2020 *Accepted:* January 2021

1. Introduction

Today, development and expanding the use of renewable energy and increasing the share of these resources in the global energy basket have been of great interest among different industrial and academic sections. Non-renewability of fossil fuels, diversification of energy sources, sustainable development, creating energy security, and environmental problems due to fossil energy consumption, on one hand, and the renewability and cleanness of new energy sources (e.g., sun and wind), on the other, have led to serious efforts in this regard. Therefore, a significant increase is seen in the activities and budgets of governments and companies in the research, development, and supply of renewable energy systems. These activities and spending these budgets will ultimately reduce the cost of renewable energy and competitiveness with existing traditional energy systems. This goal has been reached in the case of wind and solar energy, and a rapid downward trend in prices for other renewable energy sources is underway. In this respect, the use of renewable energies is increasing worldwide with energy consumption considered as one of the development indices. In line with the plans made, this type of energy has created an increasingly high share in the energy supply system. From 2015 to 2020, more than 25.6 $ was invested in capacity building, power plant construction, and the research and development of new energy sources [3, 12].

Renewable energy capacities accounted for less than 20% of the world's electricity generation until the end of 2010. Renewable energy currently supplies more than 26% of the world's primary energy [18]. However, it has not had a significant role in some countries. Therefore, it is considered a warning sign in the consumption of fossil fuels. A suitable platform for the development of renewable energy in all countries is the support and creative government policy and the existence of a suitable platform for investment and technology transfer to developing countries. The renewable energy industries are now at a transitional state to be delivered in a technically and economically competitive way in many countries. Hence, they will significantly contribute to advancing the national interests of developed countries after the depletion of oil products resources and the global problem of global warming. These industries can operationalize investment in the development and completion of energy recycling technologies in the markets of every country [13]. Several major factors are involved in expanding market attraction to renewable energy, with the most important one being national energy security. Studies show that oil consumption is on the rise and will soon exceed domestic production, making developed countries increasingly dependent on oil markets. This will render the economy of the western countries vulnerable to any disruption in oil imports. The rapid growth of developing countries will put increasing pressure on global oil markets that will worsen with time. Therefore, renewable energy will help western countries to rely on domestic energy sources, reduce their need for fossil fuels, and stop consumption growth. The main cause of problems with renewable energy is the concern over climate change. Renewable energy can meet the need for energy and reduce greenhouse gas emissions at the same time [8]. Greenhouse gases like carbon dioxide and methane constantly concentrate in the thin layer of the Earth's atmosphere. This volume of gases, in turn, will increase the Earth's temperature every day. Temperature rise will have negative and potentially catastrophic consequences such that some measures (e.g., using carbon-free renewable energy) must be taken to prevent it. Another noteworthy point is the ultimate and high costs of renewable energy that declines in recent years and will continue in the coming years, as well [10]. Unfortunately, attention to renewable energies in Iran in recent decades has been merely focused on studying and following the activities of other countries. However, using this type of energy has improved with the installation of wind turbines and photovoltaic power plants in recent years. Although the potentials of using this type of energy in Iran have not been completed yet, modulating the price of energy carriers will allow using these energies. Hence, it is necessary to put a codified and strategic plan for using various approaches of new energy according to the status quo and the existing potential to reach an appropriate share of energy supply during the planning of a schedule. In [19], the possibility of access to different energies like wind and photovoltaic energy was considered to take effective measures within the framework of a strategic plan for the development of renewable energies.

Given the growing energy consumption and the increase in pollution in the world, industrialized countries have shifted to using more efficient and effective tools and equipment. With the establishment of the electricity and energy market in many countries of the world, the issue of energy supply with good reliability has involved other dimensions. Additionally, a widespread global movement has initiated toward grid smartening and the development of electric and hybrid vehicles, as one of the requirements of smart grids in the leading countries of the world [7]. These vehicles have a great effect on reducing environmental pollution and transportation costs, particularly in large cities. One of the main challenges of using electric vehicles is finding the optimal location and size of vehicle charging stations. Thus, the size and location of charging stations for electric vehicles can affect the development of these vehicles, the design of the city traffic network, driver comfort, profits and benefits in the grid, and voltage profile changes in some nodes [21].

Different approaches have been proposed to solve the problem of optimal planning of the location of the charging station and distributed generation resources. In [17], the multi-purpose location of the charging station was performed to improve voltage, reliability, and reduce costs, regardless of the vehicle battery charging model. In the proposed approach, the vehicle charging station is considered as a distributed generation source and a genetic algorithm is used to solve it. In [11], electric vehicles were considered as a source of production to flatten the load curve of the grid. Then, the optimal location of the parking of electric vehicles was performed to reduce losses and the need for vehicle batteries to be charged, regardless of the possible model. An elite genetic algorithm was proposed and used to solve the optimization problem. In [23], GA was used to locate and determine the capacity of distributed generation sources and charging stations of electric vehicles simultaneously. The objective function includes reducing the active and reactive losses of the grid. A backward and forward method was used to solve the load distribution and the proposed method was implemented in a 30-bus network. In the proposed method, the effects of changing the number of vehicles and battery charge rate were examined as well. In [15], the effect of electric vehicles on a medium voltage network was examined, followed by exploring the advantages of operating a distribution system because of using intelligent charging applications. According to this study, network stability, the need to establish infrastructure, and other challenges can be resolved by smart charging designs. In [14], the optimal use of electric vehicles in the current trading market was investigated. In these markets, the next-day price of electricity is available on an hourly basis. Under these conditions, the owners of electric vehicles may be willing to plan to reduce their charging and discharging costs. In this approach, accurate mathematical models are proposed to optimize the cost of charging and discharging electric vehicles. The calculations provided are done hourly, as the price of electricity is available hourly. The approach presented was tested on the Danish electricity market. In [6], photovoltaic parking lots to develop electricity are introduced. In addition to providing shade for the vehicles parked in them, photovoltaic panels generate electricity to charge electric vehicles parked under them and address technical and economic issues, limitations, and other issues related to this project. In [2], the optimal size of an electric vehicle charging station was designed according to the probabilistic support of reactive power for photovoltaic units at medium voltage and in commercial networks. The objective function is to minimize network losses, with a numerical method used to solve the problem. In this system, the charging stations are seen as a network and a special type of distributed generation sources (except the electric vehicles) can be used depending on the type of operation as the load or generator in electrical networks [24]. The objective function of this problem involves reducing losses, charging station installation costs, and maximizing parking utility profits. In [1], the optimal location of wind farms and charging stations were studied considering uncertainties with the help of NSBSA to maximize profits. Renewable energy technologies like wind and photovoltaic have grown in the power system. In [22], China plans to install and operate 150-180 gigawatts of wind energy and 20 gigawatts of solar energy for 2020. Nevertheless, generation in these sources has always been intermittent and unpredictable. The prerequisite for the presence of renewable resources in the power system is using huge electrical energy storage. Electric vehicles can supply their electrical power need using these sources and use the vehicle technology to the grid as storage of electrical energy for the power system.

2. Problem formulation

In this paper, the cost function is defined so that the power of the electricity grid is provided by the partnership of the private company and the public sector. The energy of the private company is integrated through the cooperation of wind and photovoltaic power plants and the energy of the government system through the operation of the charging station such that to supply energy to the electricity network together. Moreover, there are some uncertainties regarding electricity prices, load, wind speed, and sunlight intensity that can be reached by modeling them with more accurate and comprehensive outcomes. The Price Level Factor and Demand Level Factor were modeled in [1]. The output of this model is given in Figs. 1 and 2. Additionally, in [1], modeling was done on an IEEE 9-bus network; however, in the present study, the network was changed to IEEE 33-bus.

