

Optimal Configuration Of Hybrid Energy Sources For Sustainable Off-Grid EV Charging Stations

Lokesh Chadokar¹, Dr. Mukesh Kirar², Dr. Abhishek Pratap Singh³

^{1,2,3}Department of Electrical Engineering, Maulana Azad National Institute of Technology,
Bhopal.

Abstract:

In this article focused on design of fast electric vehicle charging station to satisfy the EV consumer demand with the help of renewable energy sources like solar energy and wind energy etc. Renewable energy sources have uncertainty so that to enhance the reliability of EVCS used a battery accumulator. The reliability of EVCS is modeled based on loss of power supply probability (LPSP). This research proposes a strategy for sizing an off-grid hybrid microgrid (MG) system to meet a certain demanded load requirement. The hybrid MG is made up of a solar photovoltaic (PV) system, a wind turbine (TW), and a battery storage system (BSS). The MG system's reliability is modelled using the chance of power supply failure.

Keywords: Electric vehicle charging station (EVCS); Hybrid renewable energy system; Loss of power supply probability (LPSP); Off-grid microgrid; Optimal sizing; Particle swarm optimization (PSO).

1. Introduction

The global push towards sustainable energy and electrification of transport has accelerated the need for reliable off-grid electric vehicle charging infrastructure. This study focuses on designing an off-grid EVCS powered by renewable sources such as solar and wind [1], [2]. Integrating these renewable energy sources can reduce reliance on fossil fuels, though it introduces challenges due to their variability. To ensure system reliability, an energy storage system (ESS) is included, allowing the system to store surplus energy for periods when generation does not meet demand. However, improper sizing of charging station components may result in higher charging station cost and low reliability. For example, an oversized solar may increase the charging station investment cost and decrease system stability due to its irregular nature of power production. The deployment charging infrastructure is the pre-requisite for the spread of electric vehicles. A well-established charging network increases vehicle mile using electricity, relieves range anxiety and reduces inconvenience concerning charging process [3]. In the upcoming years, the electric vehicles population increases exponentially, due to the squandering of oil and the environmental impact associated with its use. So, the main problem with EVs development is the lack of charging infrastructure [4]. Because of power level electric vehicle charging station categorized in fast charging station, moderate charging station and slow charging station [5]. Every EV consumer has the option to charge their electric vehicle at home i.e. slow charging station but the charging time is large. To make EV user friendly, it is very necessary to install fast charging station in which charging time very less near about to 15 minutes. The demerits of fast charging stations are the high-power requirement and its impact on grid [6]. If the EV charging depends upon grid this may be extra burden on electrical grid and cannot fulfil sustainable development goal of EV. Renewable energy sources-based generation is priority to develop charging infrastructure and according to availability and potential in geographical region [7]. Among all renewable energy sources, solar and wind power sources are more popular in microgrid development. Renewable energy is irregular in

nature, which is climate dependent, but the crossing of the two sources can be ridden from this problem. Furthermore, an energy storage system helps to improve system stability [8]. The solar power is primary source supply in the system. The WT is used as secondary source to support the load when solar power generation is low. And ESS is used as a backup power support to the system when both the sources cannot handle the load demand.

Due to the waste of oil and the environmental impact of its use, the number of electric vehicles (EVs) is anticipated to rise enormously over the next few years [9]. Because of this, there is a propensity for coordinated action to lower urban pollution and greenhouse gas emissions. The lack of adequate infrastructure for charging EVs is now one of the biggest issues facing EV development [10]. Owners of electric vehicles (EVs) can charge them at home, but it takes a while. Fast-charging stations, which can fully charge an EV battery in around 15 minutes, must be installed to support the development of electric vehicles. The increased power demand and its impact on the grid, in contrast, are the drawbacks of quick charging. Renewable energy sources and energy storage devices can be put in place in these stations to solve this problem. The demand models used to build EV charging stations have been very simple, with a constant demand and load profile [11]. These load profiles don't consider when each car starts and stops charging. Instead, they are just an average number for each hour. Demand models with constant demand and load profile have been utilized in the design of EV charging stations. These load profiles only represent an average for each hour and do not consider the start and end times of each vehicle's charging. There are more sophisticated models for how EV charging stations work [12]. However, improper sizing of charging station components may result in higher charging station cost and low reliability. For example, an oversized solar may increase the charging station investment cost and decrease system stability due to its irregular nature of power production. Various reviews of studies about the appropriate system design for an EV station installation and its operation [13].

2. Mathematical Modeling of Electric Vehicle Charging Station

The variable to be found in the charging station design problem consists of the optimal number of chargers and power capacity of chargers, the installed capacity of renewable generation (solar and wind) and energy of the batteries. Figure-1 illustrates the proposed topology of electric vehicle charging stations.

