Optimal Parameter Allocation in Renewable Energy Sources Integrated Fast Charging EV Station considering hGPS Algorithm

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ABSTRACT

A maiden attempt has been made to propose the detailed modelling of fast charging electrical vehicle (EV)stations connected to a hybrid grid-renewable energy source (RES like solar, mini-hydro, and wind) system considering EV demand characteristics and arrival time, departure time, state of charge and battery capacity. This helps achieve the maximum profit and reduce energy demand from the grid. Simulations are performed with a novel meta-heuristic algorithm named by hybrid genetic with pattern search (hGPS) algorithm for the first time. They are used for optimizing the charging station's system parameters, which maximize the net present value (NPV). The investigations are performed by the probabilistic distribution of the EV demand based on EV behaviours and is simulated with the sequential Monte-Carlo method by considering hourly intervals. The obtained economic considerations using hybrid genetic with pattern search (hGPS) algorithm are compared with Genetic Algorithm (GA), Pattern Search (PS) algorithm and are observed that hybrid genetic with pattern search (hGPS) maximizes the profit over others. It is also evident that with the proposed method, the power transferred capacity limit among system network and grid reduces the impact of the grid on the system network.

Keywords: EV, Genetic Algorithm (GA), hybrid grid-RES, hybrid genetic with pattern search (hGPS) algorithm, NPV, pattern search (PS) and RES

Nomenclature:

Pph_{hr}	Supplied power for PV (kW)	$Qcharge$	Charger numbers installed
$Esoc_{hr-1}$	Level of energy in storage hour-1(kWh)	h	hour
$Eg2s_{hr}$	consumed energy from grid at hour hr (kWh)	Ew_{hr}	Energy supplied by wind generators (kWh)
$Pcharge_{inst}$	Rated power of fast charging EV station (kW)	SOC_{min}	Minimum SOC (p.u)
Pgc_{max}	Limit of power in connection point (kW)	Pw_{inst}	Rated power of wind generator installed (kW)
$EDstorage_{hr}$	Discharged energy from storage (kWh)	Eev_{hr}	Supplied energy to EV (kWh)
$Cmstorage$	cost of maintenance of storage system (€/year)	$CRMt$	maintenance & replacement of storage system (€)
$Cbuy_{hr}$	buying price in the electrical market at hour	Cw_k	Wind generator (k) cost (€)
$Pstorage_{inst}$	Power rating of storage system (kW)	SOC	State of Charge
nw	No. of types of wind generators	$Pg2s_{hr}$	Grid power consumed (kW)
$Ccharge$	charger cost (€)	$Csale_{hr}$	Selling price at electric market in hour hr (€)

$Ps2g_{hr}$	Supplied power to grid (kW)	Qw_k	No. of types k of wind generator
Spv_{inst}	Surface area of installed PV (m^2)	tev_{max}	Maximum waiting time for every vehicle
$Esoc_{hr}$	Level of energy in storage (kWh)	I	Initial investment
$Es2g_{hr}$	Supplied energy to grid (kWh)	j	Interest rate
$Cinflow_{hr}$	Cash inflow at hour (€)	Cs_{hr}	Station energy price at hour hr (€)
Pw_{hr}	Supplied power for wind generator (kW)	$PDstorage_{hr}$	Discharging power for storage system (kW)
$Pdischarge_{inst}$	Rated power of discharging from EV station (kW)	$PCstorage_{hr}$	Charging power for storage system at hour hr (kW)
tev_k	waiting time of vehicle (sec)	t	Duration (in year)
NPV	Net present value(€)	NCF_t	Net cash flow in year t (€)
$Estorage_{inst}$	Nominal energy capacity of BSS (kWh)	$ETHstorage_k$	Total energy of batteries k (kWh)
$Coutflow_{hr}$	Cash outflow at hour (€)	$C_{storage}$	Storage system cost (€/kWhr)
C_{pv}	cost of PV panel(€/m^2)	$ECstorage_{hr}$	Charged energy from storage (kWh)
Eph_{hr}	Supplied energy by PV (kWh)	$EMAXev_{hr}$	Maximum demanded energy among EVs (kWh)
y_k	Binary decision variable	GA	Genetic Algorithm
$hGPS$	Hybrid genetic with pattern search algorithm	PS	Pattern Search algorithm

I. INTRODUCTION

The rapid increase in carbon footprint and its global impact on the environment led to the exponential growth in electric vehicles (EV)s. EVs play a significant role in reducing global warming and escorts green energy. The lack of infrastructure due to the fast charging of EVs possesses a latent burden on load demand and impacts on the grid [Tan *et al.* 2016]. Integration of renewable energy sources (RES) to the grid addresses this problem. The authors proposed a method that minimizes the losses by peak load shaving considering coordinating EV charging/discharging [Kriekinge *et al.* 2021]. An optimally coordinated charging pattern can also minimize this loss through a stochastic programming technique. Based on the EVs availability, [Nimalsiri *et al.* 2021] discussed a real-time scheduling EVs method for minimizing power and voltage drop in residential premises. [Zheng *et al.* 2021] designed a user-oriented V2G scheme with different modes of operation to encourage more EV users to participate in coordinated V2G charging. The above studies reduced the power losses but didn't concentrate on reducing the power consumption from the grid, which provides scope for further investigations.