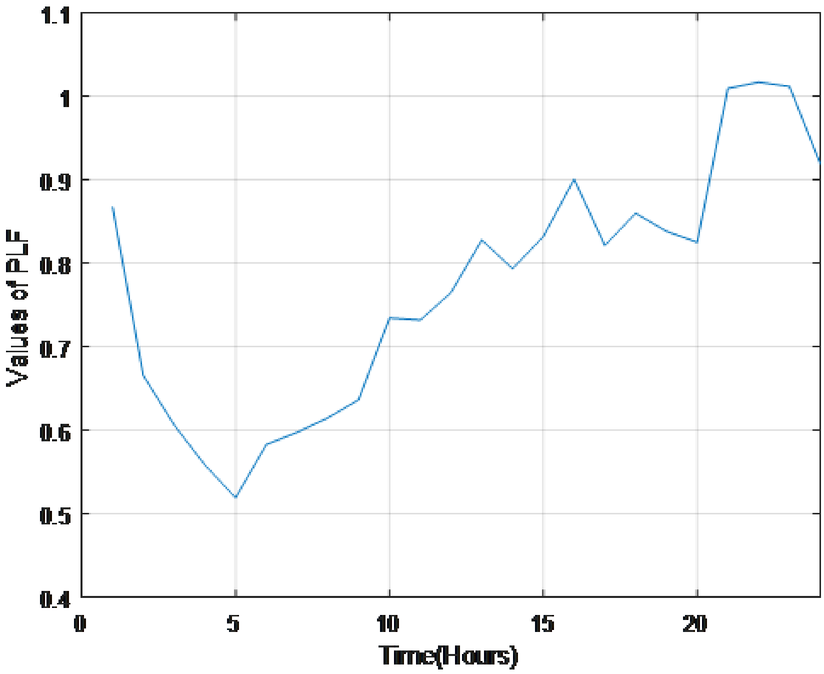

Figure 1: Price Level Factor for daily period

2.1. Charging station

The electric vehicle charging station is one of the infrastructure elements that provide the electrical energy required to recharge both electric and dual-fuel vehicles. Charging stations use various special

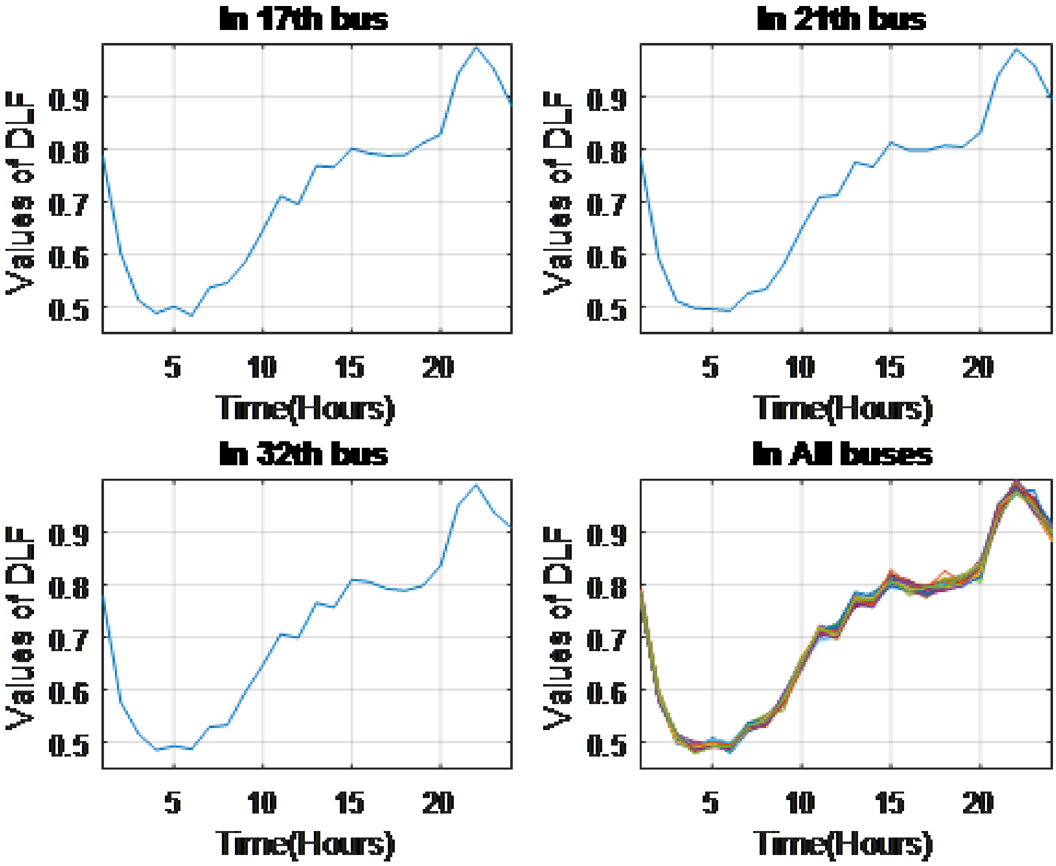

Figure 2: Demand Level Factor for daily period(33-Bus)

connectors built according to the standards. For the conventional direct current fast charging, the use of two or more chargers with several standards (i.e., Combo1, Combo2, and CHAdeMO) and an alternating charger at stations has turned into the real market standard in many areas. Many charging stations on the streets have been set up by distribution companies, and the existing stations are managed by private companies. Public charging stations generally use the second type of AC charging methods or fast DC charging. Charging time relies on battery capacity and charging power. The charge level is associated with the tolerable voltage capacity of the batteries and the electronics used in them. The capacity considered for the vehicle's batteries in this paper is 10 kWh. Battery life is estimated to be 10 years. The accessibility of each vehicle depends on its arrival to and departure from that charging station, both of which are accidentally caused by human behavior. The arrival time of the vehicles to the charging station and their departure from the parking lot is obtained using the data related to the arrival of vehicles to charging stations with the ability to inject power from the vehicle to the existing network. Fig. 3 shows the rate of drivers' visits to charge.

With the arrival of each vehicle at the charging station, vehicle owners are asked about the vehicle-charging schedule, the initial charge, the final charge requested by the vehicle owner, and the time of departure of each vehicle from the charging station. Now, the time required for Vehicle to Grid (V2G) and Grid to Vehicle (G2V) of the vehicle batteries is calculated using the initial charge

