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End User Incentive-based Approach for Fast Charging Station

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***Abstract:* -** The development of electric vehicles (EVs) is influenced by various factors such as cost, autonomy, charging speed, and infrastructure. The objective of this research paper is to model an EV fast-charging station that provides incentives to end users in terms of money. The charging station incorporates a renewable energy source (solar) and an energy storage system, taking into account the demand for EVs, state of charge (SOC), and vehicle arrival and departure times. This approach aims to increase the revenue of the station and reduce the high energy demand from the grid. To incentivize end users, the vehicle-to-grid (V2G) and battery swapping modes have been implemented. The Monte Carlo approach is used to model the demand for EVs and the production of renewable energy, considering hourly intervals. Subsequently, the installation and utilization of the EV fast-charging station (EVCS) are optimized using the Adaptive Harris Hawk Optimization (AHHO) algorithm. The system is analyzed with and without V2G and battery swapping modes. The comparison between the two modes reveals that the system with V2G and battery swapping provides both revenue and incentives to end users.

Keywords: Adaptive Harris Hawk algorithm (AHHO), Battery Swapping (BS), Electric Vehicle (EV), Charging Station (CS).

I. INTRODUCTION

Approximately 64% of the total global CO2 production is contributed by the electricity and transportation sectors, causing increasing concern due to their detrimental impact on the environment. To address this issue, the adoption of electric cars (EVs) and other alternative fuel vehicles (AFVs) presents a practical solution. By harnessing renewable energy sources, we have the potential to substantially reduce emissions from both the transportation and electricity industries [1]. The emergence of the electric vehicle (EV) has brought forth numerous advantages, including decreased reliance on fossil fuels, enhanced performance, and emission-free operation. As a result of the substantial increase in EV ownership, individuals are now considering electric vehicles as a viable option for transportation. However, the insufficiency of charging infrastructure remains a pressing issue that needs immediate attention in the progress of electric vehicles.

Vehicle owners have the option to recharge their electric vehicles at their own residences; however, this method is time-consuming. In order to facilitate the expansion of electric vehicles, it is essential to establish rapid charging stations. While fast charging enables EV batteries to be replenished within approximately 15 minutes, it is important to acknowledge that this approach consumes a significant amount of power and exerts a substantial impact on the grid. To address this concern, the utilization of renewable energy sources and advancements in battery technology can be employed [2]. When deploying EV charging infrastructure in a city, it is crucial to take into account various factors such as the potential locations and their space limitations, the transportation and charging needs of electric vehicles, the behavior of EV owners, and the stability requirements and charging load restrictions of the power grid. Numerous studies and research papers have been dedicated to addressing the challenges associated with the deployment of EV charging infrastructure, and several proposals have been put forward to tackle the issue of charging station placement. To meet as many EV charging requirements as feasible, flow refueling location models have been presented [3]–[5]. When deploying EV charging infrastructure in a city, it is crucial to take into account various factors such as the potential locations and their space limitations, the transportation and charging needs of electric vehicles, the behavior of EV owners, and the stability requirements and charging load restrictions of the power grid. Numerous studies and research papers have been dedicated to addressing the challenges associated with the deployment of EV charging infrastructure, and several proposals

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have been put forward to tackle the issue of charging station placement. To meet as many EV charging requirements as feasible, flow refueling location models have been presented [3]–[5].

Several charging station deployment techniques have been proposed within the limits of the power system to reduce total costs, which include power generation, power transmission loss, and charging station building costs. [3], [5]. Some publications address the issue of EV station placements and even sizing, albeit with oversimplifications about demand and operation. To place rapid-charging stations in a city, the authors [6] used a mixed integer non-linear optimization approach with targets that included expenditures associated with development, electrification, energy loss from EVs, and losses to the electric grid. They didn't account for the arrival time or station occupancy in the simulation; they only took into account the number of EVs would be coming at the station. A multi-objective planning approach for EV charging stations was created by the authors [7] in order to decrease power losses and voltage changes in the distribution system. They did not consider the functioning of price process; instead, they focused on a fixed demand. A lot of designs of EV charging stations have been found in literature in which they have shown a simple consideration of parameter i.e., only solar based, battery based, solar cum battery based, only battery swapping based station. The ideal design of an EV charging station was provided by the authors,[7] in order to reduce the lifecycle cost. They employed Homer software to optimize the process, taking into account renewable energy, grid connectivity, and batteries but ignoring arrival time.

Simple demand models with continuous demand [8] and load profile [7], [9] were used in the development of EV charging stations. These load profiles represent an average value for each hour rather than taking into account the starting and ending time during the charging of each vehicle. The operation of EV charging stations can be modelled in more intricate ways. The authors [10] employed a model, based on an M/M/s queueing theory, which was based on state-transition algorithm [11]. The author [12] employed a cell-transmission traffic model to create an M/M/s backlog, while the authors [13] used real-world traffic statistics. In this paper [9] the authors presented a model based on solar and wind and used MPPT technique.

For operating EV charging stations, complicated approaches have been discovered. In the EV charging process, author aimed to optimize incentives [14], [15] minimized total energy costs for customers For operating EV charging stations, complicated approaches have been discovered. In the EV charging process, author aimed to optimize incentives [14], [15], minimized total energy costs for customers [16], [17], reduced network power losses minimized production costs , reduced network power losses, minimized production costs [22], minimized peak load [1], avoided distribution network congestion [23], or managed frequency [24]. In [25] the authors presented a design of charging station with renewable source and battery storage but did not consider the battery swapping in this design.

The authors presented a charging station design based on the cost model and optimized the location of EVCS based on demand using genetic algorithm. The cost model includes the economic cost (infrastructure cost and fee) and environmental cost (energy consumption cost and CO2 emission cost) [26]. Some researchers have developed a design base on variable pricing to facilitate more incentive for owner of charging station. In this paper [27] authors showed the different studies for charging station, one for fixed pricing and other for variable pricing. When charging station has crowded than price of charging vehicle is increased so that charging station would get more incentive but they did not provide any type of incentive for the user. In this paper [28] authors provided the algorithm based on location. Algorithm provide the incentive based on location of charging station. Distribution system operators provided the incentive for the charging station to fulfil the demand of EV user and maintain the stability of the distribution system. The author suggested an incentive-based scheduling of EV at charging station under uncertainty [29]. In this [30] paper author developed an algorithm based on incentive in term of price and showed that this algorithm would provide better way to utilize the charging infrastructure. In this [30] paper author developed an algorithm based on incentive in term of price and showed that this algorithm would provide better way to utilize the charging infrastructure.

