Hybrid Harris Hawk Optimization of Electric Vehicle Charging Station Placement

F. Peter[1], S. Robin Divahar*[1], B. Anand[2], L M. Karthikeyan[3], Rajiv Selvam[4], R. J. Golden Renjith Nimal[2]

[1]Department of Automobile Engineering, Noorul Islam Centre for Higher Education, Thuckalay, India.
[2]Department of Mechanical Engineering, Jai Shriram Engineering College, Avinashipalayam, Tirupur, India.
[3]Department of Aerospace Engineering, Noorul Islam Centre for Higher Education, Thuckalay, India
[4]Department of Mechanical Engineering & Deputy Chairperson – School of Engineering & IT, Manipal Academy of Higher Education, Dubai Campus G04, PO Box 345050, Dubai UAE.
srobindivahar@niuniv.com

Abstract. The electric mobility sector has progressed quickly and, consequently, the need for charging facilities has increased tremendously. Therefore, the question of where to place charging stations has become a major research topic. Nevertheless, the majority of the studies carried out up to now have not incorporated a very important factor fairness regarding the location of charging stations along the network mainly because it directly affects the ease of access and user convenience. So as to close this gap, the current paper introduces a Hybrid Harris Hawk Optimization (HHO) framework integrated with an attention mechanism for determining the optimal places for EV charging stations. The proposed method has given equal importance to different factors like the station distribution, location advantages, and user comfort. Fairness was measured by how evenly the stations were distributed, and user comfort was measured by the overall charging time that users underwent. The hybrid model has succeeded in accomplishing these goals. Therefore, one can say that this method offers a superior and more sophisticated way of planning for EV charging stations.

Keywords: Electric vehicles; Charging station placement; Optimization; Attention mechanism; Deep learning.

1. Introduction

Electric vehicles (EVs) have become one of the key sectors in the strategy of many countries all over the globe, largely due to their double potential of lowering emissions and saving energy resources [1, 2]. A strong and easily reachable charging network is basically what is needed to speed up the large, scale EV takeover and thus lessen range anxiety, the worry of insufficient energy availability during a trip that is experienced by users [3, 5]. Although charging stations have been increasing in

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numbers for the past few years, however, the current infrastructure is still not enough to cater to the fast-growing charging demand [4]. Before we can bridge this gap, we need to find the best locations for the setting up of charging stations which is also referred to as the Electric vehicle Charging Station (EVCS) placement problem [6]. This dilemma can be seen as a complex variant of the facility location framework where the aim is to find the best places from a selection of possible ones while at the same time increasing different performance measures. Figuring out the best places for stations is hard as it heavily depends on various factors that are closely related to each other, such as vehicle flow, road network structures, the availability of charging stations, charging time requirement as well as the distribution of EVs in an area. On top of that, a lot of existing solutions have been found to neglect certain real, world issues, e.g., the necessity for the fair distribution of the charging resources and the intelligent, automated way of locating new possible positions. Conventional regional optimization techniques, which mainly concentrate on single parking lots or intersections, are not sufficient to address the spread and diversity of the charging needs caused by large road networks [7].

Previous research have delved into the placement of EVCS from various angles such as profit, maximization strategies [8], demand estimation through analysis of historical public charging data [9], and the adoption of machine learning models for EV charging coordination optimization [10]. Nonetheless, most of these studies have ignored the question of the disparities in public charging infrastructure accessibility among different demographic groups or city areas. Furthermore, a number of heuristic optimization methods have recently been put forward to unravel the intricacies of EVCS positioning [11], thus demonstrating excellent performance in addressing large, scale and computationally challenging problems [12,13]. Nonetheless, further investigation is necessary to find out the reasons behind the variation in the locations of charging stations and to help the infrastructure being accessible and operating efficiently in line with the rising charging needs [14]. To overcome such issues, the present study examines the Charging Station Location Problem (CSLP) and presents a new solution that combines Hybrid Harris Hawk Optimization (HHO) with an attention mechanism. The approach put forward takes into account four major factors: equitable spatial distribution, locational benefits, network, level coverage, and user satisfaction assessed through charging time. By incorporating an attention mechanism, the algorithm gains the ability to better elucidate extremely complicated interaction dependencies among the network nodes. Consequently, a more efficient decision-making process is implemented regarding the station placement that brings about the best results.