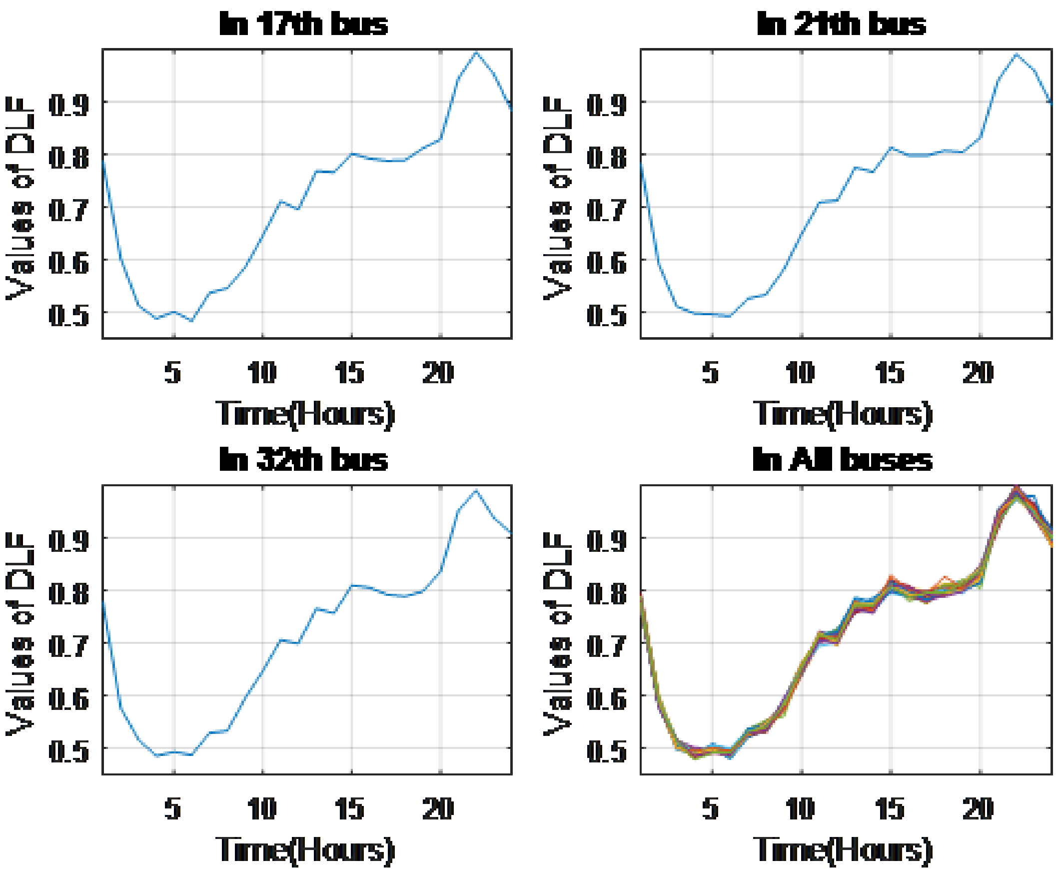

Figure 3: Percentage of electric vehicles visiting the charging station [18]

value as Equations (1) and (2).

$$t_{charge}(j) = \frac{(SOC_{max} - SOC_j) \times ES_j}{P_v} \quad (1)$$

$$t_{discharge}(j) = \frac{(SOC_j - SOC_{min}) \times ES_j}{P_v} \quad (2)$$

In the above equation, SOC_{max}, SOC_{min}, ES, and P_v are, respectively, the maximum charge, minimum charge, the vehicle battery capacity, and the power that the electric vehicle receives. Here, the charging and discharging powers of the station are calculated as Equations (3) and (4), respectively.

$$\begin{aligned} P_{charge} = &\sum_{i=1} N_i \times P_{vi} \times ES \times [(n_{charge1} + n_{charge2} + n_{charge3}) \times (SOC_{max} - SOC_{charge3}) \\ &+ (n_{charge1} + n_{charge2}) \times (SOC_{charge3} - SOC_{charge2}) + n_{charge3} \times (SOC_{charge2} - SOC_{charge1})\,] \quad (3) \end{aligned}$$

$$\begin{aligned} P_{discharge} = &\sum_{i=1} N_i \times P_{vi} \times ES \times [(n_{discharge1} + n_{discharge2} + n_{discharge3}) \times (SOC_{discharge1} - SOC_{min}) \\ &+ (n_{discharge1} + n_{discharge2}) \times (SOC_{discharge2} - SOC_{discharge1}) \\ &+ n_{discharge3} \times (SOC_{discharge3} - SOC_{discharge2})\,] \quad (4) \end{aligned}$$

where $N$and P_{vi} are the capacities and the percentage of vehicles at the ith charging station, and $n_{dischargei}$ and $n_{chargei}$ are the number of vehicles with the initial charge $SOC_{dischargei}$ and $SOC_{chargei}$ at the ith charging station, respectively.

2.2. Photovoltaic system

Different approaches can be used to model a photovoltaic power plant. Solar radiation changes temporally and spatially. Important elements like weather conditions affect the solar radiation value. Hence, this type of energy involves some uncertainties, as well. However, these uncertainties are less than those of wind speed. The change in this energy may change the stability of the power system accordingly. This energy can account for a large share of the load. Thus, it must have a certain value in the whole system. On the other hand, effective measures like providing adequate primary and secondary reservations have to be considered. The output power of photovoltaic cells is related to solar radiation. Therefore, the output power of photovoltaic cells is obtained from Equation (5).

$$P = \begin{cases} P_r(\frac{R^2}{R_{STD}R_c}) & 0 \leq R < R_c \\ \\ P_r(\frac{R}{R_{STD}}) & R_c \leq R < R_{STD} \\ \\ P_r & R_{STD} \leq R \end{cases} \qquad (5)$$

where P is the output power of a photovoltaic cell (watts), R solar radiation (W/m^2), R_{STD} sunlight in standard radiation, P_r the rated power of a photovoltaic cell (watts), and R_c is a certain value of radiation, usually 150 (W/m^2). The purpose of the paper is to use the productive power of the photovoltaic system and it does not deal with the simulation of solar radiation uncertainty. So, the power generation profile is considered for this purpose as it suffices for the simulation. The production capacity of the photovoltaic system in a daily period is shown in Fig. 4.

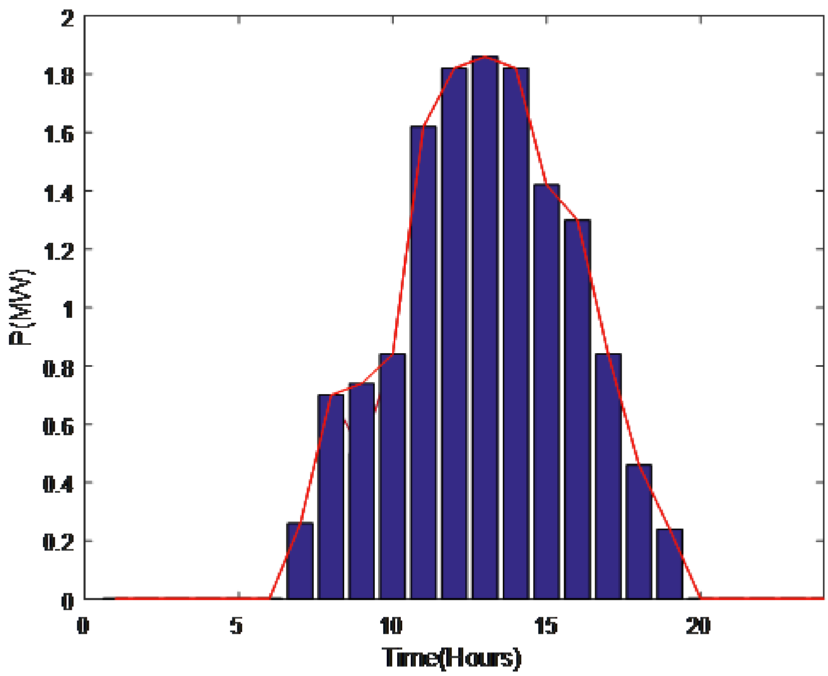

Figure 4: Power output profile by photovoltaic system

2.3. Wind power plant

Wind farms have managed to compete with conventional fossil resources because of technological advances. In wind farms, the cost of generating electricity is equal to the cost of generating electricity in new coal-fired and gas-fired power plants. If the environmental and social costs of electricity generation are considered, wind power is cheaper than other power generation technologies. For a long time, the cost of wind power has been compared to the cost of running conventional power plants. However, conventional power plants have received huge subsidies during the construction and have depreciated over time. Nonetheless, wind energy must compete with the much higher cost of upgrading new thermal or nuclear power plants in developing and developed countries given the need for additional capacity and the obsolescence of old power plants. In evaluating wind farms, project costs and revenues, return on investment time, price of generated electricity, and internal rate of return on capital are the final indices for a complete comparison of the different components. The wind turbine power generation program relies on wind speed. This parameter does not have a definite value and is random. Hence, this estimate was made and used in reference [1]. After modeling the wind speed parameter, the power generated by the wind turbine is obtained according to Equation (6).