A platform called the Battery Swapping System (BSS) allows for the quick swapping of fully charged batteries within a certain amount of time. The Charging station can last for hours, but in battery swap mode, the EV car driver simply goes to his BSS and uses a mechanical arm to swap the battery pack with a fully charged one. This process only takes a few minutes, regardless of battery capacity. BSS addresses to some extent the trade-off between battery charging speed and cycle life. Using BSS has many other advantages. (1) BSS helps to extend battery life by charging more slowly. (2) BSS helps utilities balance price demands, transmission and distribution (T&D) costs.

The majority of earlier publications have focused on operations or grid effect, with only a handful addressing the architecture of EV charging stations. Since they must change the input data into an optimization tool like Homer, which is not intended to address this type of problem, they did not include the charging dynamic (the arrival time and amount of charge of each electric car) in the design papers. In the literature, lot of issues related to charging station have been pointed out and the lot of solution have been provided for them but very less work is done as far as the EV user ‘concerned.

The novelty of this research paper is as follows:

- This design of fast charging station problem incorporates a wide range of energy sources, including solar, the grid, and energy storage considering the arrival and departure time, soc and battery capacity.
- An Adaptive Harris-Hawks optimization is first time used to optimize the such type of design.
- Investigations are performed and compared with station fed from grid, Station fed from solar and energy storage and station fed from hybrid mode i.e grid, solar and energy storage.
- This study shows the approach toward the end user incentives are proposed for the first time.
- Comparison between with and without use of V2G and Battery swapping at fast charging station is discussed.

The rest of the paper is laid out in the following manner. Section II deals with system description. In Section III, mathematical modelling for designing the EV station is presented. In Section IV, the properties of an adaptive Harris hawk’s optimization are displayed. Finally, in Section V, three situations are examined and compared to demonstrate design changes, and the study is concluded in Section VI.

II. System Explaination

A fast-charging station shown in fig.1 is designed considering detail parameter to provide the revenue to the station owner as well as end user. For extracting the profit to the station owner, a two-way exchange of power, i.e., grid to EV and EV to grid, is considered and to provide the end user benefit, system used the V2G and Battery swapping facility at station. The energy storage with renewable source integrated with grid to increase the benefit of owner. The parameters of renewable (solar), energy storage is optimized by the AHHO algorithm. The EV demand pattern such as arrival line, departure time, waiting time, battery capacity and SOC are considered for further investigations. The goal of this paper is achieved by using (a) station fed by grid only (b) station feed by RES and Battery only (c) station feed by hybrid mode, i.e., grid, RES and energy storage. An AHHO algorithm is used to optimize the system parameter to get revenue and incentive to end user.

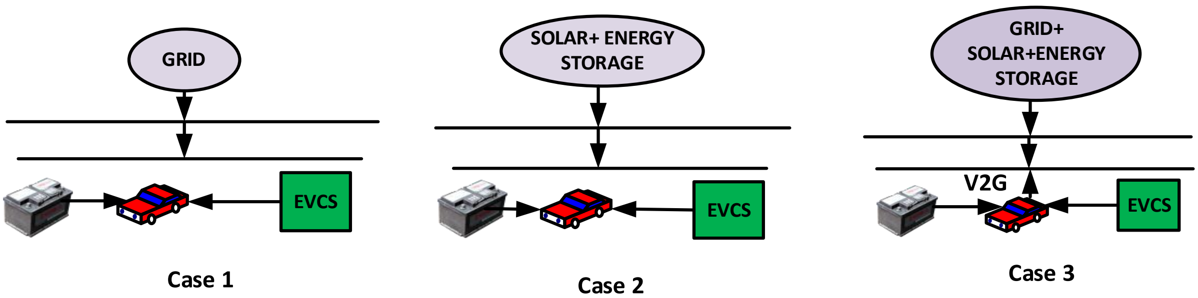

Fig.1 System investigated

III. MATHEMATICAL MODELING OF EVCS

The EVCS under investigation in this study is equipped with a large number of chargers for recharging the batteries of EV users, as well as solar panel and Energy storage system facilities to boost their profitability and lessen their influence on the power grid. The following equations are used in the design of the charging station.

$$Cost\ Function = \sum_{k=1}^{p} \frac{net\ cash\ flow\ at\ year\ p}{(1+r)^k} - S \tag{1}$$

S is Initial investment (€), r= interest rate, k= a year index, p= no. of year considers, 20 years in this case

$$A_k = \sum_{h=1}^{8760} (Income_{hrs} - Expand_{hrs}) - E_k \tag{2}$$

A_k= Net cash flow at year k (€), E_k= replacement and maintenance cost of battery at year k (€).

$$Income_{hrs} = ES_{hrs} \times CE_{hrs} + ESG_{hrs} \times \ CESG_{hrs} + \ CBS_{hrs} \tag{3}$$

$Income_{hrs}$= Income at hour hrs(€), ES_{hrs}= Energy supplied to EV used in hour hrs (kWh), CE_{hrs}= Price of energy in hour hrs (€), ESG_{hrs}= Delivered energy to grid in hour hrs (kWh), $CESG_{hrs}$= Selling price of energy to grid in hour(€), CBS_{hrs}= Price of battery system (€).

$$Expend_{hrs} = ETG_{hrs} \times CETG_{hrs} \tag{4}$$

$Expend_{hrs}$= expenditure at hour (€), ETG_{hrs}= Energy taken from grid in hour, $CETG_{hrs}$= price of enegy taken from grid in hour (€).

$$E_k = \frac{\sum_{h=1}^{8760} EDB_{hrs}}{TEB} \times CB \times CIBS + MCD_k \tag{5}$$

EDB_{hrs}= energy discharged from storage system at hour hrs (kWh), TEB= Total energy of battery during their life cycle (kWh), CB=Price of batteries (€), $CIBS$= nominal capacity of battery system in (kWh), MCD_k= maintenance cost of batteries at year k (€).