2. Related Works

Numerous research works have delved into various aspects of the problem of locating an electric vehicle charging station (EVCS), thereby figuring out pricing strategies, integration with the grid, behaviour of drivers, coordination with the renewable energy sources, and heuristic optimization approaches. Zhang and co, authors [15] propose an optimal pricing strategy to lower the service drop rate at dual, mode charging stations. In their model, the charging station is a multi, server queuing network with variable service rates. Besides, they consider the impact of pricing on the EV selection behavior and customer loss. They bring in a pricing mechanism aimed at controlling and stabilizing EV charging operations as a result of creating an attrition, minimization problem. Khan et al. [16] developed a concept for a fast, charging station that can be connected to the grid, which is able to deliver power of high quality with very low harmonic distortion. The whole setup revolves around an ACDC converter that supplies power to a DC bus to which the different EV chargers are connected. Charging at the level of a vehicle is handled by a local controller, whereas the exchange of power with the grid is supervised by a supervisory control system. Furthermore, in order to alleviate the load caused by fast charging on the grid, they include a solar PV system and suggest an optimal, power, flow, based energy management strategy.

Kabir et al. [17] developed a rate-dependent pricing model to ensure fairness in charging, where higher charging rates incur proportionately higher costs. The uncertainty is dealt with by their technique which includes future load demand and forecasting of PV generation. Initially, they develop an integer linear programming (ILP)–based centralized solution to minimalize total charging costs and then introduce two quicker game-theoretic methods. Both approaches converge to Nash equilibrium, with Game 2 achieving optimality comparable to the centralized model but with significantly reduced computational overhead. Pal et al. [18] studied EVCS allocation within a road network superimposed on a radial power distribution system. Their model accounts for weighted factors such as intersections, residential zones, and commercial areas. The primary objectives were to minimize power loss, voltage deviations, and land-use costs while maximizing EV accommodation. They partitioned the study area into three zones to ensure balanced distribution of stations. To address uncertainties in EV behaviour and power demand, they applied the 2m-Point Estimation Method (2m-PEM). Optimization was carried out using Harris Hawks Optimization (HHO) and Differential Evolution, demonstrating effective performance for multiobjective EVCS planning. Xiong et al. [19] suggested with a driver behavior model that is realistic and that allows analyzing the decision-making process of EV users while charging. They applied level-k thinking and Quantal Response Equilibrium concepts to create a k-Level Nested QRE model that reflects the bounded rationality of driver choice. The team took a series of experiments with users to calibrate behaviour parameters. Their findings point out that the model based on user behaviour is now able to track the charging choice made in the real world even better than the traditional rational-agent models. Li et al. [20] focused on the micro-grid environment where EVCS sits, comprising wind power, photovoltaic (PV) systems, energy storage and EV charging. The optimization model that was developed is sturdy and takes into consideration the uncertainties in both the generation from renewable sources and the EV charging demand. They put forward a new technique for sizing both the wind/PV systems and battery capacity through the analysis of loads variations to match the generation profiles with the charging patterns. In addition to that, they resolve the problem of the over-conservatism of the traditional optimization by implementing kernel density estimation which in turn leads to a planning model that is more adaptable and closer to reality.

3. Problem Definition

The charging station location problem can actually be formulated as an optimization problem. The objective function gain(p) helps to determine optimal plan $p*$ which is the best match with our criteria. The equation (1) objective function gain(p) raises in our research the profit term profit(p), the cost term cost(p), and the fairness term fairness(p).

Optimal plan, $p^* = arg\ arg\ gain(p)$

$$gain(p) = k_1 profit(p) - k_2 cost(p) + k_3 fairness(p) \quad (1)$$

where k_1, k_2, and k_3 signify the weight coefficients assigned to various terms, satisfying $k_1 \geq 0$, $k_2 \geq 0$, $k_3 \geq 0$, and $k_1 + k_2 + k_3 = 1$.