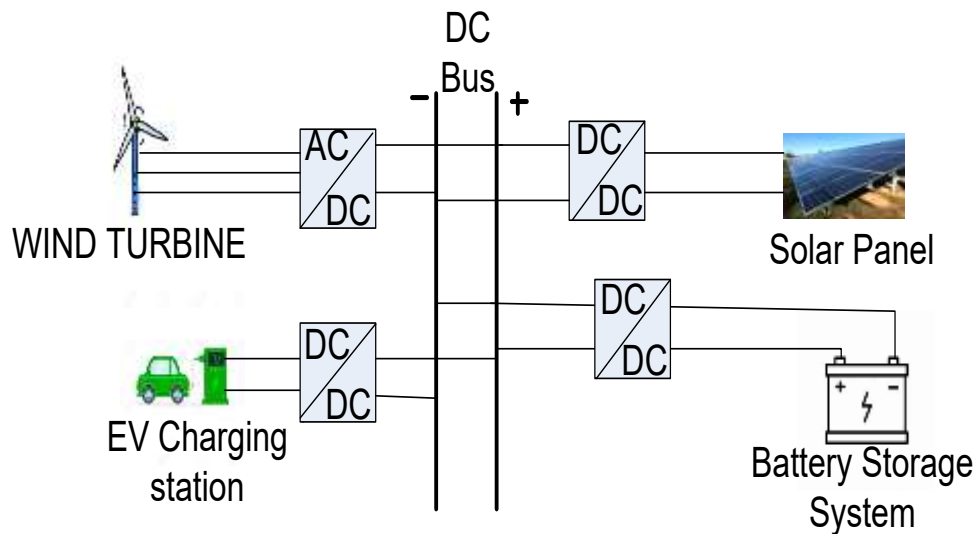


Figure-1: Proposed topology for electric vehicle charging station.**2.1 EV load demand**

This demand for EVs is contingent not only on the quantity of electric vehicles that visit the charging station but also on the storage capacity of their batteries and the degree to which they are charged. However, we must also consider that the charging station has a limited number of chargers, and that if a customer arrives at the station and there is none available, they will leave the charging station because there are no available. Electric vehicles depend upon the battery capacity as well as state of charge of EV battery. Charging station capacity decides on the flowing of electric vehicle arrival and battery SOC level. But I have considered that finite number of chargers. When vehicles arrive at the charging station and no charges are free, but still there are infinitely waiting positions. This type of model is called Erlang C queueing model or M/M/n/∞. The EV load profile decides the needs of power supply from hybrid renewable energy system. The EV load portraits are dynamically modelled according to required power at times t. In off-grid hybrid microgrid based EV charging station load is the driver. In figure shows that an example of a per hour daily EV charging station load demand for the different electric vehicles arrives at the charging station, With the help of monte Carlo simulation method. The EV load depends upon the type of vehicle arrives at the charging station and arrival and departure time of vehicle. The first step to determine when each vehicle arrives at the station, also corresponding to the initial soc. The second step is to find out the departure time of vehicle.

$$\tau_h(x) = 1 - e^{-\sigma_h \cdot x}$$

$$SOC(E; \vartheta, \theta) = \frac{1}{E\theta \sqrt{2\pi}} \cdot e^{-(\ln E - \vartheta)} \quad (1)$$

As previously mentioned, the first stage is to model the demand for Evs at the charging station. The number of electric vehicles that arrive at the charging station, as well as its capacity and state, all affect this EV demand for their battery power. However, we also take into account that the billing station has a limited number of chargers, so when a customer comes at the station and there aren't any available charges, he or she will depart the charging station This kind of system is comparable to an Erlang B. M/M/c/c, often known as the queueing model. Identifying the arrival time of each vehicle is the first stage at the charging station. This can be modelled as a modulated Poisson procedure. The different types of EV battery capacity given in table-1.

Table-1: Different EV battery capacity

Electric vehicle types	Battery capacity (KWh)	Probability (%)	Accumulated Probability (%)
E-bikes	4	0.238	0.238
Small car	15	0.332	0.57
Large car	24	0.268	0.838
E-bus	60	0.162	1

In the first step of the EV charging station modeling, we consider the arrival of electrical vehicles (EVs) at the station, which depends on the flow of EVs and the state of their batteries. The system has a finite number of chargers, and if all chargers are occupied, a customer arriving consumer will leave the station. This system can be represented using an Erlang B queuing model or M/M/c/c. To determine the arrival times of EVs, a modulated Poisson process is used. The time passed between two consecutive vehicle arrivals follows an exponential distribution, where λh represents the average arrival time for each hour h . The arrival times are simulated using the sequential Monte Carlo method, generating a sequence of random numbers. In the second step, the energy required to charge the batteries of arriving vehicles is calculated. The battery capacity is associated with the vehicle type, which includes motorbikes, cars, and vans. The battery capacity is determined using a discrete distribution based on registration data. The state of charge (SOC) of the battery is modeled using a lognormal distribution with parameters μ and σ , where E represents the initial SOC. In the third step, the charging time for each vehicle is calculated using a simplified equation that considers the battery capacity and SOC. This equation provides an estimation of the charging time based on a constant power load assumption. The vehicles are then distributed among the available chargers based on their charging time. If all chargers are busy when a new vehicle arrives, it will not wait and will be lost. This is because charging periods are usually relatively long, and consumers tend to move to the next charging station if all chargers are occupied. Figure-2 illustrates EV the hourly load demand for a day.