$$P_{i,t,h}^{wg} = \begin{cases} 0 & if\ v \leq v_{in}^{cut}\ or\ v \geq v_{out}^{cut} \\ P_{i,r}^{wg} \dfrac{v - v_{in}^{cut}}{v_{rated} - v_{in}^{cut}} & v_{in}^{cut} \leq v \leq v_{rated} \\ P_{i,r}^{w} & else \end{cases} \quad (6)$$

where $P_{i,t,h}^{wg}$ is the allowable capacity of power generation per wind unit. v_{in}^{cut} , v_{out}^{cut} , v_{rated}^{cut} and are, respectively, the Cut in Speed of Wind Turbine, Cut out Speed of Wind Turbine, and Rated Speed of Wind Turbine for power generation. Fig. 5 is the generating capacity of a wind farm in a daily period.

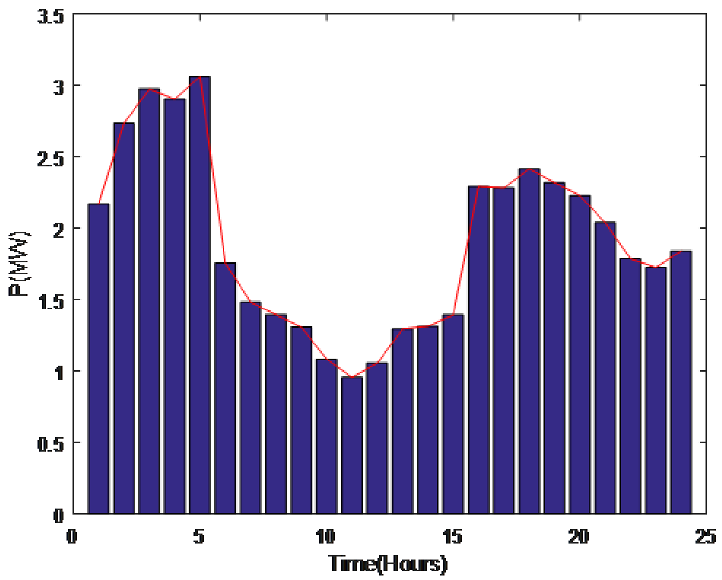

Figure 5: Power output profile by wind generator system

3. Objective function

The objective function is presented in two parts of the paper. In the first part, known as Distribution System Manager (DSM), the charging station is considered as a subset of it. In the second part, known as the private system, two subsets of Wind Generator (WG) and Photo Voltaic (PV) are used.

$$OF1 = (1-\alpha) \times DSM \quad (7)$$
$$OF2 = (WG + PV) + (\alpha \times DSM) \quad (8)$$
$$DSM = B_{total}^{charge} + B_{total}^{discharge} + B_{total}^{load} + B_{total}^{loss} - C_{total}^{inv} \quad (9)$$

In these equations, is a number between 0 and 1 that shows the degree of partnership between the public and private systems that are generated completely randomly in MATLAB. OF1 and OF2 functions are the public and private sectors' profit rates, respectively. DSM function has the following benefit (B) and cost (C) functions.

3.1. Charging station investment cost

Each electric vehicle charging station has sections like land required for construction, office building, charging units, and grid connection facilities. Given the limited capacity of home meters, one cannot charge an electric vehicle with a normal battery capacity as the current consumption is much higher than the capacity of a home meter. Hence, charging should be considered in the form of public stations. The space needed to build a charging station in cities varies with the number of charging units. The cost of installing a charging station includes items like the cost of equipment and construction of the station. These costs are calculated from Equation (10).

$$C_{total}^{inv} = \sum_{i=1}^{N_{cs}} (C_i^{equipment} + C_i^{construction}) \times C_{Pi} = \sum_{i=1}^{N_{cs}} C_{investment} \times C_{Pi} \quad (10)$$

3.2. Benefits of the charging program

When visiting electric vehicle drivers, the charging station manager can increase his profit by providing charging services. To this end, the benefit from recharging the vehicle battery is obtained according to Equation (13) [1].

$$R_{total}^{charge} = \sum_{t=1}^{T} \sum_{h=1}^{N_h} \sum_{i=1}^{N_{cs}} \rho_{t,h} \times P_{i,t,h}^{cs} \times \tau_{t,h} \times (\frac{1+InfR}{1+IntR})^t \quad (11)$$
$$C_{total}^{charge} = \sum_{t=1}^{T} \sum_{h=1}^{N_h} \sum_{i=1}^{N_{cs}} (\frac{\rho_{t,h,pur}^{grid}}{\mu_{conv}} + c_d) \times P_{i,t,h}^{cs} \times \tau_{t,h} \times (\frac{1+InfR}{1+IntR})^t \quad (12)$$
$$B_{total}^{charge} = R_{total}^{charge} - C_{total}^{charge} \quad (13)$$

3.3. Benefits of discharge program

At peak times, batteries can deliver energy to the grid cheaper than upstream grid energy [1]. The benefit is obtained for using power injection technology from the vehicle to the grid according to Equation (16).

$$R_{total}^{discharge} = \sum_{t=1}^{T}\sum_{h=1}^{N_b}\sum_{i=1}^{N_{cs}} \rho_{t,h} \times P_{i,t,h}^{cs} \times \tau_{t,h} \times (\frac{1+InfR}{1+IntR})^t \quad (14)$$

$$C_{total}^{discharge} = \sum_{t=1}^{T}\sum_{h=1}^{N_b}\sum_{i=1}^{N_{cs}} (\frac{\rho_{t,h,pur}^{EV}}{\mu_{conv}} + C_d) \times P_{i,t,h}^{cs} \times \tau_{t,h} \times (\frac{1+InfR}{1+IntR})^t \quad (15)$$

$$B_{total}^{discharge} = R_{total}^{discharge} - C_{total}^{discharge} \quad (16)$$

C_d is the cost of equipment depreciation because of $V2G$ and the efficiency rate of inverter charging stations.