The equation (2) profit function for charging station s is planned by taking into account the service area scope of the charging station (s) and the locational vector v of the charging station $cov(v)$.

$$scope\ (s) = |\{vs. \in V | d(v,s) \leq r(s)\}|$$

$$cov(v) = |\{s \in S | d(v,s) \leq r(s)\}| \quad (2)$$

In this context, $r(s)$ refers to the effective radius that is calculated to indicate the area where the charging station attracts electric cars and is defined in the same way for the remaining charging stations equation (3). The Euclidean distance from charging station s to vertex v is denoted as $d(v,s)$. The number of vertices that make up the area of charging station s is the value of scope (s). In the same way, coverage $cov(v)$ for vertices v represents charging stations that are located within the influence radius of vertex v.

$$profit\ (p) = \left[\frac{1}{|V|} cov(v) + \frac{1}{|S|} scope(s)\right] \quad (3)$$

The cost function cost(p) is associated with the entire time invested by the drivers during charging process, which is composed of travel time T_t, charging time T_c, and waiting time T_w. Here, travel time is considered as the total time taken for every electric vehicle in the whole network to arrive at the charging station. The charging time, on the contrary, is the cumulative time that all electric vehicles have consumed for charging. Along with that, waiting time is defined as the total time that electric cars waiting for charging have spent in the queue. In this study, we considered the total of these times as drivers' comfort and thus, a shortcoming of driver comfort is linked to a longer time duration.

The equation (4) congestion at junction v is determined by demand(v); the following step is to determine the destination of the vehicles at junction v. If electric vehicles at junction v are moving to station s, then it is shown by $\sigma(v,s)$:

$$\sigma(v,s) = \{1\ if\ d(v,s) \leq r(s)\ 0\ otherwise \quad (4)$$

The total travel time on the road network for each $plan\ p$, thereby affecting by the $j-th$ EV if it is injected into plan p, is equal to equation (5).

$$T_t = \frac{\sigma(v,s)\ demand(v)\ dis(v,s)}{EV_{sp}} \tag{5}$$

where EV_{sp} is constant, on the road, as an average speed in the behavior of an EV. The charging time of an EV. T_c is expressed as follows equation (6).

$$T_c = \frac{\sigma(v,s)\ demand(v)}{C(s)} \tag{6}$$

Where $C(s)$: total capacity of charging station. The waiting time T_w is stated as follows equation (7).

$$T_w = D(s)\ W(s) \tag{7}$$

Where D signifies the service time is a deterministic function equation (8), $D(s) = \sigma(v, s) * demand(v)$; $W(s) = \frac{\rho(s)}{2\mu(s)(1-\rho(s))}$; $\rho(s) = \frac{D(s)}{\mu(s)}$.

Thus, total time cost is expressed as:

$$cost(p) = T_t + T_c + T_w \tag{8}$$

The provision of electric vehicle services is anticipated to be similarly spread out over the whole city road network equation (9). Hence, the main measure of performance is the average number of charging stations that are found to be coincident at each intersection and the fairness is measured by mean square error (MSE) equation (10). The average number of aligned charging stations for a single node is illustrated below:

$$scope_{avg}(V) = \frac{1}{|V|} scope(V) \tag{9}$$

Furthermore, fairness of plan p is measured as follows:

$$fairness(p) = \frac{1}{|V|} \left[scope(v) - scope_{avg}(V)\right]^2 \tag{10}$$

4. Proposed Methodology

The problem of locating charging stations has greatly caught the attention of scholars during the last couple of years, leading to different studies exploring this issue from various aspects and viewpoints. Nevertheless, the issue of fairness in charging station location planning has not been extensively treated in published works. Our method considers health various aspects such as the fair allotment of charging stations, the advantages of their placement, and the ease of access for drivers. The fair distribution of charging stations across the network can be seen as a measure of justice, while the charging time taken by drivers can be seen as a measure of comfort equation (11). The proposed system is built upon a hybrid Harris hawk optimization with an attention mechanism shown in Fig 1.

$$profit\ (p) = \left[\frac{1}{|V|} cov(v) + \frac{1}{|S|} scope(s)\right] \tag{11}$$

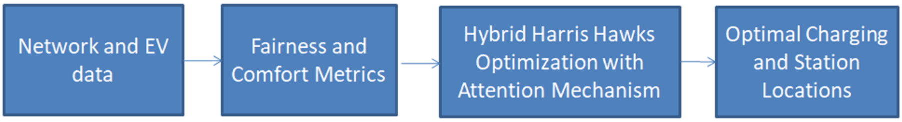

Fig 1: Block diagram of the Proposed System

4.1 Baseline SMOTE:

For preprocessing the input dataset, the baseline SMOTE algorithm was used. Borderline SMOTE, which is the better SMOTE solution, improves the distribution of the sample categories by the new samples created using only a small number of class samples on the border. The samples formed by borderline SMOTE are classified into three categories: safe, dangerous, and noisy. Finally, there were very limited amplified Danger samples. The following are the steps in the algorithm:

- For each sample $x_i$belonging to selected classes, identify its nearest $m$neighbors from the entire dataset. Let m'denote the number of neighboring samples that belong to different classes among these $m$nearest samples.
- The samples are categorized based on the following conditions:
- If all $m$neighboring samples belong to other classes $(m' = m)$, the surrounding samples are considered noise. In this case, $x_i$is excluded from the data generation process, as such samples may degrade the quality of the generated data.
- If more than half of the $m$nearest neighbors belong to different classes $(m/2 \leq m' < m)$, $x_i$is identified as a boundary (Danger) sample.
- If fewer than half of the $m$nearest neighbors belong to different classes $(0 \leq m' < m/2)$, $x_i$is classified as a Safe sample, since most of its neighbors share the same class.
- After labeling the samples, the SMOTE technique is applied to increase the number of Danger samples. For each Danger sample x_i, its $k$nearest neighbors $x_{zi}$from the same class are selected. New synthetic samples $x_n$are then generated randomly using the formula provided equation (12).

$$x_n = x_i + \beta(x_{zi} - x_i) \tag{12}$$

4.2 Harris Hawk Optimization:

The HHO algorithm which is a novel metaheuristic algorithm imitates the Harris hawks' natural behavior and, in a way, takes the whole cycle of hunting into account by applying the concepts of exploring the prey, surprising pouncing, and using different types of attack strategies. HHO takes the hawks as symbols of the candidate solutions, while the prey are best (or almost optimal) options. Before making a surprise pounce to take what they have already marked, the Harris hawks try to follow their target with their sharpest eyes.

HHO naturally separates its operations into two parts to carry out the exploration and exploitation phases. The exploration movement can also be influenced by the altering of the prey's fleeing energy through the transfer of HHO from exploration to exploitation equation (13). The escape energy of the prey can be mathematically calculated as:

$$E = 2E_0\left(1 - \frac{t}{T}\right) \quad (13)$$

$$E_0 = 2r - 1 \quad (14)$$

In this context, r stands for a number produced at random whose value lies between $[0, 1]$, E_0 is the initial energy that is allotted randomly from the range of [-1,1], and t refers to the current iteration while T stands for the overall iterations set as maximum equation (14). The figure portrays the alteration in the energy of the prey's escape throughout 300 iterations, revealing a strong diminishing trend that becomes clearer as the iterations continue.

When the absolute value of the prey's escape energy meets the condition of $| E | \geq 1$, the hawks can conduct a global search. On the other hand, when $| E | < 1$, HHO algorithm changes its strategy to local exploitation and search around the received and almost optimal solutions.

Hard Besiege with Progressive Rapid Dives:

When the predator is about to pounce and capture or kill the prey, a hard besiege is constructed if |E|<0.5 and r<0.5, as the prey does not have the energy to run away equation 15,16. The prey, side condition of this stage resembles the mild besiege scenario to some extent, however, here the hawks are attempting to reduce the distance between their mean position and the fleeing prey equation (17). This circumstance calls for two new solutions in the next way:

$$Y = X_p(t) - E\left|JX_p(t) - X_m(t)\right| \quad (15)$$

$$Z = Y + \alpha \times LF(D) \quad (16)$$

Afterward, the position of hawk is updated as:

$$X(t+1) = \{Y \ if \ F(Y) < F(X(t)) \ Z \ if \ F(Z) < F(X(t)) \quad (17)$$

4.3 Attention Mechanism:

We use an attention model architecture on the present methodology to amplify the algorithm in capturing relations between network nodes. The attention model, together with encoder and decoder components, is explained in detail in this section.

For a road network represented as $G = (V, E)$, where each vertex $v$is described by a feature vector $\vec{v}$, the target charging strategy $p$is defined as a permutation of the vertices, denoted by $\pi = (\pi_1, \dots, \pi_n)$, within a deep learning–based reinforcement learning framework. A stochastic policy $P(\pi \mid s_i)$is formulated to select a permutation πbased on current state s_i. In general, this policy is parameterized by $\theta$and expressed as follows:

$$P(s_i) = P_\theta(\pi_t | s_i, \pi_{1:t-1}) \quad (17)$$

In the context of a continuous state space S, the policy function $P(s_i)$ is typically approximated using a neural network. Based on the Encoder-Decoder Framework, we provide a unique policy network that aims to achieve faster convergence and improved performance.