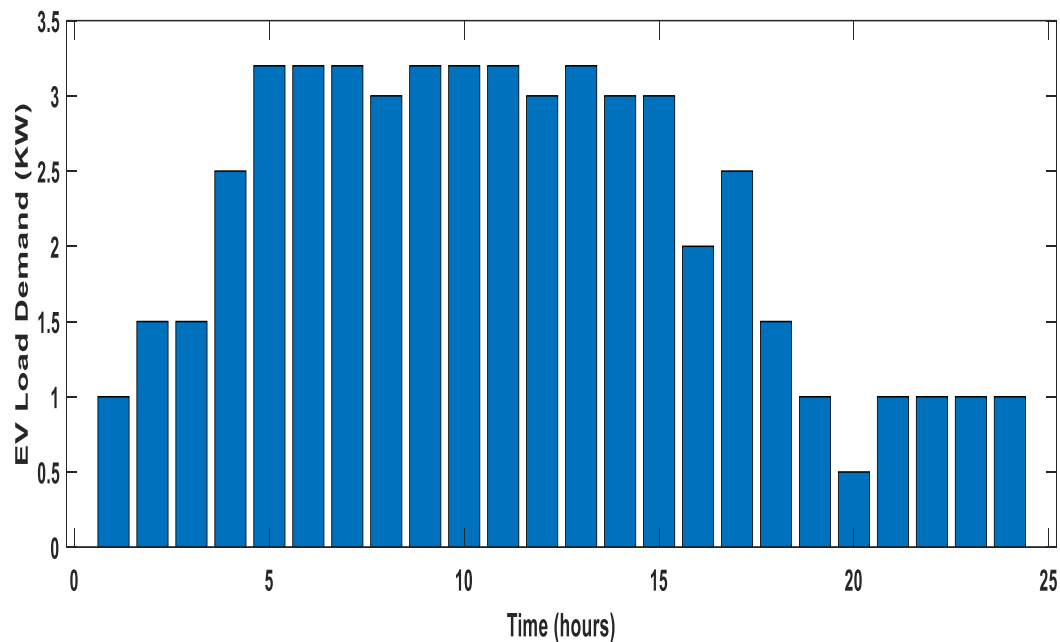


Figure-2: Hourly load demand for a day

Finally, considering the fast-charging power and the number of chargers supplying power, the total demand of the EV station is calculated by summing the power demands of all charging stations.

2.2 Solar PV System

The solar PV system is the main source of power supply in EVCS, the output power is estimated with equation (2) based on irradiance and temperature at time t sec and regulation of the PV module is given by (3) [14].

$$P_{PV}(t) = n_s \cdot A_s \cdot G(t) \quad (2)$$

$$n_s = n_{STC} \cdot n_{MPPT} [1 - \alpha(T_c - T_{stc})] \quad (3)$$

where, A_s is solar panel area in (m^2), $G(t)$ is the total solar irradiance in (W/m^2), n_s is the efficiency of solar PV array, n_{STC} is the reference efficiency of the PV cell at standard temperature condition (STC), n_{MPPT} is the efficiency of the maximum peak power tracker, T_c is the PV cell temperature in ($^{\circ}C$), T_{stc} is reference temperature of the PV cell at STC ($25^{\circ}C$) and α is the temperature coefficient of the PV cell.

2.3 Wind turbine model

The output expression of a WT in terms of ambient wind speed can be obtained by a piecewise function [15].

$$P(v) = \begin{cases} \frac{P_r(v - v_{ci})}{(v_r - v_{ci})} & v_{ci} \leq v \leq v_r \\ P_r & v_r \leq v \leq v_{co} \\ 0 & v < v_{ci} \text{ or } v > v_{co} \end{cases} \quad (4)$$

Where $P_w(v)$ is wind turbine generator output with ambient wind speed v , P_r is power of wind turbine at rated speed and v_{ci} is cut in wind speed, v_{co} is the cut-out wind speed and v_r is rated wind speed.

2.4 Battery storage system

Energy storage-system can supply power to electric vehicle charging stations when there is deficiency of electricity & ESS can store power it totally depends upon the state of charge of battery. The discharging and charging energies of the ESS at a time can be obtained [16], [17], [18], [19].

2.5 Reliability model

Whenever the EV load demand requirement is greater than power supplied through PV, WT and storage system for a t hour. This put the system in the loss of power supply (LPS) scenario [20], [21]. Loss in the power supply (LPS) is expressed in equation (5)

$$LPS(t) = PEV_LOAD(t) - [PPV(t) + PWT(t) + PESS(t)] \cdot \eta_{conv} \quad (5)$$

Where η_{conv} is the efficiency of converter.

The loss of power supply probability (LPSP) is defined as the ratio of sum of power failure time to sum of total EV load.

$$LPSP = \frac{\sum_{t=0}^T LPS(t)}{\sum_{t=0}^T P_{EV_Load}(t)} \quad (6)$$

In other words, a reliable electrical power system has a low probability of losing power supply and has enough power to meet the load demand for a specific duration (LPSP) [22]. If the hybrid system (PV array, wind turbine, and battery storage) is unable to meet the load requirement, LPSP is the likelihood that there will be an inadequate power supply.

It is a feasible measure of the system performance for an assumed or known distribution of load. A LPSP of 0 means the load will always be satisfied; and an LPSP of 1 means that the load will never be satisfied. Loss of power supply probability (LPSP) is a statistical parameter; its calculation is not only focused on the abundant or bad resource period. Therefore, in a bad resource year, the system will suffer from a higher probability of losing power. Table-2 provides the key parameters of the PV, WT, and energy storage system (ESS) used in this study.