3.4. Benefits from reduced power purchases from the upstream grid

Most of the distribution network power is provided by the upstream network. This power can be reduced by infiltrating the charging stations. It now reduces the cost of purchased energy and increases benefits for the distribution system manager.

$$P_{t,h}^{grid} = \begin{cases} P_{t,h}^{load} + P_{t,h}^{loss} - \sum_{i=1}^{N_{cs}} P_{i,t,h}^{cs} \; for\ peak\ demand\ levels \\ P_{t,h}^{load} + P_{t,h}^{loss} - \sum_{i=1}^{N_{cs}} P_{i,t,h}^{cs} \; for\ medium\ demand\ levels \\ P_{t,h}^{load} + P_{t,h}^{loss} - \sum_{i=1}^{N_{cs}} P_{i,t,h}^{cs} \; for\ low\ demand\ levels \end{cases} \quad (17)$$

$$R_{total}^{load} = \sum_{t=1}^{T}\sum_{h=1}^{N_h} \rho_{t,h} \times P_{t,h}^{load} \times \tau_{t,h}^{load} \times (\frac{1+InfR}{1+IntR})^t \quad (18)$$

$$C_{total}^{load} = \sum_{t=1}^{T}\sum_{h=1}^{N_b} \rho_{t,h}^{grid} \times P_{t,h,pur}^{grid} \tau_{t,h}^{grid} \times (\frac{1+InfR}{1+IntR})^t \quad (19)$$

$$B_{total}^{load} = R_{total}^{load} - C_{total}^{load} \quad (20)$$

3.5. Benefits from reducing active power losses

Losses reduce with the presence of wind power plants and photovoltaic systems in the distribution network and the injection of power into the network by electric vehicles. The benefit from the sale of electricity to customers increases for the distribution system manager, which is calculated from Equation (21).

$$B_{total}^{loss} = \sum_{t=1}^{T}\sum_{h=1}^{N_h} \left[\left(Ploss_{t,h}^{withoutCSandWG} - Ploss_{t,h}^{withoutCSandWG} \right) \times \rho_{t,h} \times \tau_{t,h} \right] \times (\frac{1+InfR}{1+IntR})^t \quad (21)$$

3.6. Benefit and investment cost from operation of wind and photovoltaic power plants

Here, the operation cost of wind and photovoltaic production units, fuel cost, and annual maintenance cost of wind and photovoltaic units are considered for calculating this cost. In this paper, the cost of fuel is considered to be almost zero [24]. The benefit from the wind unit and the photovoltaic system is calculated using Equation (31).

$$C1(WG) = \sum_{t=1}^{T}\sum_{h=1}^{N_h}\sum_{i=1}^{N_b}\sum_{wg=1}^{N_{wg}}(P_{i,t,h}^{wg} \times OC_{wg} \times \tau_{t,h} + Cost_{main,wgi}) \times (\frac{1+InfR}{1+IntR})^t \quad (22)$$

$$R1(WG) = \sum_{t=1}^{T}\sum_{h=1}^{N_h}\sum_{i=1}^{N_b}\sum_{wg=1}^{N_{wg}}(P_{i,t,h}^{wg} \times \rho_{t,h} \times \tau_{t,h}) \times (\frac{1+InfR}{1+IntR})^t \quad (23)$$

$$B1(WG) = R(WG) - C(WG) \quad (24)$$

$$C2(PV) = \sum_{t=1}^{T}\sum_{h=1}^{N_h}\sum_{i=1}^{N_b}\sum_{pv=1}^{N_{pv}}(P_{i,t,h}^{pv} \times OC_{pv} \times \tau_{t,h} + Cost_{main,pvi}) \times (\frac{1+InfR}{1+IntR})^t \quad (25)$$

$$R2(PV) = \sum_{t=1}^{T}\sum_{h=1}^{N_h}\sum_{i=1}^{N_b}\sum_{pv=1}^{N_{pv}}(P_{i,t,h}^{pv} \times \rho_{t,h} \times \tau_{t,h}) \times (\frac{1+InfR}{1+IntR})^t \quad (26)$$

$$B2(PV) = R(PV) - C(PV) \quad (27)$$

$$B = B1(WG) + B2(PV) \quad (28)$$

$$WG(InvestmentCost) = \sum_{t=1}^{T}\sum_{i=1}^{N_b}\sum_{wg=1}^{N_{wg}}(S_{i,max}^{wg} \times IC_{wg}) \times (\frac{1+InfR}{1+IntR})^t \quad (29)$$

$$PV(InvestmentCost) = \sum_{t=1}^{T}\sum_{i=1}^{N_b}\sum_{pv=1}^{N_{pv}}(S_{i,max}^{pv} \times IC_{PV}) \times (\frac{1+InfR}{1+IntR})^t \quad (30)$$

$$C = WG(InvestmentCost) + PV(InvestmentCost) \quad (31)$$

$$B(final) = B - C \quad (32)$$

3.7. Distribution of the load and the problem constraints

Newton-Raphson method is used to solve the load distribution [22]. For each level h of demand, load distribution equations for the problem are calculated in each year of the planning period. Moreover, voltage and current constraints across the distribution network equipment are considered for each level.

$$P_{t,h}^{grid} \pm P_{i,t,h}^{CS} + P_{i,t,h}^{wg} - P_{i,t,h}^{D.e} - V_{i,t,h}^{e}\sum Y_{ij}V_{j,t,h}^{e} \times cos(\delta_{i,t,h}^{e} - \delta_{i,t,h}^{e} - \theta_{ij}) = 0 \quad (33)$$

$$Q_{t,h}^{grid} - Q_{i,t,h}^{D.e} - V_{i,t,h}^{e}\sum Y_{ij}V_{j,t,h}^{e} \times sin(\delta_{i,t,h}^{e} - \delta_{i,t,h}^{e} - \theta_{ij}) = 0 \quad (34)$$

$$I_{l,t,h} \leq I_{max}^{l} \quad , \quad S_{t,h}^{grid} \leq S_{max}^{grid} \quad (35)$$

$$V_{min} \leq V_{i,t,h}^{e} \leq V_{max} \quad (36)$$

$$P_{i,t,h}^{wg} \leq P_{imax}^{wg} \quad i = 1, 2, 3, \ldots, N_b, \quad CP \leq CP_{max} \quad (37)$$

4. The proposed NSBSA

The paper used Backtracking Search Algorithm (BSA) to solve the optimization problem. The development of this algorithm strengthens the search algorithm with the studies created. This population-based algorithm has five processes [9]. The initialization, the first choice, mutation, the intersection, and the second choice are its steps. Fig. 6 presents the performance flowchart of NSBSA. NSBSAs have a single control parameter and their simple structure along with speed can

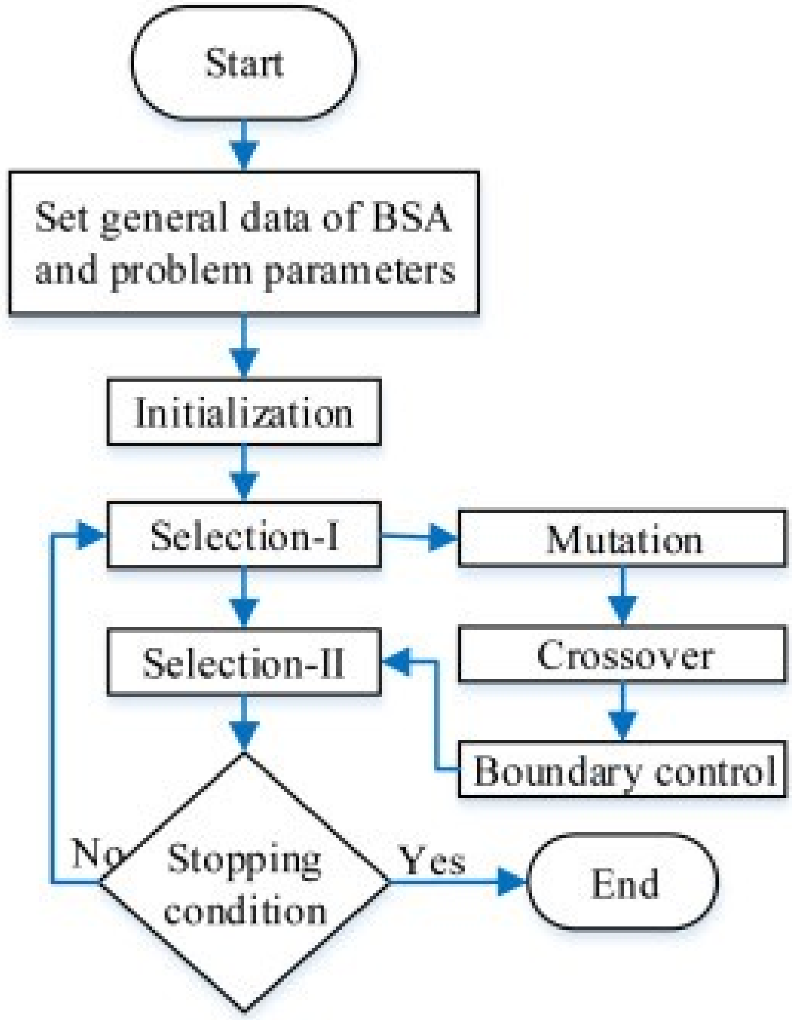

Figure 6: Flowchart of NSBSA Algorithm [22]

solve multi-model problems enabling easy adaptation to various numerical optimization problems [5]. Fig. 6 shows the flowchart of the NSBSA.