Linear layer and attention layer are the two components that make up the encoder. All of the original vertices are first embedded using the linear projection, and weighted messages are passed through to the attention layer. Our model's encoder is devoid of a positional encoding module, in contrast to the one found in the Transformer Model.

At equation (18) the initial stage, each input vertex, represented by a d_x-dimensional feature vector, is transformed by a linear layer that maps the node features from $d_x$dimensions to $d_h$dimensions:

$$h_i^0 = W^X x_i + b^X \tag{18}$$

Afterwards, the attention layer—which could have N layers—gets the embedded information. The two sublayers that make up each attention layer are the fully linked feed-forward (FF) layer and the multi-head attention (MHA) layer, which exchanges weighted messages between vertices. Experimental methods including batch normalisation (BN) and skip-connection are applied equation (19,20). The vertex embedding of the outcome of layer $l \in \{1, \ldots, N\}$ is denoted by. And so, we have:

$$\widehat{h_l} = BN^l\left[h_i^{l-1} + MHA_i^l(h_1^{l-1}, \ldots h_n^{l-1})\right] \tag{19}$$

$$h_i^l = BN^l\left(\widehat{h_l} + FF^l(h_i)\right) \tag{20}$$

The forward pass through attention layer is represented by these equations, where the input is h_i^{l-1}, the output is h_i^l after applying the FF layer, and the intermediate result is $\widehat{h_l}$ after the MHA layer. The encoder captures the dependencies and interrelations among vertices in the road network through the stacking of multiple attention layers.

A Multiple Layer Perceptron (MLP) is employed by the decoder part to interpret the data from the encoder. This part is made up of two linear layers. The last output of the decoder, which is a seven-dimensional vector $\vec{v}$ indicating the probability distribution across the possible actions in the road network's action space, represents the output of the policy network.

The final action probabilities are obtained by the decoder by processing the encoded vertex information (h_i^N) through the MLP layers equation (21). The computation of the output $\vec{v}$ is as follows:

$$\vec{v} = MLP(h_i^N) \tag{21}$$

The action with the highest probability is the one that will be chosen as the final option for vertex.

The HHO-Attention algorithm, through the use of an attention mechanism, increases the policy network's capability to identify and represent the interrelation of nodes in a road network. To be more precise, the attention layer that is fused with the encoder part of the policy network allocates varying weights to the vertices in accordance with their significance and connection to the charging stations' location determination. By doing this, the model gains proficiency in locating crucial nodes and coming to well-informed conclusions that take the road network's larger context into account.

The attention-based policy network mentioned above is used in place of the traditional policy network in the HHO-Attention algorithm, which otherwise adheres to the fundamental principles of HHO. While training, the algorithm obtains trajectories through its interaction with the environment, and it also calculates the advantage estimates for all the state, action pairs. After that, the policy network is changed according to the trust, region, constrained advantage estimates which guarantee that the changes in the policy remain within the given limits and, therefore, are stable with respect to changes.

The use of attention mechanisms and reinforcement learning in the HHO, Attention algorithm makes it possible to efficiently solve the problem of the optimal placement of charging stations in road networks with consideration for multiple factors and by understanding the interactions of the different nodes in the network.

5. Experimentation Results

This part of the paper is about the data gathering for the experiments, the experimental results, and the performance comparison of the proposed method with the other leading methods for the optimal positioning of electric vehicle charging stations.

5.1 Data Collection:

The data collection was designed to include various parameters such as total area, population density, the total number of EVs and their percentage increase in each selected state, the number and types of EVSE ports and charging stations, temperature, humidity, cost and source of electricity, EV incentives, traffic flow, and average and median household income in each state.

5.2 Performance Metrics:

The proposed model was put through the test of various performance measures, which included Accuracy, Precision, Recall, F1, Score, ROC curve, mean absolute error (MAE), mean square error (MSE), and root mean square error (RMSE). In this case, the focus is on two classes: positive and negative Fig.2.

TP denotes True Positive examples, FP (False Positive), TN (True Negative), and FN (False Negative) equation (22).

Accuracy:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{22}$$

Here, accuracy metric provides a fraction or ratio- the number of valid placements divided by total number of suggestions.

Recall:

$$Recall = Sensitivity = \frac{TP}{TP+FN} \tag{23}$$

Recall is a metric that determines the number of places that have been correctly selected out of all the suggestions given in the collected data equation (23). It is also referred to as sensitivity.