Table-2: Parameters of system components

	Parameter	Value
PV Data	Max power	255 W
	Efficiency at STC	15.7%
	Length	1.64 m
	Width	0.99 m
	Capital Cost	\$ 0.80/W
	Operation Cost	\$0.04/W
	Lifetime	25 yr
Wind turbine Data	Rated Power	1500 W
	Cut- out wind speed	17 m/s
	Rated wind speed	12 m/s
	Capital Cost	\$0.67/W
	Operation cost	\$0.1005/W
	Lifetime	20 yr
BSS Data	Charging efficiency	80%
	Discharge efficiency	100%
	Capital cost	\$0.15/Wh
	Operation cost	\$0.015/Wh
	Lifetime	5 yr

2.6 Particle Swarm Optimization (PSO)

Particle swarm optimization is first introduced in 1995 through Kennedy and Eberhart. A concept of optimization technique based on population of swarms. The optimization of EV residential stations is nonlinear and stochastic problem, for that a heuristic technique will be appropriate [23]. Particle swarm optimization (PSO) will be employed to address our problem in this research. It's a heuristic technique for simulating the social behavior of swarm animals like birds and fish. The search for the best solution by randomly presenting candidate solutions in a wide search space defined by velocity and position, and the particles iteratively update their position based on their own and the flock's experiences. Figure-3 illustrates the flow chart of the modified PSO. The update is done as follows:

$$V_t^{k+1} = w * V_t^k + C_1 * r_1 (P_{best} - X_t^k) + C_2 * r_2 (G_{best} - X_t^k) \quad (7)$$

$$X_t^{k+1} = X_t^k + V_t^{k+1} \quad (8)$$

Where, V is particles velocity, X particles position, Pbest is the best position of the particle, Gbest is the best position of the swarm, C₁ and C₂ are the weight of local and global information respectively, r1 and r2 are random variables, w is the inertia weight. In this study, consider swarm size is 100, no. of max iteration is 1200, C₁= C₂ = 2, w = 0.9.

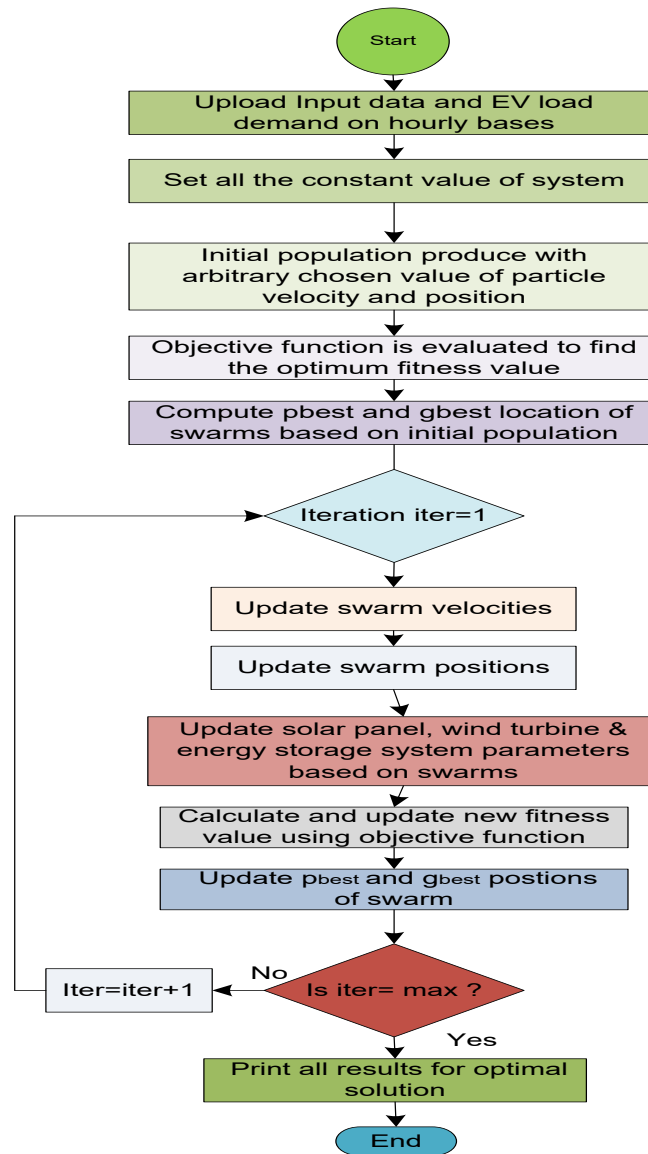


Figure-3: Flow chart of modified PSO

3. Problem Formulation

The EV fast charging station considered in this study to replenish the batteries of EV customers and employed hybrid renewable energy sources such solar PV system, wind turbine, etc. coupled with stationary battery storage units to improve station dependability and profitability. The variables in renewable energy based electric vehicle charging stations are the number of solar PV panels, number of wind turbines, capacity of stationary battery storage unit and total power rating of chargers.

