A Novel Beluga Whale-Jaya Optimization for Effective EV Charge Scheduling in Power Generation

***Abstract*—While considering the provision of the safest environment, it leads to the rapid growth of Electric Vehicles (EVs) that spread over the markets based on features like improvement of charging stations, economy, battery technology, and price. Moreover, the EV charging station placement issues are regarded as facility location issues. In addition, EV charging station placement issues have concerns about the electric distribution systems, the system losses, and the total number of convergences over the traffic network for voltage deviations. The voltage profile enhancement and loss minimization are considered two major issues obtained over the distributed model and are commonly equipped along with the shunt capacitors for reactive power compensations. A novel EV charging model is developed based on hybrid optimization approaches to tackle the issue. The charge level parameters of regional EV charging schedules are tuned with the help of a developed hybrid approach named Beluga Whale-Jaya Optimization (BWJO) derived via Beluga whale optimization (BWO) and JAYA optimization (JA) to attain the minimization of greenhouse gas emission acquired from electricity. Thus, the developed model has offered an enhanced performance rate when contrasted with conventional EV charging schedules schemes.**

Keywords*— Electric Vehicle; Charge Scheduling; Power Generation ; Beluga Whale-Jaya Optimization;

I. INTRODUCTION

Recently, the usage of the Electric vehicle (EV) has been considered a crucial process and utilized by various academics, general customers, and governments [6]. Thus, the EV has used electricity to run the vehicles; they are more reliable and produce fewer emissions. When assimilated over other traditional vehicles along with the inner combustion engines, the EV model is more convenient, popular, environment friendly, and economically better [7]. The vehicle can extract energy from all other sources like nuclear, wind, tidal and solar, among all the resources gained through electricity, which is considered the best choice [8]. Further, the rapid growth of EVs has been negatively impacted due to the unavailability of proper charging stations [9]. To enhance the social acceptance of the EV, there is a requirement for an adequate Electric Vehicle Charging Station (EVCS) and a sufficient parking facility [10]. EVs have been charged even at public charging stations or at home through residential charging stations. Numerous studies have been carried out in this domain.

Over the decades, numerous optimization issues have been utilized to detect the optimal orientation of EV charging stations [11-14]. Thus, the charging station-related orientation issues have operational planning, and the solution directly impacts the total investment cost. Hence, the choice of a good optimization algorithm is crucial. Moreover, along with the current techniques, most sites cannot install more than a few charging ports due to the restricted capacity infrastructure and fear of higher electricity bills [15]. The smart charging process has permitted the sites to scale the port's capacity without upgrading the infrastructure. The scheduling algorithms have minimized the operation costs by optimizing the on-site renewable generation, demand charge, and time-of-use tariffs. Algorithms have also assured additional revenue by providing grid services. The proposed EV charge scheduling model is developed with a hybrid BWJO algorithm to tackle the issues in the conventional model.

Some contributions to the proposed model are detailed below.

- To develop the novel EV charge scheduling model is developed with the aid of a hybrid BWJO algorithm for enhancing the performance of the model over power generation.
- To recommend the hybrid BWJO algorithm designed via BWO and JAYA algorithm for optimizing the parameter of regional charge level in the EV charge scheduling to minimize greenhouse gas emission acquired from electricity.
- To validate the performance of the given EV charge scheduling framework regarding the statistical and convergence analysis to justify the model's effectiveness.

The upcoming sections in the proposed model are given as follows. Section II details the literature survey, section III gives the energy consumption model of EVs with daily trip trajectory, section IV depicts the BWJO optimization-based electric vehicle charge scheduling, section V provides the result and discussion, and Section VI concludes the conclusion.

II. LITERATURE SURVEY

A. Related works

In 2020, Tu *et al.* [1] recommended novel conventional algorithmic techniques for optimizing the regional EV charging schedules by reducing "greenhouse gas emissions" through electricity generation. The marginal emission mode has been utilized to determine the emission from the charging demand calibrated with historical data. Further, the recommended techniques have been validated in Hamilton and Greater Toronto. The research has determined that the most pollutants is released during the recharging cycle towards per journey completion. The biggest energizing moments which the workplace has observed are taken place at home-oriented venues.