Initial investment

$$S = CC \times TNCI \times RPC + CSP \times IASP + \ CBS \times ECIBS \tag{6}$$

CC= Price of charger (€), $TNCI$=Total no. of charger installed, RPC=Power of EV charger, CSP=cost of solar panel (€), $IASP$=Installed area of solar panel in meter^2, CBS=Price of battery system (€), $ECIBS$=Energy capacity of installed battery (kWh).

Energy balance at a charging station at hour h

$$EG_{hrs} + ESP_{hrs} + EDB_{hrs} = ES_{hrs} + ESG_{hrs} + EPB_{hrs} \tag{7}$$

EG_{hrs}=Energy provided by the grid in an hour hrs (kWh), ESP_{hrs}=Energy provided by the solar panel in an hour hrs (kWh), EDB_{hrs}=Energy provided by the batteries in an hour hrs (kWh), ES_{hrs}=Energy supplied to EV in an hour hrs (kWh), ESG_{hrs}=Delivered energy to grid in an hour hrs (kWh), EPB_{hrs}=Energy supplied to batteries in an hour hrs (kWh).

Energy stored in batteries at hour hrs

$$EBSH_{hrs} = EBSH_{hrs-1} + EPB_{hrs} - \ EDB_{hrs} - \ EPBBS_{hrs} \tag{8}$$

$EBSH_{hrs}$=Energy in batteries in an hour hrs (kWh), $EBSH_{hrs-1}$= Energy in batteries in an hrs-1 (kWh), EPB_{hrs} = Energy provided by batteries in an hour hrs. (kWh), EDB_{hrs}= Energy discharged in charging batteries in an hour (kWh), $EPBBS_{hrs}$=Energy provided by the batteries during battery swapping at an hour (kWh).

Condition for power supplied by the installed solar panel

$$PSP_h \le PSP_{install} \tag{9}$$

PSP_h=Power supplied by solar panel in an hour hrs (kW), $PSP_{install}$=Installed power of solar panel (kW).

Condition for power charging and discharging of the batteries

$$PDB_h \le PIB_{install} \tag{10}$$

$$PCB_h \le PIB_{install} \tag{11}$$

PDB_h=power after discharge batteries at an hour hrs (kW), PCB_h=charging power for batteries in an hour hrs (kW), $PIB_{install}$=Rated power of installed batteries (kW).

Condition for energy charging and discharging of the batteries

$$EDB_{hrs} \le ESB_{hrs-1} \tag{12}$$

$$ECB_{hrs} \le ECIBS - ESB_{hrs-1} \tag{13}$$

EDB_{hrs}=energy discharged by the batteries in hour hrs (kWh), ECB_{hrs}= energy charged from batteries in hour hrs (kWh), ESB_{hrs-1}=energy store in batteries in hour hrs-1 (kWh), $ECIBS$=energy capacity of installed battery system (kWh).

Condition for the stored energy in batteries

$$ESB_{hrs} \leq ESB_{hrs-1} \quad (14)$$

$$ESB_{hrs} \geq SOC_{min} \times ECIBS \quad (15)$$

ESB_{hrs}=energy store in batteries in hour hrs (kWh), SOC_{min}= minimum state of charge(p.u.).

Condition for consumed and supplied power from the grid

$$PSG_{hrs} \leq PGCP \quad (16)$$

$$PCG_{hrs} \leq PGCP \quad (17)$$

PSG_{hrs}= power delivered to grid in hour hrs (KW), PCG_{hrs}=power consumed from the grid in hour hrs (KW), $PGCP$= power constraint at grid connection point.

Condition for EV-supplied power at each EVCS Supplier

$$PEV_{hrs} \leq PCH_{install} \quad (18)$$

PEV_{hrs}= power supplied to EV from charger in hour hrs (KW)), $PCH_{install}$= power of charging supplier (KW).

Condition for energy supplied to EV in hour hrs

$$ES_{hrs} \leq MEDEV_{hrs} \quad (19)$$

ES_{hrs}= energy supplied to EV customers at hour hrs (kWh), $MEDEV_{hrs}$= peak energy demand by EV user in hour hrs (KWh).

Condition for waiting time for each EV

$$t_w \leq t_{mw} \quad (20)$$

t_w= waiting time (min.), t_{mw}= maximum waiting time, 0 in this case.

As was already said, the initial step entails estimating the EV usage at the charging station. The number of electric vehicles that arrive at the charging station, as well as their battery size and level of charge, define this EV usage. However, we also assume that there are only a certain number of chargers at the charging station, and then if none is available for a new client, he will leave. This system is known as an Erlang B queuing model or M/M/c/c queuing model shown. The arrival time chosen for this investigation is displayed in Figure 1 as

$$T_A(t) = 1 - e^{-\lambda_{hrs} t} \quad (21)$$

T_A(t)= time between arrivals of two vehicle

λ_{hrs}= time interval between two arrivals or the average arrival time

In the interval [0, 1], a list of random integers is generated, and each number represents the arrival time of the next car to be introduced into the equation (21) parameter t, figure 1-figure 4 provides the sequence's example.

The energy required to charge the battery is determined in the second phase for each car that arrives. The capacity and level of charge of the EV's battery must be determined for this. The vehicle type is linked to the battery capacity. Motorbikes, cars, and vans are thought to be among the vehicles that can arrive at the station.

The EV battery's state of charge (SOC) can be predicted using the following equation

$$SOC = \frac{1}{E\sigma\sqrt{2\pi}} e^{-(lnE-\mu)^2/2\sigma^2} \quad (22)$$

E= initial state of SOC of EV battery, value varies from 0 to 1, average (μ) and typical deviation (σ) of the logarithm of the SOC variable, μ= 3 and σ=0.6.