Algorithm NSBSA
1.Initialization
repeat
2.Selection 1
Generation of Trial-Population
3.Mutation
4.Crossover
end
5.Selection 2
until stopping conditions are met
Control Mechanism of NSBSA
Input: T, Search space limits $(i.e, low_j, up_j)$
Output: T
for i **from** 1 **to** N do
for j **from** 1 **to** D do

if $(T_{i,j} < low_j) or (T_{i,j} > up_j)$ then
$T_{i,j} = rnd.(up_j - low_j) + low_j$
end
end
end

In this optimization, to maximize the benefits of the two-way search idea algorithm, which is uninformed search strategies, two searches are performed simultaneously. One of them starts from the start mode to the target mode and the other goes from the target mode to the start mode to bring the two searches together. BSA examines whether the two searches intersect rather than examining the target test. An answer has been found in case of interruption [4]. The selection criterion in the two-way search algorithm is the quality factor with the rank parameter. The set of answers to be selected is ranked first, and any answer with a lower rating provides better quality. The ranking is done using the dominance mechanism. In this way, the set of answers that dominate the other answers but cannot overcome the members of their own set is placed in a Pareto Front with the same rank. Additionally, after sorting the answers by rank, the selection is made based on Crowding Distance (order). If the rank is the same, the Crowding Distance is the criterion for selection [20]. The Crowding Distance shows the answers in Pareto Front: the larger the variety of answers, the better they will be. The mathematical expression of this parameter is presented by Equation (38) and in Fig. 7.

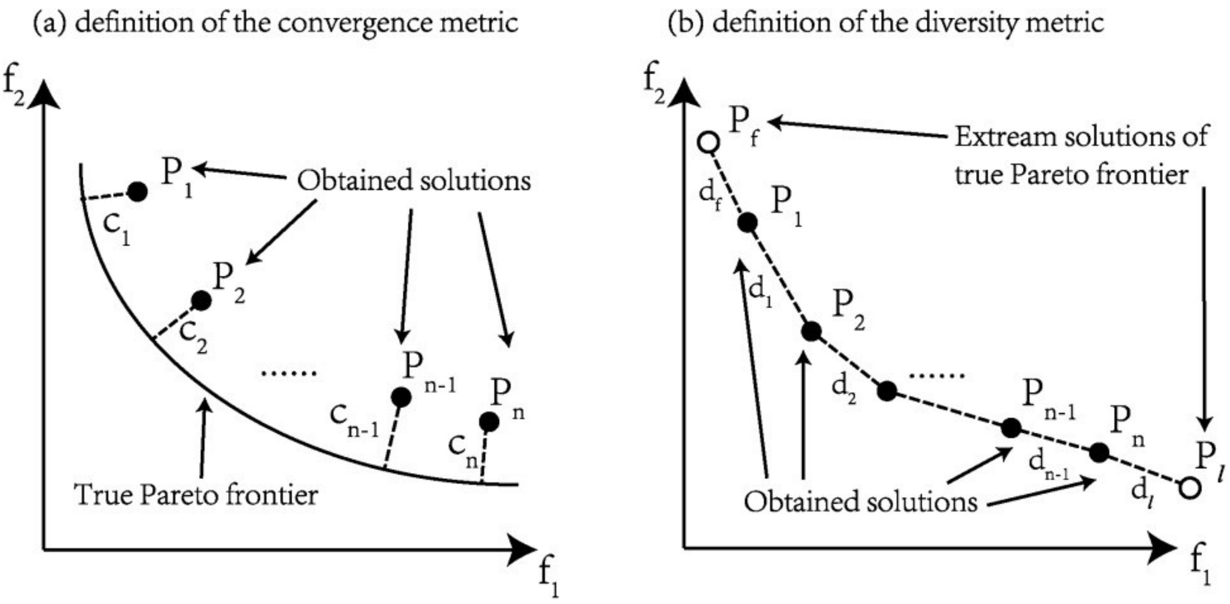

Figure 7: Crowding Distance [20]

$$d_i = \frac{|OF_1^{i+1} - OF_1^{i-1}|}{|OF_1^{max} - OF_1^{min}|} + \frac{|OF_2^{i+1} - OF_2^{i-1}|}{|OF_2^{max} - OF_2^{min}|} \quad (38)$$

5. The network examined

The IEEE 33-bus distribution network with a voltage level of 12.6 Kv was used in the paper. There are 32 candidate locations for charging stations, wind farms, and photovoltaic plants. The model and parameters of the network examined are given in Fig. 8 and Table 1.

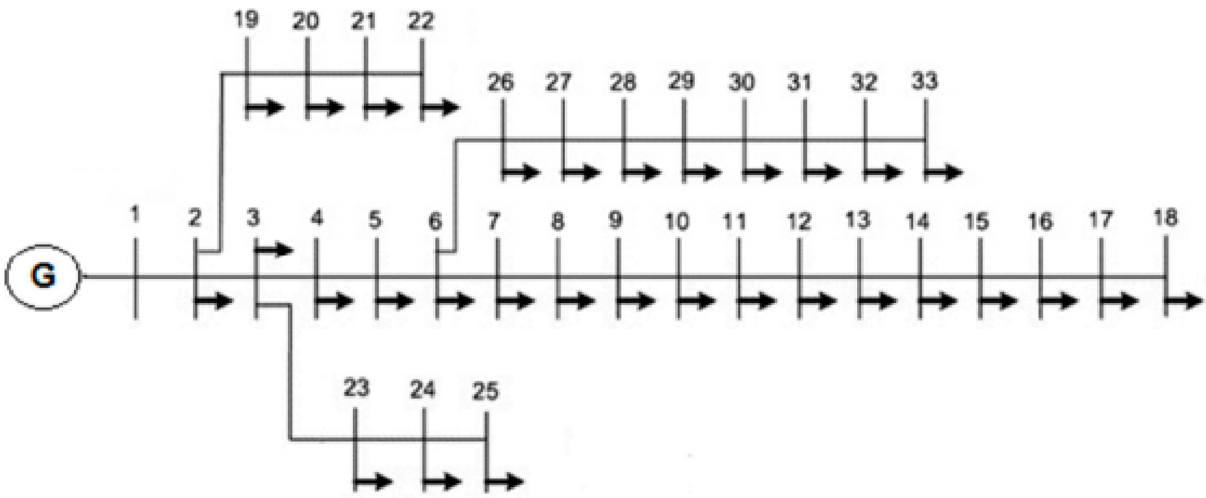

Figure 8: IEEE 33 bus distribution network under study [19]

Table 1: System data for 33-bus radial distribution network [19]