Precision:

$$Precision = \frac{TP}{TP+FP} \tag{24}$$

Precision represents that the percentage of positive outcome that were estimated correctly as optimal places equation (24).

F1-Score:

$$F1 - Score = \frac{2*Recall*Precision}{Recall+Precision} = \frac{2TP}{2TP+FP+FN} \tag{25}$$

The F1 score or F-measure is a harmonic mean of precise and recall Table 1. It is a standard measure of how robust a system equation (25).

Table 1: Performance metrices

S.No	Metrics	Obtained
1	Accuracy	98.6%
2	Recall	97.6%
3	Precision	99.2%
4	F1-Score	98.7%
5	MAE	0.015
6	MSE	0.017
7	RMSE	0.115

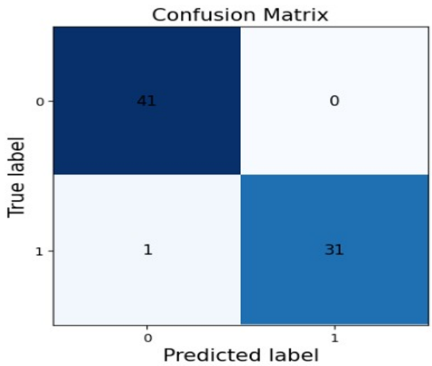

Fig 2: Confusion matrix of the proposed system

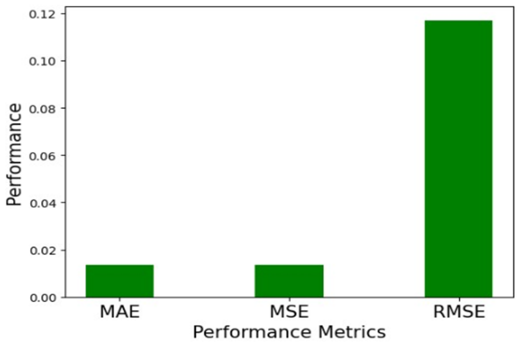

Fig 3: Error metrics

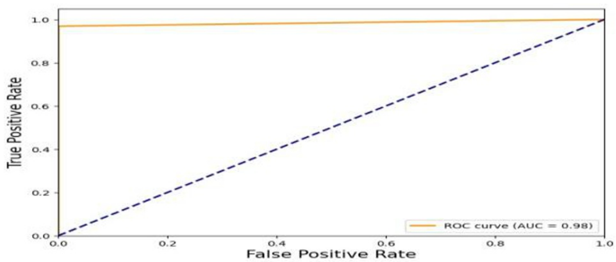

Fig 4: ROC curve

The performance metric values obtained are briefly summarized in table 1. The effectiveness of the system is indicated by the accuracy, precision, recall, and f1, score metrics mainly. The error metrics were illustrated in Fig 3, 4 and showed performance enhancements with the minimum error values. The ROC curve drawn by the TPR and FPR results in an AUC of 0.98. Therefore, all the performance metrics highlight that the proposed system is performing at a high level.

5.3 Comparative Analysis:

Here, the different parameters of the proposed system for placing EVCS with attention and Harris hawk optimization are compared with various previous models. Various metrics such as accuracy, recall, precision, and F1 score have been compared between the present models and the state, of, the, art ones such as SVM, Logistic regression, and KNN.

The confusion matrices of the compared models such as SVM, logistic regression, and KNN are shown in Fig 5, 6 respectively.