After calculating the SOC and battery capacity in the third stage, use this simplified formula to calculate the charging time for each vehicle:

$$T_{ch} = \frac{B_c \times (1-SOC)}{P_{ch}} \quad (23)$$

T_{ch}= Charing time (min.), B_c = Battery capacity, P_{ch}= power of charger (KW)

If a new EV shows up when every charger is occupied, it does not wait and is lost. Customers typically do not wait if all of the chargers are filled because the charging intervals are so long and instead move on to the next charging station.

The power for quick charging and supplying is:

$$P_{st} = \sum_{i=1}^{n} P_{ch}, i(t) \tag{24}$$

P_{st}= power of charging station (KW), n= no. of charger

The solar panel power output in an hour can be given by

$$PSP_h = G_i A.\eta \tag{25}$$

Where G_i is the solar irradiance, A is the installed surface, and η the efficiency of the Solar panel Maintaining the Integrity of the Specifications

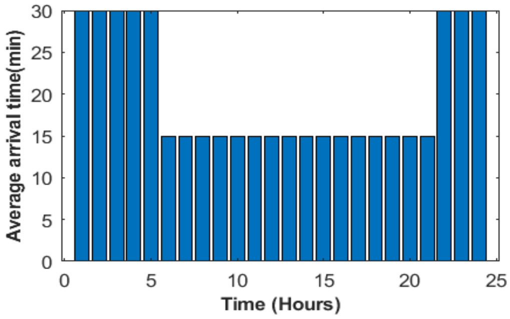

Fig. 1 Average arrival time of EV (min)

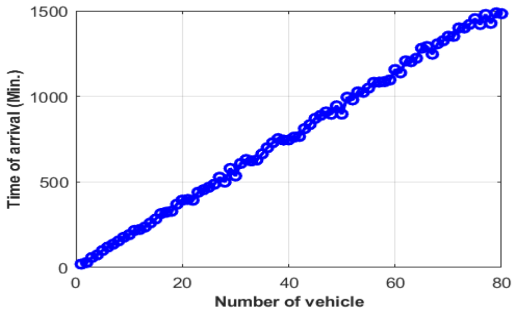

Fig. 2 Time of arrival (min)

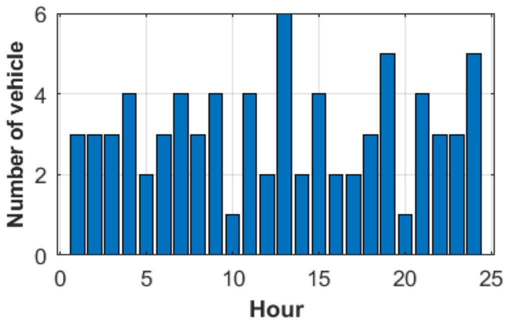

Fig. 3 No. of EV/hour

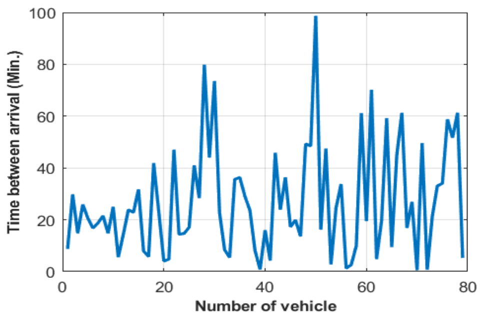

Fig. 4 Time between EV arrivals (min)

Energy prices: In this paper, the distinction in electricity buys and promoting charges because of the phrases stated above changed into computed to be 0.0828 and 0.0022 €/kWh, respectively. The electricity sale fee to electric powered cars changed calculated by including 0.04 €/kWh to the electricity buy fee as a benefit. The vehicles considered are shown in Table 1.

Table 1. Type of Vehicle [25]

Type of Vehicle	Battery capacity (KWh)	Probability (%)	Accumulated probability (%)
Two-Wheeler	3600	0.115	0.115
Small Vehicle	16000	0.370	0.458
Large Vehicle	25000	0.380	0.865
Van	63000	0.135	1

IV. OPTIMIZATION ALGORITHM

In Harris Hawks optimization (HHO) [31], a meta-heuristic approach that is good for optimization, is gaining popularity within its family. In this strategy, when the escape energy is equal to zero, the prey gets exhausted and thus fails to pursue anymore. The stochastic operator in the current technique wastes candidate solutions (Harris Hawk). To overcome this challenge, we propose an adaptive Harris Hawks optimization (AHHO) [32] technique. Except for the mutation interval, the mutation is used in this study to keep the escape energy within the range. Our approach uses average fitness to adaptively determine whether the Harris hawk will sit with the rest of the family or go to a random tall tree.

An AHHO [32] with the premise that, as "no free lunch" (NFL) [33] suggests, no technique is optimal for all classes of problems and that there is always scope for further improvement in search efficacy.

AHHO's modeling and prediction: The adaptive Harris hawks optimization (AHHO) method was created using the basic theory of prey escape energy and the perching technique of the Harris hawk of HHO [31]. The three steps of the AHHO method—exploration, transition, and exploitation—can be expressed mathematically as follows.

Let's define X(t) as the hawks' position vector, the prey position vector $X_{prey}(t)$, $X_{rand}(t)$ as a randomly picked hawk from the existing population at the latest iteration t, and t_{max} is the highest number of iterations.

Exploration phase: The new position of hawks can be obtained by following the equation

$$X(t+1) = \begin{cases} X_{rand}(t) - r_{d1}|X_{rand}(t) - 2r_{d2}(t)| & v \geq 0.5 \\ \big(X_{prey}(t) - X_m(t)\big) - r_{d3}\big(LB + r_{d4}(UB - LB)\big) & v < 0.5 \end{cases} \tag{26}$$

Where r_{d1}, r_{d2}, r_{d3}, and r_{d4} are all random values between 0 and 1. UB seems to be the upper margin of the search area, LB seems to be the lower margin of the search area, $X_m(t)$ is the mean position vector of the present population of k hawks, and $X_{prey}(t)$ is the optimal location of the pray, all of which are updated in each iteration.

$$Xm(t) = \frac{1}{k}\sum_{i=1}^{k} X_i(t) \tag{27}$$

The position of the i^{th} hawk in iteration t is represented by $X_i(t)$.