Further, the site is convenient for major recharging operations and has a high concentration of verified commercial charging outlets. The improved plants then gained the second-most consumer charging outlets. Greenhouse gas footprints, expenditures in electric vehicle charging infrastructure, and vehicle charging layout are all implicated in the proposed approach. The results showed that the best strategy, in which the vehicles were fueled by gasoline, substantially reduced their contribution to global warming.

In 2021, Lee *et al.* [2] explored a new model termed an "Adaptive Charging Network (ACN)" that has enabled real-time control and monitoring as well as it has also supported EV charging at the scale. Then, the ACN techniques have been considered the adequate scheduling algorithm model depending upon the predictive control and the convex optimization model. It has faced numerous limitations over the real-time charging system, including quantized control signals, non-ideal battery charging behavior, and unbalanced three-phase infrastructure. Here, the adaptive scheduling algorithm techniques have been utilized to tackle the limitations and then assimilated its performance against the baseline algorithms. Considering the realistic settings, the explored scheduling algorithmic model has enhanced the operator's performance and outperformed consistently while delivering the energy in a highly congested model.

B. *Problem Specifications*

Nowadays, various technological advancements in the vehicle industry have led to an enhanced growth rate in electric vehicles. But, these vehicles face several challenges: high-carbon grid profile, cost-effectiveness, low number of charging stations, and more time to recharge. Different conventional electric vehicle charging models based on optimization approaches in presented in Table 1. Genetic algorithm [1] can minimize the emission of greenhouse gas effectively. But, it needs more electrical power generation capability rate due to EV enhancement.ASA [2] provides essential enhancement concerning the energy delivered in a constrained framework and can also enhance operator profit easily. However, the system performance rate is reduced rapidly at the time of overload, and it requires more time for execution. PSO-DS [3] effectively reduces the loss and enhances the voltage profile, and it is easy to implement, and execution is simple. At the same time, it has a very slow convergence rate when the iterative process is performed and offers only low-quality outcomes. Column and constraint generation [4] has a high robustness rate and resolves upper-level issues effectively. But, it is highly complex to decide the issues attained at the time of execution. TLBO [5] effectively reduces the design cost and enhances the charging capacity. But, it easily falls in local optima and has minimal population diversity. So, it is highly essential to design a new electrical vehicle charging model based on optimization approaches.

TABLE I. ADVANTAGES AND LIMITATIONS OVER EXISTING EV CHARGING MODELS BASED ON OPTIMIZATION

Author [citation]	Methodology	Features	Challenges
Tu *et al.*[1]	Genetic algorithm	• It can minimize the emission of greenhouse gas effectively.	• It needs more electrical power generation capability rate due to the enhancement of EVs.
Lee *et al.*[2]	ASA	• It provides essential enhancement concerning the energy delivered in a constrained framework. • It can enhance operator profit easily.	• Something reduces rapidly the system performance rate when the overload happens, and it requires more time for execution.
Muthukannan and Karthikaikannan [3]	PSO-DS	• It effectively reduces the loss and enhances the voltage profile. • It is easy to implement, and execution is simple.	• It has a very slow convergence rate when the iterative process is performed. • It offers only low-quality outcomes.
Zeng *et al.*[4]	Column and constraint generation	• It has a high robustness rate and resolves upper-level issues effectively.	• It is highly complex to decide the issues which are attained at the time of execution.
Duan and Poursoleiman [5]	TLBO	• It effectively reduces the design cost and also enhances the charging capacity.	• It easily falls in local optima and has minimal population diversity.

III. ENERGY CONSUMPTION MODEL OF AN ELECTRIC VEHICLE WITH DAILY TRIP TRAJECTORY

A. *Energy Consumption Model of Electric Vehicles*

Validating the energy consumed by the proposed EV model at the time of the trip has been detailed in this phase. The speed-dependent energy consumption evaluation and power-dependent energy consumption model development have also been entailed. When the second-by-second speed is given as the input, then the proposed model has carried out both the charge regenerating process and the charge depleting model for processing and provides energy consumption rate in terms of Joule per unit time as the output. The second-by-second energy model has been implemented using the EV dynamometer data from the "Downloadable Dynamometer Database (D3)". To design the realistic driving cycle over the GTHA, the GPS data has been aggregated through the survey of drivers in the region. Then the gathered GPS data are then disaggregated to the road segment level, and the sub-trips are classified into average speed bins.