The objective function that minimizes the total investment cost of EVCS, which is the sum of capital cost and maintenance cost of the off grid electric vehicle charging station over a life span of 20 years. Also minimize the solar PV panel, wind turbine and storage unit capacity based on depth of discharge (DOD) of storage unit and loss of power supply probability (LPSP).

The objective of the optimization problem is to minimize the total investment cost of hybrid energy based electric vehicle charging station is expressed by equation (9)

$$\text{Min } f(N_{PV}, N_{WT}, E_{BSS}) = C_{PV} \cdot N_{PV} + C_{WT} \cdot N_{WT} + C_{BSS} \cdot E_{BSS} \quad (9)$$

$$C_{PV} = (C_{cap}^{PV} + T \cdot C_{op}^{PV}) \cdot P_{PV} \quad (10)$$

$$C_{WT} = (C_{cap}^{WT} + T \cdot C_{op}^{WT}) \cdot P_{WT} \quad (11)$$

$$C_{BSS} = C_{cap}^{BSS} + R_{BSS} \cdot C_{cap}^{BSS} + (T - R_{BSS} - 1) \cdot C_{op}^{BSS} \quad (12)$$

Where N_{PV} is the number of PV panels; N_{WT} is the wind turbine; E_{BSS} is the total storage capacity of BSS unit. C_{PV} and C_{WT} are the total costs of solar PV and WT respectively; C_{BSS} is the cost of per/Wh of BSS; C_{cap}^{PV} , C_{cap}^{WT} and C_{cap}^{BSS} are the capital costs of the Solar PV, WT and BSS respectively; C_{op}^{PV} , C_{op}^{WT} and C_{op}^{BSS} are the operating cost of Solar PV, WT and BSS respectively; R_{BSS} is the expected number of BSS replaced over the life span of project. T is the life span of project, i.e. 20 years in this case. All the charges of charging station are included in capital and operation cost from the installation to operation.

3.1 Constraints

The optimization problem is also subject to some constraints:

Power balance in the charging station (13) [24]. Each hour, the sum of the photovoltaic and wind energy generated, and the energy discharged from the batteries is equal to power supplied to electric vehicle charging stations.

$$P_{pv}(t) + P_{WT}(t) + P_{BSS}(t) - P_{EV_{Load}}(t) = 0 \quad (13)$$

Loss of power supply probability should be less than set value of loss of power supply probability to make system more reliable.

$$LPSP \leq LPSP_{set}$$

Limit of PV power supplied by panels. The power generated by the solar PV panel is always less than the installed capacity.

$$P_{PV_{min}} \leq P_{PV}(t) \leq P_{PV_{max}}$$

Limit of WT power generation. The power generation through wind turbines is always less than installed capacity.

$$P_{WT_{min}} \leq P_{WT}(t) \leq P_{WT_{max}}$$

Energy balance

$$E_{BSS(0)} = E_{BSS}(t) = E_{BSS(stored)}$$

BSS stored energy and power limits.

$$E_{BSS_{min}} \leq E_{BSS}(t) \leq E_{BSS_{max}}$$

$$E_{BSS_{min}} = (1 - DOD) \cdot E_{BSS_{max}}$$

Limit of storage in BSS

$$E_{SOC} \leq E_{BSS_{inst}}$$

4. Results and Discussion

The modified PSO is used to minimize total system cost, while taking different LPSP values for system reliability. The results were compared with enhanced GA [25]. The comparison between two strategies is shown in table-3. The effect of depth of discharge (DOD) on the dc fast charging station is shown in table-4. It is found that the optimal size proposed charging station is 170 solar panels, 5 wind turbines with 220 kWh of energy storage for the minimum total 20 years based on the desired operation and reliability constraints with 60% DOD and LPSP less than or equal to 0.10. Figure-4 and Figure-5 illustrate the solar irradiance, ambient temperature of the year. The hourly wind speed of the year is shown by figure-6. All data were obtained from the Typical Meteorological Year (TMY) dataset. These values were used to determine the output power of the photovoltaic (PV) and wind turbine (WT) systems. Figure-7 illustrates the estimated hourly load demand.