Let us define the mean fitness (F_{mean}) value of the Harris Hawk search locations $(X_i | i = 1,2,3, \dots \dots \dots k)$ as

$$F_{mean} = \frac{1}{k}\sum_{i=1}^{k} F(X_i) \tag{28}$$

where $F(X_i)$signifies the individual Harris hawk's fitness value

The new search location $X_i(t+1)$ of harris hawks in the exploration phase can be modeled as

$$X_i(t+1) = \begin{cases} X_{rand}(t) - r_{d1}|X_{rand}(t) - 2r_{d2}X_i(t)| & F(X_i) \geq F_{mean} \\ \big(X_{prey}(t) - X_m(t)\big) - r_{d3}\big(LB + r_{d4}(UB - LB)\big) & F(X_i) < F_{mean} \end{cases} \tag{29}$$

Where r_{d1}, r_{d2}, r_{d3}, and r_{d4} are all random values between 0 and 1. UB seems to be the upper margin of the search area, LB seems to be the lower margin of the search area, $X_m(t)$ is the mean position vector of the present population of k hawks, and $X_{prey}(t)$ is the optimal location of the pray, all of which are updated in each iteration.

Transition phases: Harris hawks' foraging behavior is determined by the prey's escape energy, which further determines the exploratory, exploitative, and transition phases. HHO's escape energy is calculated as follows:

$$E = 2E_o\left(1 - \frac{t}{T_m}\right) \tag{30}$$

Where E and E_o refer to the initial prey escaping energy and energy state respectively.
The time-dependent behavior of E_{AHHO} is depicted in Eq. (30), which models the escape energy of AHHO.

$$E_{AHHO} = E_1 \times E_m \tag{31}$$

Where,

$$E_1 = 2\left(1 - \frac{t}{T_m}\right) \tag{32}$$

E_m= mutation energy

Table 2. Limit of optimization parameter

S. No	Description	Lower range	Upper range
1	No charger	1	10
2	Charger power	44	220
3	Area covered by solar panel	0sq. meter	1875 sq. meter
4	Battery capacity	0KWh	500KWh
5	Power transfer to the grid	0Kwh	600Kwh

V. RESULTS AND DISCUSSION

This paper presents a design of algorithm of fast charging station that provide the incentive to EV user as well as incentive to Charging station owner. The design of charging station includes the solar resources, battery storage, grid connection. Lithium-ion batteries with a minimum SOC level of 10%, were investigated for use in the storage system. Table 1 lists the parameters for optimization variables subjected to a constraint given in equations (2- 20) and an objective function given in equation (1) using the adaptive Harris hawk's algorithm.

In this paper, charging station works in two modes, one when charging station charge the EV only in three different case and second when charging station charge the EV as well as using Vehicle to Grid mode and EV battery swapping. By using these two concepts we provide the incentive to the user in term of money and time and same time make the charging system profitable.

Design 1: - When charging station charge the EV only

Case 1: When charging station feeding from grid only

The charging station is connected to the grid only, and it purchases all of its energy from it. The contracted power and the energy consumed are two terms in the energy pricing. The result of this case is shown in table 3.

Case 2: When charging station feeding from solar resource and storage system: The charging station is only connected to solar resources and energy storage system and not connected to grid. Because renewable energy is unpredictable, batteries are placed to ensure the EV station's operation. The design includes constraints for the amount of solar energy that may be placed, which vary depending on the region; in this scenario, the boundaries are listed in Table 3.

Case 3: When charging station feeding from grid, solar resource and storage system

The charging station is powered by a combination of renewable and grid energy. The charging station in this scenario uses renewable energy and is connected to the grid. This is the most adaptable concept because it combines the best of both worlds: low-cost energy from renewable sources and safe grid feeding. It is also possible to sell the extra energy to the grid.

Table 3: Optimal NPV using AHHO for design 1

Case No1	NPV (€)	Investment (€)	PIR (p.u)	IIR (Year)	Cost of Battery Replacement (€)	Cost of Maintenance (€/year)	CBEG (€)	IESG (€)	IESEV (€/year)	ISEBEV
1	69271	88204	0.3679	8	0	1000	10608	0	36725	0
2	90272	104190	0.3368	8	1923.4	1000	0	0	36725	0
3	94396	112250	0.2905	8	1685.8	1000	9765.2	0	36725	0

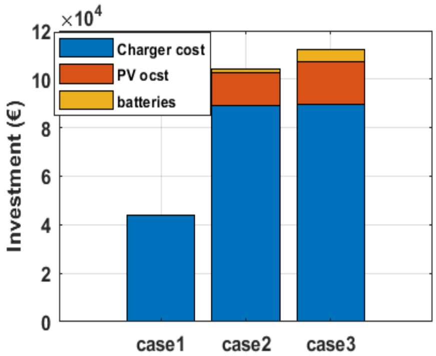

Fig. 5 Investment for all cases

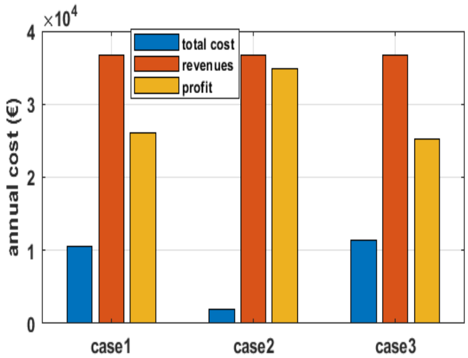

Fig.6 Comparison of annual cost for all cases

Table-4 Optimal configuration for all the cases

Case No	No. of charger	Charger Power (KW)	Solar Surface(m^2)	Battery (KWH)	Grid Power (KW)
1	4	44.232	0	0	83.63
2	4	44.859	272.2	65.5	0
3	4	44.084	462.26	68.799	36.058