Even better, a prototype of energy utilization based on the mean speed has been validated with respect to power-dependent methods. The energy coefficient for each leg of the trip has been calculated using the power-dependent energy utilization method. The median value of the energy utilization coefficient across each speed bin was already selected and afterwards integrated to the several linear regression equations using the mean speed as an input. The final function of the adjusted energy utilization equation is equated in Eq (1).

$$EneCon = \xi_0 + \xi_1 \times \omega + \xi_2 \times \frac{1}{\omega} + \xi_3 \times \omega^2 \tag{1}$$

Here, the constant co-efficient is termed as ξ_0, ξ_1, ξ_2, and ξ_3 the average speed is given asω.

B. Daily Trajectory

The average speed-dependent energy utilization equation has determined the electric energy utilized per journey. In this phase, every driver has owned a vehicle and completed all their driving trip over a day by utilizing the vehicle for validation.

- The "Transportation Tomorrow Survey (TTS)" dataset has been used for attaining individual daily trip information like trip ending time, trip starting time, purpose, destination, and trip origin.
- The duration and travel distance among Traffic Analysis Zone (TAZ) within the specified time in a day have been produced through user equilibrium traffic assignment techniques.
- In the end, the outcomes have been employed for every trip to determine the vehicle's average speed.

To minimize the computational burden, the TTS data randomly selected as a sample has been optimized and allotted an EV to every driver in the sample. a charging plan has been enhanced for every sample along with the proposed BWJO algorithm. The major intentions of designing the random sample are: to assure that the optimization BWJO algorithm can run within the reasonable computational time for considerable resources and to test the transferability and stability of the proposed algorithm when assimilated over optimal outcomes.

IV. Beluga Whale-Jaya Optimization-Based Electric Vehicle Charge Scheduling

A. Proposed BWJO Algorithm

The newly developed hybrid BWJO algorithm has been developed in this model via BWO [16] and JAYA [17] algorithms for optimizing the parameters in the proposed EV charging scheduling framework. The BWO algorithm can balance the exploration and the exploitation phase to resolve the global convergence rate. But, there is an issue in solving the discrete problems. Consequently, the JAYA algorithm is regarded as the simplest model for implementation without depending upon the specific parameter. But, it has faced over-fitting issues. To tackle the issues in both the traditional model, the hybrid BWJO is developed by modifying the random number, which is given in Eq. (2).

$$rd_1 = \left(\frac{(objfn_{bst} + objfn_{wrst})}{2 * objfn_{wrst}}\right) \tag{2}$$

Here, the term $objfn_{wrst}$is the best fitness, $objfn_{bst}$ denoted the best fitness function, and rd_1indicates the random number. When $rd_1 > 0.5$then, the update is carried out using the BWO algorithm or the update is made using the JAYA algorithm.

BWO: Here, the BOW algorithm is designed by keenly observing the mannerism of the whale. While considering the population-based BWO mechanism, the beluga whale is considered a searching agent. Further, the matrix for the location of the searching agent is equated in Eq. (3).

$$M = \begin{bmatrix} m_{1,1} & m_{1,2} & \cdots & m_{1,h} \\ m_{2,1} & m_{2,2} & \cdots & m_{2,h} \\ \vdots & \vdots & \vdots & \vdots \\ m_{k,1} & m_{k,2} & \cdots & m_{k,h} \end{bmatrix} \tag{3}$$

Here, the term h defines the dimension over the variable and indicates the population size. Then, each beluga whale's corresponding fitness value function is equated in Eq. (4).

$$S_m = \begin{bmatrix} ss(m_{1,1}, m_{1,2}, \cdots, m_{1,h}) \\ ss(m_{2,1}, m_{2,2}, \cdots, m_{2,h}) \\ \vdots \\ ss(m_{k,1}, m_{k,2}, \cdots, m_{k,h}) \end{bmatrix} \tag{4}$$

Exploration phase: The swimming mannerism of the beluga whale is effectively determined using the exploration phase. The location of the beluga whale is updated using this phase and expressed in Eq. (5).