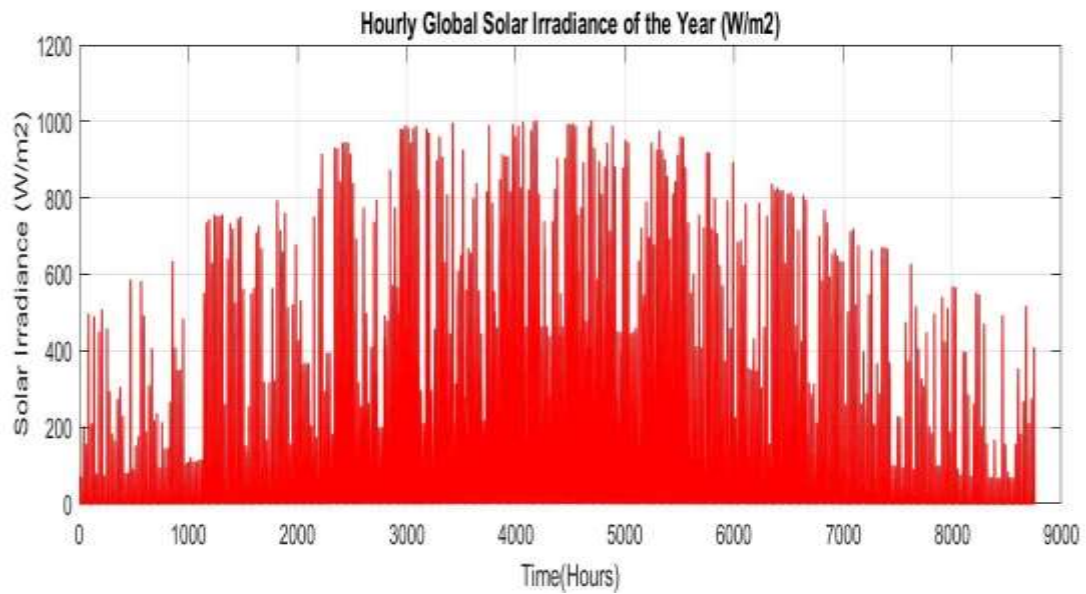


Figure-4: Hourly global irradiance of the year (W/m2)

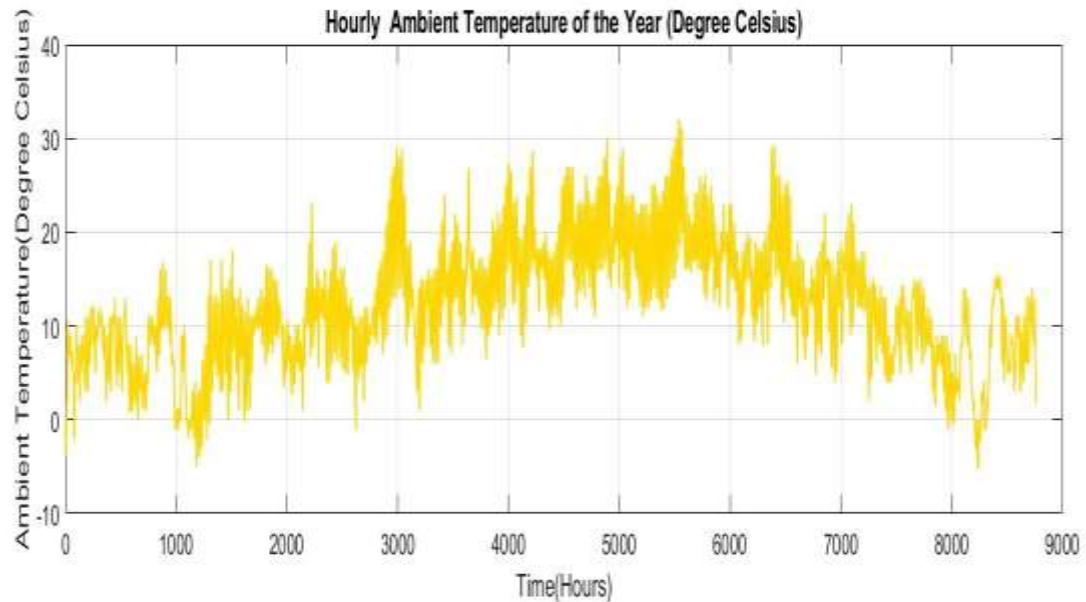


Figure-5: Hourly ambient temperature of the year

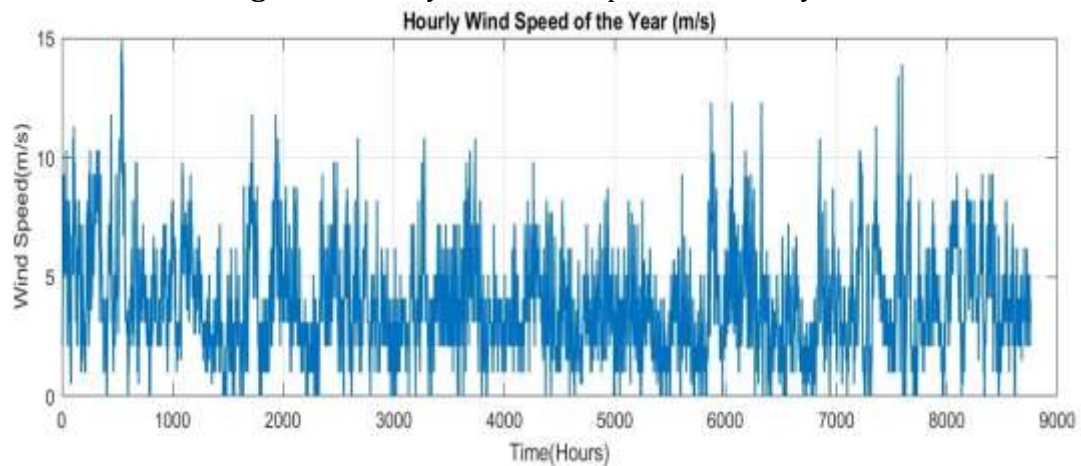
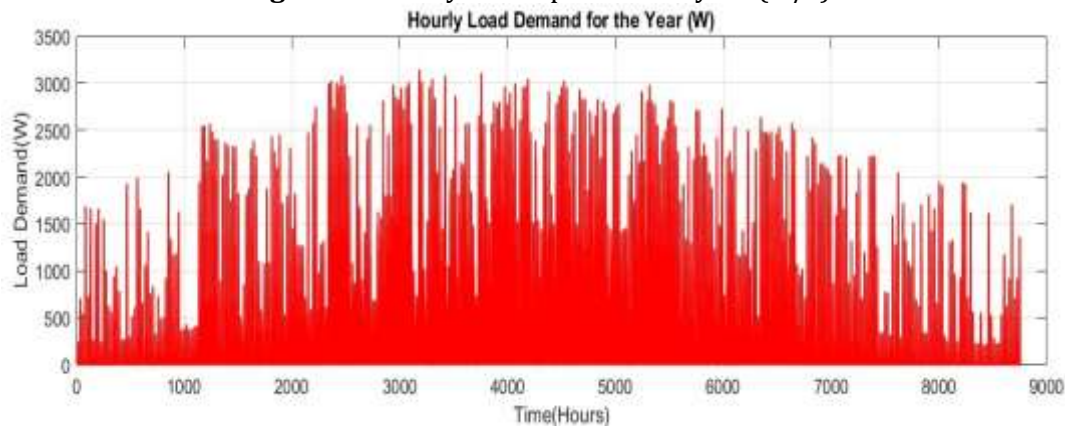