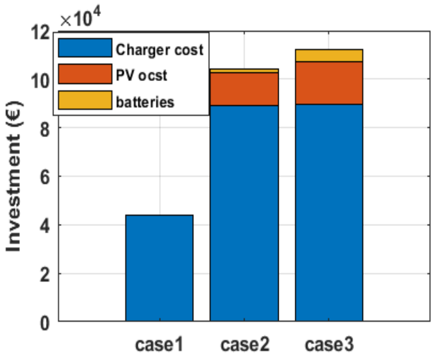

Fig. 5 Investment for all cases

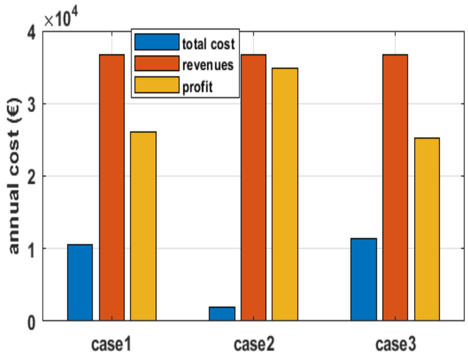

Fig. 6 Comparison of annual cost for all cases

Design 2: - When the charging station charge the EV as well as considering the vehicle to Grid mode and battery swapping.

Case 1: When charging station feeding from grid only.

The charging station is connected to the grid only, and it purchases all of its energy from grid. The supply is utilized for providing the charging of EV and battery. Battery swapping facility will be available at the peak hours. Those EV users will utilize this facility at non peak hour, some incentive will be given to the user. The result of this case is shown in table 5.

Case 2: When charging station feeding from solar resource and storage system.

The charging station is only connected to solar resources as well as energy storage system and not connected to grid. Because renewable energy is unpredictable, batteries are placed to ensure the EV station's operation. The design includes constraints for the amount of solar energy that may be placed, which vary depending on the region; in this scenario, the boundaries are listed in Table 6. In this case battery swapping is also utilized for developing the incentive. The result of this case is shown in table 5.

Case 3: When charging station feeding from grid, solar resource and storage system

The charging station is powered by a combination of renewable and grid energy. The charging station in this scenario uses renewable energy and is connected to the grid. This concept is the most adaptable because it combines the best of both worlds: low-cost energy from renewable sources and safe grid feeding. It is also possible to sell the extra energy to the grid as well as battery swapping also utilized in this case. The result of this case is shown in table 5.

Table 5: Optimal NPV using AHHO for design 2

Case No1	NPV (€)	Investment (€)	PIR (p.u)	IIR (Year)	Cost of Battery Replacement (€)	Cost of Maintenance (€/year)	CBEG (€)	IESG (€)	IESEV (€/year)	ISEBEV (€/year)
1	2069.2	89405	1.2039	9	0	1000	54283	0	190130	15590
2	43935	104340	0.9486	9	38918	1000	0	0	189920	16164
3	25071	100870	1.4087	9	5692.9	1000	29000	16141	200360	16107

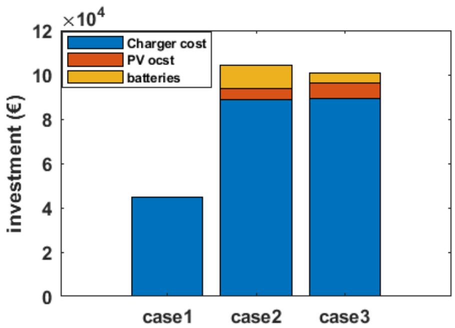

Fig. 7 Investment for all cases

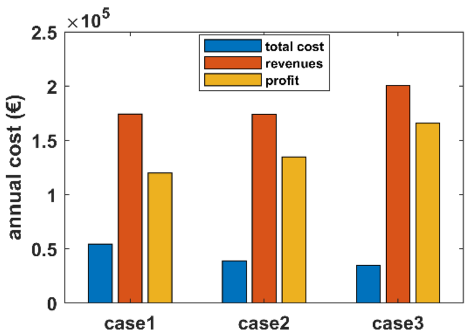

Fig. 8 comparison of annual cost for all cases

Table 6: Optimal configuration for design 2

Case No	No. of charger	Charger Power (KW)	Solar Surface(m^2)	Battery (KWH)	Grid Power (KW)
1	4	44.702	0	0	225.91
2	4	44.483	46.27	71.618	0
3	4	44.553	71.219	75.918	46.482

Design 1

The number of charger and power of charger depend on the demand of EV and these factors are calculated by the optimization technique. The number of chargers is same for both the design in all the case.

In case 1 the grid power is more as compared to case 3. In case 1 only grid is used to feed the charging station and energy is used to charge the EV battery and charge the drain battery of charging battery.

The comparison of case 2 and case 3, the maximum power of installed solar panel is 462.26m2 and battery capacity is 68.79 kwh while in case 2 the power of installed solar panel is 272.2 m2 and battery capacity is 65.5 kwh. In case 2 only renewable source (solar panel) and battery are used to charge the EV battery and drain battery of the charging station. Energy selling to grid and buying from EV owner is zero. The energy that is not sold to EV and not use in battery charging is wasted.

In case 3 provide the solution of case 2 which used the more battery capacity that provide the reliable operation of charging station when renewable source produced less power. In this case station is fed by Grid, renewable source (solar panel) and battery. But dependency on grid supply is reduced in this case. The charging station can sell their energy to EV user only.

According to table 3 and fig. 5, installation cost due to installed capacity and operational cost of case 2 and case 3 is higher than case 1. These costs are compensated easily by operational cost and cost of the energy used. The cost of buying energy from grid in case 1 is 10608 €/year but in case 3 is 9765.20 €/year and in case 2 is zero. In case 1,2, and 3 the cost of selling energy to the grid is 0 €/year. Form this point of view impact on grid, in case 2 is better because all energy is provided from renewable source and energy storage while there is no exchange of energy to or from the grid.

The initial input into the optimization process is the hypothetical demand produced by the EVs at the site of the charging station, which is the same in all three situations. However, the actual demand that each station can meet varies based on the number of chargers that optimization of its design awarded to it as well as the amount of energy that is available at any given time according to the energy supply configuration that optimization assigned to it. Given that case I contains four chargers, some users won't stop until every available charger is taken. case 2 can accommodate more consumers thanks to its five chargers, however occasionally energy shortfalls might arise due to changes in renewable energy. Fig 6 shows the annual equivalent value of all three cases. The high operational cost in Case 1 results in a high overall cost. Due to the fact case 3, has the highest revenue.