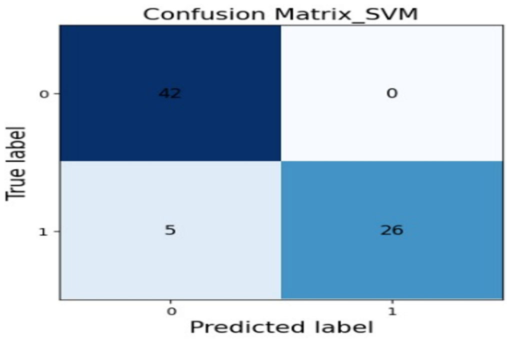

Fig 5: Confusion matrix of the SVM

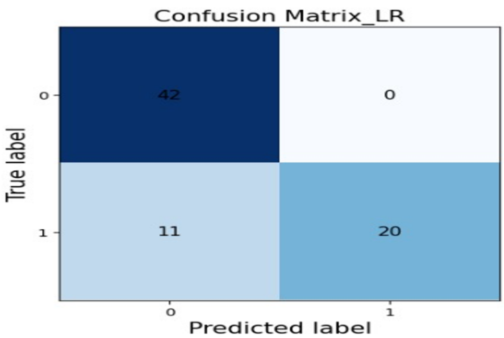

Fig 6: Confusion matrix of the logistic regression

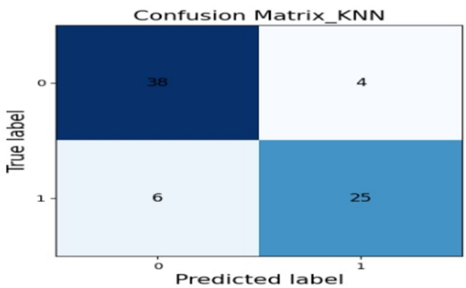

Fig 7: Confusion matrix of the KNN

Using the acquired TP, TN, FP, and FN values, the performance metrics like accuracy, precision, recall, and F1-score of the existing models are calculated for comparative analysis Fig 7.

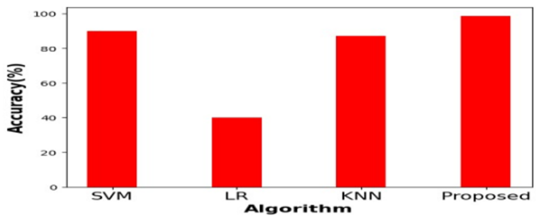

Fig 8: Accuracy comparison

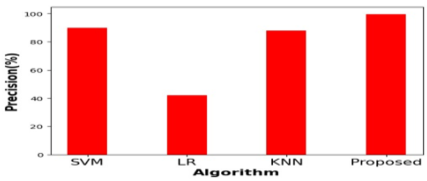

Fig 9: Precision comparison

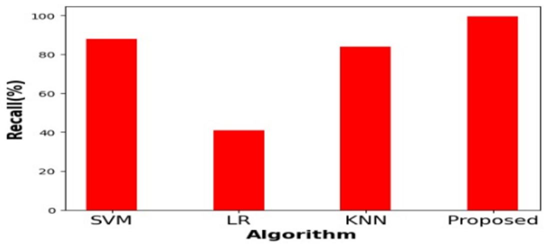

Fig 10: Recall comparison

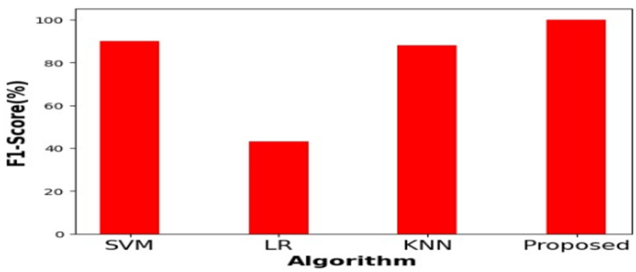

Fig 11: F1-score comparison

Fig 8 show the comparison of the SVM, LR, KNN, and the proposed system in a visual manner. The accuracy comparison is presented in Fig 9. Precision comparison is represented by figure 9. Recall comparison is depicted by Fig 11. The comparison of F1, score is illustrated. As the comparative analysis indicates, the proposed system outperforms the existing models.

6. Conclusion

The strategic planning and optimal placement of EVCS are key factors in increasing charge efficiency, exploiting the use of infrastructure, and bringing more benefits to the society as a whole. We dealt with the EVCS positioning issue in this paper by including several realistic factors, such as the benefits of locations, drivers' waiting and charging times, distribution of network nodes for the purpose of fairness, and operational constraints. We introduced an Attention, based Hybrid Harris Hawk Optimization (HHO, Attention) model to tackle this complicated multi, objective optimization problem. The proposed method, by embedding an attention mechanism into the optimization framework, can very well identify the dependencies between the nodes of the network, thus it can make more intelligent decisions regarding the charging station placement. Testing results tell that the method we propose is far better than the traditional baseline models. The performance measuresAccuracy, Precision, Recall, and F1, Scoreare all more than 98%, quite convincingly pointing to the strength and trustworthiness of the model. Besides that, the error measures (MAE, MSE, RMSE) are all under 0.2, thus pointing to the prediction that is very stable and with a very small deviation. Overall, the proposed HHO-Attention framework provides an efficient, fair, and scalable solution for optimal EV charging station deployment. It holds strong potential for real-world implementation, supporting sustainable transportation expansion and accelerating the transition towards widespread electric mobility.

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