$$\begin{cases} M_{o,p}^{ci+1} = \\ M_{o,i_j}^{ci} + \left(M_{rd,i_j}^{ci} - M_{o,i_j}^{ci}\right)(1 + rd_1)\sin(2\pi r rd_2), & j = even \\ M_{o,p}^{ci+1} = \\ M_{o,i_j}^{ci} + \left(M_{rd,i_j}^{ci} - M_{o,i_j}^{ci}\right)(1 + rd_1)\cos(2\pi r rd_2) & j = odd \end{cases} \tag{5}$$

Here, the term $M_{rd,i_j}^{ci}, M_{o,i_j}^{ci}$defines the current location for o^{th} and rd^{th}BW, $M_{o,p}^{ci+1}$ indicates the new position for the o^{th} BW and j^{th} dimension, rd_1,rd_2 denotes the random number among (0, 1), depicts the current iteration, and represents the mirrored BW's fins towards the surface. Thus, the term rd_1,rd_2 enhances the random operator in the exploration phase.

JAYA: The major intention of this algorithm is to attain the best solution and to neglect the worst solution as well, as it is regarded as a powerful optimization algorithm for resolving unconstrained and constrained issues. The updating equation in the JAYA algorithm is derived in Eq. (6).

$$H'_{u,v,w} = H_{u,v,w} + rd_{1,u,w}\left(H_{u,bst,w} - |H_{u,v,w}|\right) - rd_{2,u,w}\left(H_{u,wrst,w} - |H_{u,v,w}|\right) \tag{6}$$

Here, the tendency of the solution to move closer to the best solution is given as$rd_{1,u,w}\left(H_{u,bst,w} - |H_{u,v,w}|\right)$, the tendency of the solution to neglect the worst solution is indicated as $rd_{2,u,w}\left(H_{u,wrst,w} - |H_{u,v,w}|\right)$, and two random numbers are termed as $rd_{1,u,w}, rd_{2,u,w}$. The pseudo-code for the developed hybrid BWJO algorithm is given in Algorithm 1.

Algorithm 1: BWJO
Initialize the population size and maximum iteration
While $ci \leq ci_{mx}$
Compute the value of rd using Eq. (2)
If $rd > 0.5$
Update new position in the exploration phase of BWO using Eq. (5)
else
Update new position in the JAYA algorithm using Eq. (6)
End if
End while
End
Output best solution

The flowchart for the newly developed hybrid BWJO algorithm is depicted in Fig. 1.

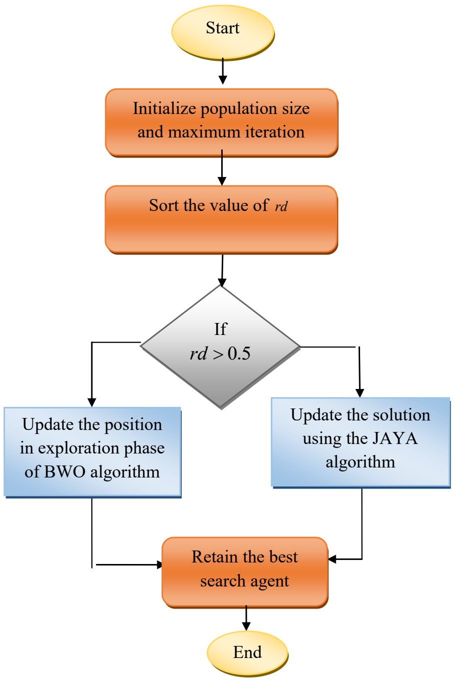


Fig. 1. Flowchart depiction for the newly developed hybrid BWJO algorithm

B. BWJO-based Optimizing EV Charge Scheduling

The main intention of the newly developed hybrid BWJO algorithm is to optimize the regional charging level to improve the performance of the EV charge scheduling model by using the objective function. So, the optimization problem has been designed. Thus, the objective function of the proposed model has been demonstrated as the sum of GHG emissions validated for every time interval, and the product denoted as the product of the Marginal Emission Factor (MEF) over the time interval b as the complete EV charging requirement. Here, the MEF is determined as the variation in emission Δe concerning the variation in the electricity load Δr.