[Tushar *et al.* 2016] proposed a method that concentrates on reducing the total energy cost of an EV. [Zhou *et al.* 2020] proposed a coordinated charge scheduling optimization model to minimize the peak load valley difference based on different charging modes of EV. [Hashim *et al.* 2021] modelled an intelligent priority-based V2G charging mechanism that minimizes the load power using peak load shaving and valley filling. [Yin *et al.* 2021] developed an algorithm for optimal charging of EV scheduling, pricing, and energy storage to extract the profits of charging stations. [Mousavi *et al.* 2016] presented a method for optimal EV charge scheduling modelling framework to investigate the impact on energy loss in a distributed system. However, the above studies did not consider the maximum utilization of renewable energy sources.

Further, the studies are not focused on the sizing of the renewable station, which provides scope for further investigations. Authors in [Iacobucci *et al.* 2019, Wang *et al.* 2013] discussed the problems in sizing and allocation of EV charging stations considering constant demand. [Eldeeb *et al.* 2018] presented a MOF methodology that aims at maximizing the revenues of the solar-based EV station while minimizing the BESS capacity. Authors in [Yue *et al.* 2016] demonstrated the sizing of EVCS, but they did not consider various energy sources and the sizing of EVCS. The authors considered constant demand in the above cases but did not focus on the probabilistic hourly distribution of EV demand characteristics such as arrival time, waiting time, departure time, EV battery capacity, and battery state-of-charge (SOC). Further, the studies with EVCS and BSS operational costs are not included.

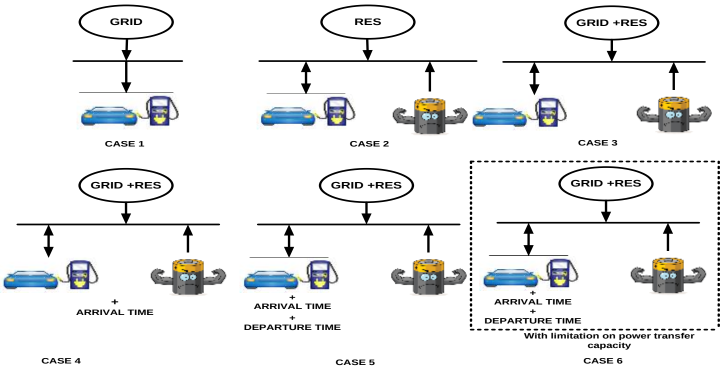
A multi-objective optimization technology for charging/discharging EV is proposed using a genetic algorithm [Merhy *et al.* 2020]. An optimal power flow-based energy management strategy is proposed in [Khan *et al.* 2019] to improve the effectiveness of a fast-charging station on the grid. In [Iacobucci *et al.* 2019], the authors designed an optimal EVCS that minimizes the EVs life cycle considering RES and BSS. [Koufakis *et al.* 2020] proposed a virtual demand technique for increasing the EV demand to maximize the storage of EV energy for vehicle-to-vehicle integration. However, the authors in the above literature did not consider the detailed modelling of EVCS/system network parameters such as solar surface area, generated mini-hydropower, EVCS battery capacity, number, and type of wind generators. Further, the system network parameters are not optimized to maximize profits. Optimum parameters can be obtained by traditional and bio-inspired algorithms like gradient search, direct stick at local optima, and takes more iterations which provides suboptimal results. Bio-inspired or evolutionary algorithms (EA) take less iteration with faster convergence [N. Ram Babu *et al.* 2019]. EA's like particle swarm optimization [Kennedy et al. 2010], genetic [Bashash *et al.* 2011], the sparrow search algorithm [Raghav *et al.* 2022], bilayer optimization [Yang *et al.* 2021], etc., are utilized for optimization of SOC, EVs charging rate and system components. A new hybrid algorithm named by hybrid genetic with pattern search (hGPS) [Lok *et al.* 2017] is available in the literature, which provides scopes for finding the optimal parameters that lie out of the range, which helps in finding system network optimal parameters.

From the literature review, the research objectives of this work are:

a. A realistic hybrid grid-RES (solar, mini-hydro, and wind) based EV fast-charging stations considering EV demand characteristics are proposed for the first time.
b. The system parameters are optimized by hybrid genetic with pattern search (hGPS) algorithm and are compared with Genetic Algorithm (GA), Pattern Search (PS) algorithms.
c. Investigations are performed and compared among EVs fed by the grid, EVs fed by RES, and hybrid grid-RES system.
d. The performance indices of the proposed station (state of charge (SOC), battery capacity, arrival and departure time on grid demand with NPV maximization) are examined, and the effect of maximum power transfer capacity limit on the power station is also studied.