Design 2

In case 1 the grid power is more as compared to case 3. In case 1 only grid is used to feed the charging station and energy is used to charge the EV battery and it will charge the drain battery of charging station. The charged battery will be utilized by battery swapping scheme and generate the incentive to station owner and incentive to EV user in term of time.

The comparison of case 2 and case 3, the maximum power of installed solar panel is 462.26 m2 and battery capacity is 68.79 kwh while in case 2 the power of installed solar panel is 272.2 m2 and battery capacity is 65.5 kwh. In case 2 only renewable source (solar panel) and battery capacity is used to charge the EV battery and drain battery of the charging station. The charging station battery can be utilized for battery swapping when required. Energy selling to grid and buying from EV owner is zero. The energy that is not sold to EV and not use in battery charging is wasted.

In case 3 provide the solution of case 2 which is used the more battery capacity that provides the reliable operation of charging station when renewable source produced less power. In this case station is feed by Grid, renewable source (solar) and battery. But dependency on grid supply is reduced in this case. The charging station have the facility of battery swapping for the EV user.

According to table 5 and fig. 7, Installation cost due to installed capacity and operational cost of case 2 and case 3 is higher than case 1. These costs are compensated easily by operational cost and cost of the energy used. The cost of buying energy from grid in case 1 is 54283 €/year but in case 3 is 29000 €/year and in case 2 is zero. In case 1, and 2 the cost of selling energy to the grid is 0 €/year but case 3 is 16141€/year. In case 1,2, and 3 incentives provided to EV user for utilizing the Battery swapping and V2G scheme. Form this point of view impact on grid, in case 2 is better because all energy is provided from renewable source and energy storage while there is no exchange of energy to or from the grid.

Fig 8 shows the annual equivalent value of all three case. The high operational costs in case 1 result in a high overall cost. Due to the fact case 2, has the highest revenue and provides the highest incentive to EV user.

VI. Conclusion

An AHHO optimized the design of EV fast-charging stations using technological and budgetary considerations. This design shows the profitable income for EV user in term of money and time. More realistically modelled EV demand and renewable generation were probabilistic distributions. More information was added to the EV demand model, specifically the arrival time, EV battery capacity, SOC, and the distribution of EVs during the day. An EV charging station can be lucrative, as shown by the three simulated instances. The biggest drawback of EV fast charging is the high-power requirement. To overcome this issue Solar panel is used in the design. Solar Panel can increase a station's profitability, but to balance the intermittent nature of solar energy, it needs to be connected to the grid or have a battery storage system.

The significant focal is technological advancement is trending toward cost reductions, which is extremely interesting in the case of energy storage devices, both for the storage system and for EVs. Both designs have compared with different case. The results show that this design provide incentive to end user and the case 2 of design 2 is provide the optimal incentive to end user.

References

[1] A. Y. Saber and G. K. Venayagamoorthy, "Plug-in vehicles and renewable energy sources for cost and emission reductions," IEEE Trans. Ind. Electron., vol. 58, no. 4, pp. 1229–1238, 2011, doi: 10.1109/TIE.2010.2047828.

[2] G. Mauri and A. Valsecchi, "E N E R G Y S O U R C E S . POWER DEMAND OF FAST CHARGING," 2020.

[3] N. MacHiels, N. Leemput, F. Geth, J. Van Roy, J. Buscher, and J. Driesen, "Design criteria for electric vehicle fast charge infrastructure based on flemish mobility behavior," IEEE Trans. Smart Grid, vol. 5, no. 1, pp. 320–327, 2014, doi: 10.1109/TSG.2013.2278723.

[4] H. Cai, X. Jia, A. S. F. Chiu, X. Hu, and M. Xu, "Siting public electric vehicle charging stations in Beijing using big-data informed travel patterns of the taxi fleet," Transp. Res. Part D Transp. Environ., vol. 33, pp. 39–46, 2014, doi: 10.1016/j.trd.2014.09.003.

[5] A. Awasthi, D. Chandra, S. Rajasekar, A. K. Singh, A. D. V. Raj, and K. M. Perumal, "Optimal infrastructure planning of electric vehicle charging stations using hybrid optimization algorithm," 2016 Natl. Power Syst. Conf. NPSC 2016, 2017, doi: 10.1109/NPSC.2016.7858941.

[6] P. Sadeghi-Barzani, A. Rajabi-Ghahnavieh, and H. Kazemi-Karegar, "Optimal fast charging station placing and sizing," Appl. Energy, vol. 125, pp. 289–299, 2014, doi: 10.1016/j.apenergy.2014.03.077.

[7] 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.

[8] H. J. Vermaak and K. Kusakana, "Design of a photovoltaic-wind charging station for small electric Tuk-tuk in D.R.Congo," Renew. Energy, vol. 67, pp. 40–45, 2014, doi: 10.1016/j.renene.2013.11.019.

[9] H. Fathabadi, "Novel wind powered electric vehicle charging station with vehicle-to-grid (V2G) connection capability," Energy Convers. Manag., vol. 136, pp. 229–239, 2017, doi: 10.1016/j.enconman.2016.12.045.

[10] S. Bae and A. Kwasinski, "Spatial and temporal model for electric vehicle rapid charging demand," 2012 IEEE Veh. Power Propuls. Conf. VPPC 2012, vol. 3, no. 1, pp. 345–348, 2012, doi: 10.1109/VPPC.2012.6422675.

[11] S. Shrestha and T. M. Hansen, "Distribution feeder impacts of electric vehicles charging in an integrated traffic and power network," NAPS 2016 - 48th North Am. Power Symp. Proc., pp. 227–232, 2016, doi: 10.1109/NAPS.2016.7747888.

[12] X. Bai, Z. Wang, L. Zou, H. Liu, Q. Sun, and F. E. Alsaadi, "Electric vehicle charging station planning with dynamic prediction of elastic charging demand: a hybrid particle swarm optimization algorithm," Complex Intell. Syst., vol. 8, no. 2, pp. 1035–1046, 2022, doi: 10.1007/s40747-021-00575-8.