The optimization has included four constraints. In the initial stage, when the vehicle b is determined as driving during the a time interval where the vehicle $b$has consumed the energy, this vehicle cannot be charged. Second, the total electric energy consumed by $a = 1$ to $a = c$ vehicle b cannot extend the remaining electric charge of this vehicle. Third, the equilibrium between the consumed and energy charged for the vehicle b throughout the day; thus, the difference between consumed and electric charge is lower than the minimal charging volume. In the end, the complete energy charged at the time interval a should not go beyond the spare capacity d_a over the electricity network. Then, the objective function derived for the optimization scheme is derived in Eq. (7).

$$objfc = \arg\min_{\{CL\}}(A) \tag{7}$$

$$\text{Where } A = \frac{\sum_a \sum_b MEF_a \times z_{a,b}}{\xi \times (1-\psi)} \tag{8}$$

Here, the regional charging level termed as CL among the range [0, 1.6, 7, and 50] is optimized with the help of the BWJO algorithm, and $objfc$is the objective function.

$$\text{And } R_a = V_a + \sum_{b=1}^{c} z_{a,b} \tag{9}$$

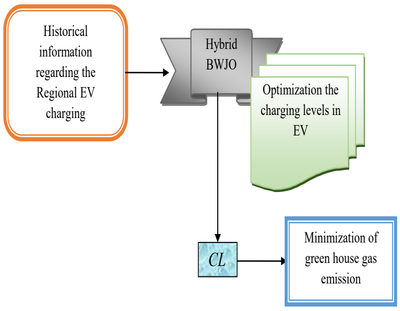


Fig. 2. Diagrammatic depiction of solution encoding in EV charge scheduling model

Here, the network electricity load at the time a defined as the total of present requirement V_a and additional charging requirement is indicated as R_a. Here, all constraints are derived from Eq. (10) to (13).

a) $er_{a,b} \times z_{a,b} = 0, \forall\, a, b$ (10)

b) $\sum_{a=1}^{c}\left(er_{a,b} - z_{a,b}\right) \leq zx, \forall\, b, c \in [1,2,\ldots,C]$ (11)

c) $\left|\sum_{a=1}^{c}\left(er_{a,b} - z_{a,b}\right)\right| \leq \mu, \forall\, b$ (12)

d) $\sum_{a=1}^{c} z_{a,b} \leq d_a, \forall\, a$ (13)

Here, the energy consumption of the vehicle $b$at the time $a$is indicated $er_{a,b}$, the EV's maximum available electrical energy is given as zx, the spare capacity in the electricity network is depicted as d_a, and the minimal charging volume is denoted as μ the total number of time intervals in one day is given as C, the total number of vehicles involved is termed as$c$, and the charging efficiency rate is mentioned as ξ. Thus, the BWJO-based optimization has been carried out to improve the computational speed of the proposed EV charging scheduling framework, and the overall process is depicted in Fig. 2.

Some of the parameter optimized in the EV charge scheduling model using the BWJO algorithm is tabulated in Table II.

TABLE II. LIST OF PARAMETERS OPTIMIZED USING BWJO ALGORITHM

Parameters	Values				
Charging efficiency rate	89.4%				
Transmission and distribution line loss rate	9%				
Constant co-efficient	0.2				
Average speed	30 (km/distance)				
Terms	PSO [18]	HBA [19]	BWO [16]	JAYA [17]	BWJO
Best	2681	2581.5	2569.8	2593.4	2699.8
Worst	3118.4	3114.6	3118.4	3118.4	3033.6
Mean	2769.6	2642.7	2650.4	2714.5	2825.2
Median	2703.6	2583.6	2569.9	2606.7	2869.8
Standard Deviation	136.16	153.62	170.75	174.62	175.22
Charge levels	0, 1.6, 7, 50 (KW)				
Time	24 (in hours)				
Number of vehicles	10				
Population size	10				
Chromosome length	Time*vehicle				
Axman (level 1)	0				
X max (level 4)	50				
Maximum iteration	25				
Levels of charging	0, 1.6, 7, 50				

V. RESULTS AND DISCUSSION

A. Simulation setup

The proposed EV charging schedule model based on optimization was implemented in MATLAB 2020a, and the analysis was carried out. Here, the performance of the proposed model was compared with the conventional models based on convergence analysis and statistical analysis. Some algorithms, like Particle Swarm Optimization (PSO) [18], and Honey Badger Algorithm (HBA) [19], have been used for validation. The maximum iteration was 25, the chromosome length was 2, and the number of Populations was 10.