Branch Number	Sending Bus	Receiving Bus	Resistance Ω	Reactance Ω	Nominal Load at Receiving Bus	
					P(kW)	Q(kVAr)
1	1	2	0.0922	0.047	100	60
2	2	3	0.493	0.2511	90	40
3	3	4	0.366	0.1864	120	80
4	4	5	0.3811	0.1941	60	30
5	5	6	0.819	0.707	60	20
6	6	7	0.1872	0.6188	200	100
7	7	8	0.7114	0.2351	200	100
8	8	9	1.03	0.74	60	20
9	9	10	1.044	0.74	60	20
10	10	11	0.1966	0.065	45	30
11	11	12	0.3744	0.1298	60	35
12	12	13	1.468	1.155	60	35
13	13	14	0.5416	0.7129	120	80
14	14	15	0.591	0.526	60	10
15	15	16	0.7463	0.545	60	20
16	16	17	1.289	1.721	60	20
17	17	18	0.732	0.574	90	40
18	2	19	0.164	0.1565	90	40
19	19	20	1.5042	1.3554	90	40
20	20	21	0.4095	0.4784	90	40
21	21	22	0.7089	0.9373	90	40
22	3	23	0.4512	0.3083	90	50
23	23	24	0.898	0.7091	420	200
24	24	25	0.896	0.7011	420	200

Branch Number	**Sending Bus**	**Receiving Bus**	**Resistance Ω**	**Reactance Ω**	**Nominal Load at Receiving Bus**	
					P(kW)	**Q(kVAr)**
25	6	26	0.203	0.1034	60	25
26	26	27	0.2842	0.1447	60	25
27	27	28	1.059	0.9337	60	20
28	28	29	0.8042	0.7006	120	70
29	29	30	0.5075	0.2585	200	600
30	30	31	0.9744	0.963	150	70
31	31	32	0.3105	0.3619	210	100
32	32	33	0.341	0.5302	60	40

All the points are usually selected as candidate buses for the installation of distributed generation units. The minimum and maximum allowable capacity of wind generating units is 1 to 4 MW, the capacity of charging stations is 50 to 350 vehicles, and the maximum capacity of the power plant's power generation profile is 2 MW. The location has been planned for 10 years and each time of the planning period is divided into 24 levels of demand, with the year set at 365 for each level of demand. The information needed for the simulation is given in Tables 2, 3, and 4.

Table 2: Required information and values [18]

Parameter	**unit**	**value**
Demand growth rate - γ	%	4
Minimum magnitude of voltage	Per Unit	0.95
Maximum magnitude of voltage	Per Unit	1.05
Inflation rate - InfR	%	4
Interest rate - IntR	%	5
V_{in}^{cut}	m/s	4
V_{out}^{cut}	m/s	31
V_{rated}^{cut}	m/s	18

Table 3: CS Data [18]

Parameter	**units**	**value**
Initial charging of vehicles	SOC1,2,3	85-90-95
Number of charging Vehicle	%	50-25-25
Initial discharging of vehicles	SOC1,2,3	10-12.5-15
Number of discharging Vehicle	%	35-40-25
Charging/discharging power rate	Kw	10
Vehicle to Grid equipment - μ_{conv}	%	95

6. Simulation results

After simulating the introduced systems, first, α is considered 0, and the program is run. This is done in the private sector to invest in the system but not have a role in the operation. Thus,

Table 4: Information electricity market [18]

Parameter	**unit**	**value**
Electricity wholesale purchase price	\$/MWh	71
base price electricity retail sell - ρ	\$/MWh	85
Operating cost of WGs - OC_{wg}	\$/MWh	31
Electricity purchase price from vehicle	\$/MWh	66
Degradation cost of$V2G$	\$/MWh	0.0015
Electricity price of sold to costumers	\$/MWh	74

this department will receive damages. This loss shows that the benefit of the public sector is not optimized. The results in Table 5 suggest the confirmation of the analysis performed. CD index at its best is 0.6985, in which the public sector gains 52.2966 million \$, whereas the private sector loss is 528,000 \$. A negative $OF2$ shows the loss of the private sector.

Table 5: Optimal pareto front of scenario $I \times 10^7$ with $\alpha = 0$

Solution	OF1	OF2	α	C.D
1	3.2517	-0.0528	0	Inf
2	1.2548	-0.0189	0	Inf
3	5.2896	-0.0528	0	0.6985
4	3.7770	-0.0322	0	0.6857
5	1.9889	-0.0123	0	0.5986

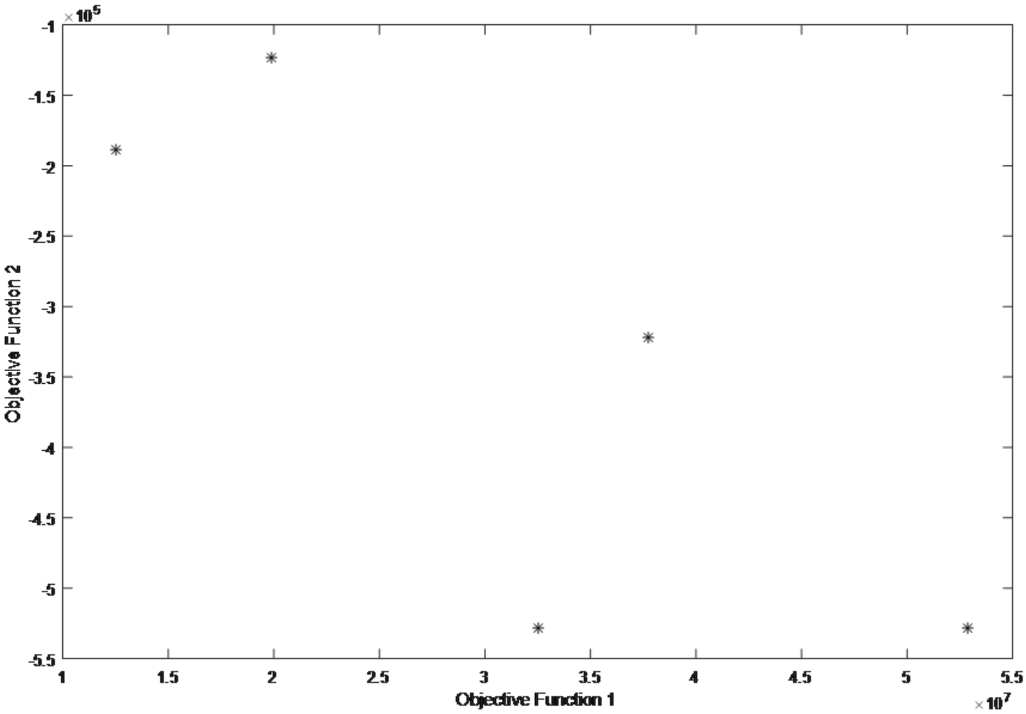

Figure 9: Optimal Pareto front ($\alpha = 0$)

In the next step, the participation of the private sector (with two wind power plants and two solar power plants) and the public sector (with two charging stations) will be used. In this case, the CD index is 0.4509 at its best and both segments receive their maximum benefit from the network. These results are presented in Table 6.