[13] V. Viswanathan, D. Zehe, J. Ivanchev, D. Pelzer, A. Knoll, and H. Aydt, "Simulation-assisted exploration of charging infrastructure requirements for electric vehicles in urban environments," J. Comput. Sci., vol. 12, pp. 1–10, 2016, doi: 10.1016/j.jocs.2015.10.012.

[14] A. Marcos-Pastor et al., "Smart Charging Strategy for Electric Vehicle Charging Stations," IEEE Trans. Transp. Electrif., vol. 4, no. 1, pp. 76–88, 2019, doi: 10.1109/TTE.2017.2753403.

[15] H. Chen, Z. Hu, H. Luo, J. Qin, R. Rajagopal, and H. Zhang, "Design and Planning of a Multiple-Charger Multiple-Port Charging System for PEV Charging Station," IEEE Trans. Smart Grid, vol. 10, no. 1, pp. 173–183, 2019, doi: 10.1109/TSG.2017.2735636.

[16] I. K. A. Aswantara, K. S. Ko, and D. K. Sung, “A Centralized EV Charging Scheme Based on User Satisfaction Fairness and Cost,” pp. 1–4, 2013.

[17] D. T. Nguyen, L. B. Le, C. Nyaruhucha, and H. Laswai, “Joint Optimization of Electric Vehicle and Home Energy Scheduling Considering User Comfort Preference,” IEEE Trans. Smart Grid, vol. 5, no. 1, 2014, doi: 10.1108/NFS-04-2016-0042.

[18] T. T. Nguyen, B. H. Dinh, T. D. Pham, and T. T. Nguyen, “Active power loss reduction for radial distribution systems by placing capacitors and PV systems with geography location constraints,” Sustain., vol. 12, no. 18, 2020, doi: 10.3390/SU12187806.

[19] R. S. Rao, K. Ravindra, K. Satish, and S. V. L. Narasimham, “Power loss minimization in distribution system using network reconfiguration in the presence of distributed generation,” IEEE Trans. Power Syst., vol. 28, no. 1, pp. 317–325, 2013, doi: 10.1109/TPWRS.2012.2197227.

[20] M. Rahmani-Andebili and M. Fotuhi-Firuzabad, “An Adaptive Approach for PEVs Charging Management and Reconfiguration of Electrical Distribution System Penetrated by Renewables,” IEEE Trans. Ind. Informatics, vol. 14, no. 5, pp. 2001–2010, 2018, doi: 10.1109/TII.2017.2761336.

[21] J. Singh and R. Tiwari, “Real power loss minimisation of smart grid with electric vehicles using distribution feeder reconfiguration,” IET Gener. Transm. Distrib., vol. 13, no. 18, pp. 4249–4261, 2019, doi: 10.1049/iet-gtd.2018.6330.

[22] Z. Zhou and T. Lin, “Spatial and temporal model for electric vehicle rapid charging demand,” 2012 IEEE Veh. Power Propuls. Conf. VPPC 2012, vol. 3, no. 1, pp. 345–348, 2012, doi: 10.1109/VPPC.2012.6422675.

[23] S. Huang, Q. Wu, S. S. Oren, R. Li, and Z. Liu, “Distribution Locational Marginal Pricing Through Quadratic Programming for Congestion Management in Distribution Networks,” IEEE Trans. Power Syst., vol. 30, no. 4, pp. 2170–2178, 2015, doi: 10.1109/TPWRS.2014.2359977.

[24] F. J. Soares, P. M. R. Almeida, and J. A. P. Lopes, “Quasi-real-time management of Electric Vehicles charging,” Electr. Power Syst. Res., vol. 108, pp. 293–303, 2014, doi: 10.1016/j.epsr.2013.11.019.

[25] 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. March 2018, pp. 46–58, 2019, doi: 10.1016/j.ijepes.2018.08.001.

[26] G. Zhou, Z. Zhu, and S. Luo, “Location optimization of electric vehicle charging stations: Based on cost model and genetic algorithm,” Energy, vol. 247, p. 123437, 2022, doi: 10.1016/j.energy.2022.123437.

[27] E. S. Rigas, E. H. Gerding, S. Stein, S. D. Ramchurn, and N. Bassiliades, “Mechanism Design for Efficient Offline and Online Allocation of Electric Vehicles to Charging Stations,” Energies, vol. 15, no. 5, pp. 1–25, 2022, doi: 10.3390/en15051660.

[28] S. W. Park, K. S. Cho, G. Hoefter, and S. Y. Son, “Electric vehicle charging management using location-based incentives for reducing renewable energy curtailment considering the distribution system,” Appl. Energy, vol. 305, no. September 2021, p. 117680, 2022, doi: 10.1016/j.apenergy.2021.117680.

[29] Y. Zhou, R. Kumar, and S. Tang, “Incentive-based distributed scheduling of electric vehicle charging under uncertainty,” IEEE Trans. Power Syst., vol. 34, no. 1, pp. 3–11, 2019, doi: 10.1109/TPWRS.2018.2868501.

[30] 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, 2020, doi: 10.1016/j.rser.2019.109618.

[31] A. A. Heidari, S. Mirjalili, H. Faris, I. Aljarah, M. Mafarja, and H. Chen, “Harris hawks optimization: Algorithm and applications,” Futur. Gener. Comput. Syst., vol. 97, pp. 849–872, 2019, doi: 10.1016/j.future.2019.02.028.

[32] A. Wunnava, M. K. Naik, R. Panda, B. Jena, and A. Abraham, “An adaptive Harris hawks optimization technique for two dimensional grey gradient based multilevel image thresholding,” Appl. Soft Comput. J., vol. 95, p. 106526, 2020, doi: 10.1016/j.asoc.2020.106526.

[33] David H. Wolpert and William G.Macready, “No free lunch theorems,” Nat. Comput. Ser., vol. 1, no. 1, pp. 287–322, 2020, doi: 10.1007/978-3-662-62007-6_12.