B. Convergence validation over various algorithms for EV charging model

Fig. 3 depicts the convergence validation performance of the EV charging scheduling framework for various conventional algorithms by varying the number of iterations. In the given graphical representation, it has been clear that the developed BWJO model has acquired lower values in terms of the cost function. Thus, the developed EV charging scheduling framework with the aid of the BWJO model has proved its efficiency.

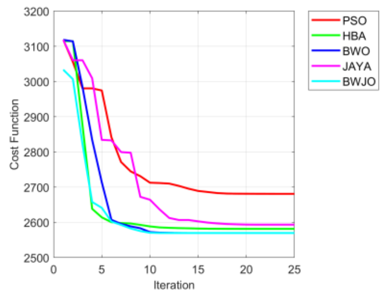
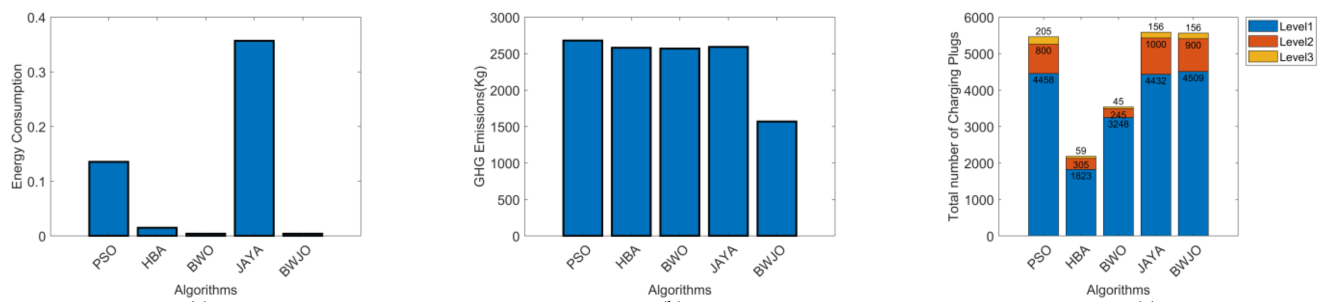


Fig. 3. Validating the convergence performance of the newly developed EV charging schedule framework over traditional algorithms

C. Various evaluations for the suggested EV charging model over algorithms

Various validations for the proposed EV charging scheduling model using numerous algorithms have been given in Fig .4. In Fig. 4 (a), it has shown that the energy consumed by the suggested BWJO model is lesser than other models. In Fig .4 (b), the value of the suggested BWJO model in terms of GHG Emissions regarding kg is 73%, 66%, 66%, and 73% lesser than PSO, HBA, BWO, and JAYA algorithms. It is similar for all total numbers of charging plugs as well. Therefore, the given EV charging scheduling model's performance is very effective and shows better performance.



(a) (b) (c)

Fig. 4. Various evaluations for the newly developed EV charging schedule framework over traditional algorithms regarding a) Energy Consumption, b) GHG Emission, and c) Total number of charging plugs

D. Statistical analysis of various algorithms for EV charging model

Table III represents the statistical performance of the EV charging scheduling model when assimilated over conventional algorithms. The worst value for the suggested BWJO model is 2.7%, 2.6%, 2.7%, and 2.7% lower compared to other algorithms like PSO, HBA, BWO, and JAYA. Thus, it has justified that the newly proposed EV charging scheduling model has provided better out performance and enhanced the model's overall performance.

TABLE III. STATISTICAL ANALYSIS USING CLASSICAL ALGORITHMS FOR THE GIVEN EV CHARGING MODEL

VI. CONCLUSION

This paper has effectively implemented the performance of the novel EV charging scheduling framework with the help of hybrid BWJO algorithm techniques. Here, the parameters of the regional EV charging schedules were tuned with the aid of a developed hybrid approach named BWJO derived via BWO and JAYA algorithm models to attain the minimization of greenhouse gas emissions acquired from electricity. The best value for the suggested BWJO model is 1%, 4%, 5%, and 4% higher than other algorithms like PSO, HBA, BWO, and JAYA. Thus, the developed model has provided improved performance assimilated with other classical EV charging schedule schemes.

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