Table 6: Optimal Pareto front of scenario $II \times 10^7$ \$ with α

Solution	OF1	OF2	α	C.D
1	7.8200	-0.09850	0.0985	Inf
2	3.7780	4.0514	0.0895	Inf
3	5.2288	2.7102	0.7986	0.4509
4	7.5786	0.3868	0.8130	0.4509
5	6.7261	1.0937	0.4569	0.4309
6	4.7276	2.9116	0.6399	0.3958
7	5.4186	2.4498	0.8693	0.3396
8	5.6824	2.1387	0.2259	0.3029
9	4.2079	3.5687	0.5693	0.2930
10	3.7967	3.6830	0.5248	0.2536
11	4.4616	3.4315	0.2639	0.2365
12	7.3901	0.5752	0.3369	0.2020
13	6.4998	1.4440	0.2356	0.1963
14	4.5551	3.0801	0.7625	0.1636
15	5.9426	1.9584	0.5698	0.1522
16	6.8882	0.7676	0.5859	0.1499
17	6.9429	0.5756	0.1852	0.1409
18	6.0250	1.7463	0.6936	0.1301
19	6.2609	1.7045	0.1525	0.1119
20	6.2655	1.4573	0.0802	0.0965

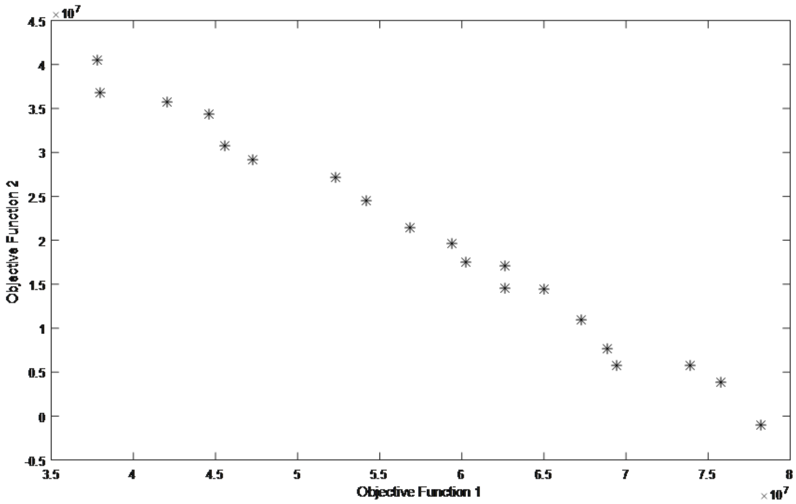

Figure 10: Optimal Pareto front ($\alpha \neq 0$)

Table 7: Optimal place/capacity of CS, WG and PV units

PV (MW)			WG (MW)			Charge Station (N)		
N	bus	Cap (MW)	N	bus	Cap (MW)	N	bus	Cap (vehicle)
2	22	1	2	18	3	2	3	89
	25	2		34	4		6	310

Table 8: Benefits for DS, WG and $PV \times 10^7$ $

Sol	Bdis	Bch	Bup	Bloss
3	0.7968	0.9852	3.9856	2.0268

As the results show, the first and second solutions have an infinite Crowding Distance index and are not suitable solutions, but the third solution with a Crowding Distance index of 0.4509 is the optimal solution. In this solution, with a participation rate of 79.86%, the distribution system manager is profitable at 52288000 $ and the private sector at 27102000 $. Moreover, Figs. 11 and 12 present the 33-bus network voltage profile in two cases before and after, respectively, using the charging station, wind power plant, and solar power plant. The efficiency of the algorithm in the optimal location of these two systems has greatly helped enhance the voltage profile.

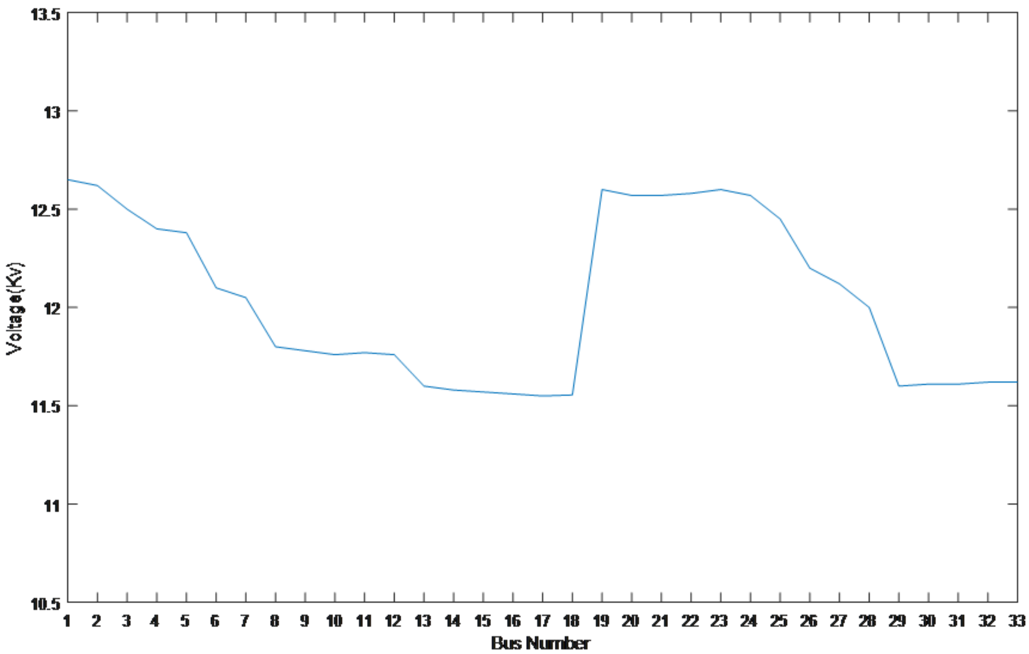

Figure 11: Voltage profiles of the case study (Without CS, WG and PV)

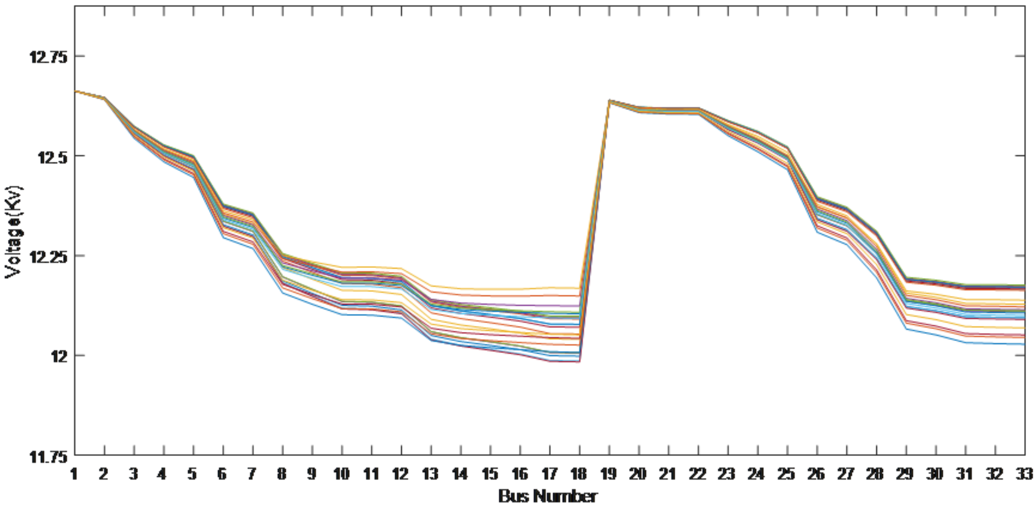

Figure 12: Voltage profiles of the case study (with CS, WG and PV)

7. Conclusion

In this study, using NSBSA in power systems and charging stations was investigated for the first time. Additionally, the optimal locating and planning of the charging station, wind power plant, and solar power plant were done with the help of the crowding distance index. The significant result of this study is that with the participation of both the private and public sectors, good benefits were gained by both sectors. Accuracy, efficiency, and control in this algorithm were found to be considerably higher compared to other meta-heuristic algorithms.

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