Figure-6: Hourly wind speed of the year (m/s)**Figure-7:** Hourly load demand for the year (W)**Table-3:** Comparison of two optimization techniques

	GA	PSO
No of trials	106,635	75,604
Computational time	172 (min)	116 (min)

Table-4: Results of optimal sizing of EVCS

	DOD=0.8	DOD=0.7	DOD=0.6	DOD=0.5
N_{PV}	162	166	170	175
N_{WT}	5	5	5	5
P_{PV}	41.3 KW	42.33 KW	43.35 KW	44.62 KW
P_{WT}	7.5 KW	7.5 KW	7.5 KW	7.5 KW
BSS_{ESS}	220 KWh	220 KWh	220 KWh	220 KWh
Total cost	\$270996.00	\$272628.07	\$274260.00	\$276300.00

5. Conclusions

This study proposes a novel approach for sizing photovoltaic (PV), wind turbine (WT), and battery storage system (BSS) hybrid off-grid microgrids based EV charging station using a particle swarm optimization (PSO). All approaches yielded identical outcomes under identical conditions, validating the suitability of the PSO for optimal EVCS sizing and the feasibility of our proposed method for sizing PV/WT/BSS hybrid off-grid charging stations.

References

- [1] A. Verma and B. Singh, "Energy Management Strategy of Solar PV-Battery and Diesel Generator Based Electric Vehicle Charging Station," 2018 IEEE Energy Convers. Congr. Expo. ECCE 2018, pp. 1043–1050, 2018, doi: 10.1109/ECCE.2018.8557669.
- [2] A. Verma and B. Singh, "Solar PV Array-WECS Based Integrated EV Charging System with Dual Mode of Operation," 8th IEEE Power India Int. Conf. PIICON 2018, no. December, pp. 1–6, 2018, doi: 10.1109/POWERI.2018.8704471.
- [3] A. Dubey and S. Santoso, "Electric Vehicle Charging on Residential Distribution Systems: Impacts and Mitigations," IEEE Access, vol. 3, pp. 1871–1893, 2015, doi: 10.1109/ACCESS.2015.2476996.

- [4] H. S. Das, M. M. Rahman, S. Li, and C. W. Tan, "Electric vehicles standards, charging infrastructure, and impact on grid integration: A technological review," *Renew. Sustain. Energy Rev.*, vol. 120, no. November 2019, 2020, doi: 10.1016/j.rser.2019.109618.
- [5] M. C. Falvo, D. Sbordon, I. S. Bayram, and M. Devetsikiotis, "EV charging stations and modes: International standards," 2014 Int. Symp. Power Electron. Electr. Drives, Autom. Motion, SPEEDAM 2014, pp. 1134–1139, 2014, doi: 10.1109/SPEEDAM.2014.6872107.
- [6] J. Donadee and M. D. Ilić, "Stochastic optimization of grid to vehicle frequency regulation capacity bids," *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 1061–1069, 2014, doi: 10.1109/TSG.2013.2290971.
- [7] R. W. Wies, R. A. Johnson, A. N. Agrawal, and T. J. Chubb, "Simulink model for economic analysis and environmental impacts of a PV with diesel-battery system for remote villages," *IEEE Trans. Power Syst.*, vol. 20, no. 2, pp. 692–700, 2005, doi: 10.1109/TPWRS.2005.846084.
- [8] J. Duan, S. Fan, F. Wu, L. Sun, and G. Wang, "Power balance control of micro gas turbine generation system based on supercapacitor energy storage," *Energy*, vol. 119, pp. 442–452, 2017, doi: 10.1016/j.energy.2016.12.063.
- [9] Y. Wan, W. Cao, and L. Wang, "A prediction method for EV charging load based on fuzzy inference algorithm," *Chinese Control Conf. CCC*, vol. 2019-July, pp. 2803–2808, 2019, doi: 10.23919/ChiCC.2019.8865243.
- [10] H. S. Das, M. M. Rahman, S. Li, and C. W. Tan, "Electric vehicles standards, charging infrastructure, and impact on grid integration: A technological review," *Renew. Sustain. Energy Rev.*, vol. 120, no. November 2019, 2020, doi: 10.1016/j.rser.2019.109618.
- [11] G. Wang, X. Ji, B. Zhou, H. Li, and H. Wang, "A radial basis function based approach for electric vehicle charging load forecasting," *IET Conf. Publ.*, vol. 2018, no. CP757, pp. 1–5, 2018, doi: 10.1049/cp.2018.1816.
- [12] J. A. Domínguez-Navarro, R. Dufo-López, J. M. Yusta-Loyo, J. S. Artal-Sevil, and J. L. Bernal-Agustín, "Design of an electric vehicle fast-charging station with integration of renewable energy and storage systems," *Int. J. Electr. Power Energy Syst.*, vol. 105, no. August 2018, pp. 46–58, 2019, doi: 10.1016/j.ijepes.2018.08.001.
- [13] O. Hafez and K. Bhattacharya, "Optimal design of electric vehicle charging stations considering various energy resources," *Renew. Energy*, vol. 107, pp. 576–589, 2017, doi: 10.1016/j.renene.2017.01.066.
- [14] N. Femia, G. Petrone, G. Spagnuolo, and M. Vitelli, "A technique for improving P&O MPPT performances of double-stage grid-connected photovoltaic systems," *IEEE Trans. Ind. Electron.*, vol. 56, no. 11, pp. 4473–4482, 2009, doi: 10.1109/TIE.2009.2029589.
- [15] S. R. Guda, C. Wang, and M. H. Nehrir, "Electric Power Components and Systems Modeling of Microturbine Power Generation Systems Modelling of Microturbine Power," vol. 5008, 2006, doi: 10.1080/15325000600596767.
- [16] R. R. Deshmukh, M. S. Ballal, H. M. Suryawanshi, and G. G. Talapur, "A control algorithm for energy management and transient mitigation in DC microgrid," 2017 Natl. Power Electron. Conf. NPEC 2017, vol. 2018-Janua, pp. 270–275, 2018, doi: 10.1109/NPEC.2017.8310470.
- [17] R. R. Deshmukh, M. S. Ballal, H. M. Suryawanshi, and G. G. Talapur, "A control algorithm for energy management and transient mitigation in DC microgrid," 2017 Natl. Power Electron. Conf. NPEC 2017, vol. 2018-Janua, pp. 270–275, 2018, doi: 10.1109/NPEC.2017.8310470.
- [18] R. R. Deshmukh, M. S. Ballal, H. M. Suryawanshi, and M. K. Mishra, "An adaptive approach for effective power management in DC microgrid based on virtual generation

- in distributed energy sources," *IEEE Trans. Ind. Informatics*, vol. 16, no. 1, pp. 362–372, 2020, doi: 10.1109/TII.2019.2919647.
- [19] R. R. Deshmukh, M. S. Ballal, H. M. Suryawanshi, and M. K. Mishra, "An adaptive approach for effective power management in DC microgrid based on virtual generation in distributed energy sources," *IEEE Trans. Ind. Informatics*, vol. 16, no. 1, pp. 362–372, 2020, doi: 10.1109/TII.2019.2919647.
- [20] Z. Yi, W. Dong, and A. H. Etemadi, "A unified control and power management scheme for PV-Battery-based hybrid microgrids for both grid-connected and islanded modes," *IEEE Trans. Smart Grid*, vol. 9, no. 6, pp. 5975–5985, 2018, doi: 10.1109/TSG.2017.2700332.
- [21] Z. Yi, W. Dong, and A. H. Etemadi, "A unified control and power management scheme for PV-Battery-based hybrid microgrids for both grid-connected and islanded modes," *IEEE Trans. Smart Grid*, vol. 9, no. 6, pp. 5975–5985, 2018, doi: 10.1109/TSG.2017.2700332.
- [22] Y. Zoka, H. Sasaki, N. Yorino, K. Kawahara, and C. C. Liu, "An interaction problem of distributed generators installed in a MicroGrid," *Proc. 2004 IEEE Int. Conf. Electr. Util. Deregulation, Restruct. Power Technol.*, vol. 2, no. April, pp. 795–799, 2004, doi: 10.1109/drpt.2004.1338091.
- [23] P. A. Gbadega and A. K. Saha, "Impact of incorporating disturbance prediction on the performance of energy management systems in micro-grid," *IEEE Access*, vol. 8, pp. 162855–162879, 2020, doi: 10.1109/ACCESS.2020.3021598.
- [24] J. M. Guerrero, J. C. Vasquez, J. Matas, L. G. De Vicuña, and M. Castilla, "Hierarchical control of droop-controlled AC and DC microgrids - A general approach toward standardization," *IEEE Trans. Ind. Electron.*, vol. 58, no. 1, pp. 158–172, 2011, doi: 10.1109/TIE.2010.2066534.
- [25] W. Dong, S. Li, and X. Fu, "Artificial Neural Network Control of a Standalone DC Microgrid," *Clemson Univ. Power Syst. Conf. PSC 2018*, 2019, doi: 10.1109/PSC.2018.8664030.