II. SYSTEM DESCRIPTION

A new hybrid grid-RES system shown in Fig. 1(b) is designed with the detailed modelling of EVCS to extract maximum profits shared among the EV owners and grid. A two-way exchange of power, i.e., selling energy from grid to EV and vice versa, is considered. BSS-based RES systems such as solar, mini-hydro, and wind stations are integrated with the existing grid system to maximize the use of RES. The RES system parameters such as solar surface, mini-hydro power generated, battery capacity, type, and a number of wind generators are optimized by considering hybrid genetic with pattern search (hGPS) algorithm. Further investigations are carried with a probabilistic hourly distribution of variable EV demand behavioural characteristics such as arrival time, departure time, waiting time, EV battery capacity, and battery SOC. The stated objectives are fulfilled by considering EVCS detailed modelling (i) with grid feeding EV station, (ii) with RES feeding EV station, (iii) with hybrid grid-RES and BSS for feeding EV station (iv) system in (iii) with EV behavioural characteristics like arrival time, (v) system in (iv) with departure time, and (vi) system in (v) with the limitation on power transfer capacity. The case studies investigated are shown in Fig.1(a). Investigations are carried by optimizing system parameters with a hybrid genetic with pattern search (hGPS) algorithm to maximize the use of RES and extract profits with less maintenance and operational costs.



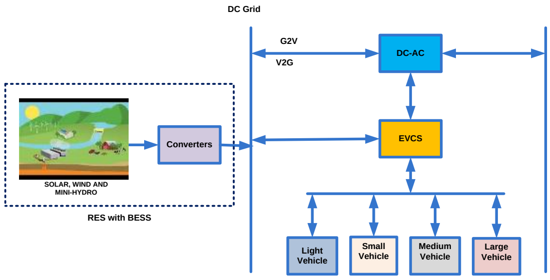


Fig.1(a) **Fig.1 (b)**

Fig.1: The proposed EVCS system. (a) System investigated (b) The hybrid grid-RES system

III. MATHEMATICAL MODELLING OF EVCS

The proposed hybrid grid-RES system with BSS works on the detailed modelling of EVCS. The data models of EVCS are mentioned below.

Calculation of EV demand&Time of Arrival: EV demand is calculated by considering the charging station with a finite number of chargers and depends on the EV behavioral characteristics such as arrival time, departure time, battery capacity, and SOC. The power required to charge the EVs from the grid depends on the arrival time of EVs at the charging station with battery SOC. The arrival time can be determined by modulated poisons formula [Kim *et al.* 2017] and is given by (1).

$$ta_h(x) = 1 - e^{-\lambda x} \tag{1}$$

where, *ta* is the arrival time between two consecutive vehicles, hour (h) and arrival rate or average arrival time is λ. Fig.2 shows the average arrival time of the investigated system with Sequential Monte Carlo method [Peng *et al.* 2012].

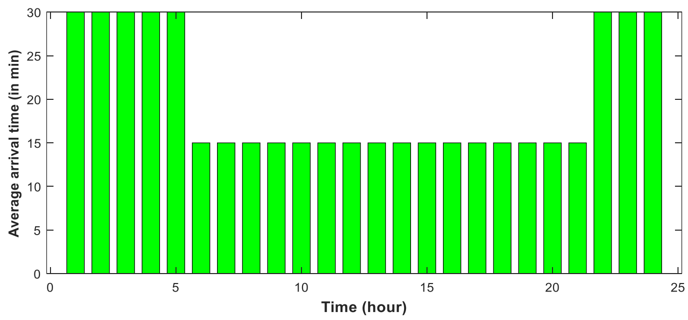


Fig.2. Average arrival time of an EV

Time of Departure: The departure time (D_t^{AM}) of an EV during AM follows a location hourly scale distribution and is given by equation (2) [Zhou *et al.* 2018].

$$f_D^{AM}(x_D^{AM} / \mu_D^{AM}, \sigma_D^{AM}, \nu_D^{AM}) = \frac{\Gamma((\nu_D^{AM}+1)/2)}{\sigma_D^{AM}.\sqrt{\nu_D^{AM}\pi}.\Gamma(\nu_D^{AM}/2)}\left[\frac{\nu_D^{AM} + ((x_D^{AM} - \mu_D^{AM})/\sigma_D^{AM})^2}{\nu_D^{AM}}\right]^{-((\nu_D^{AM}+1)/2)} \tag{2}$$

where, $f_D^{AM}(\mathrm{x}_D^{AM} / \mu_D^{AM}, \sigma_D^{AM}, \nu_D^{AM})$ is the probability distribution function of D_t^{am}, gamma function $\Gamma(.)$. Parameters like shape (v_D^{AM} = 2.16), location (μ_D^{AM} = 8.36) and scale ($\sigma_D^{AM} = 1.08$) are obtained from Monte-Carlo simulation.

The departure time (D_t^{PM}) of an EV during PM follows a normal distribution and is given by

(3): $$f_D^{PM}(\mu_D^{PM}, \sigma_D^{PM}) = \frac{1}{\sigma_D^{PM}\sqrt{2\pi}} . e^{(-(x_D^{PM} - \mu_D^{PM})^2/(2\sigma_D^{PM})^2} \quad (3)$$

where, expectation (μ_D^{PM} = 18.36) and the standard variance ($\sigma_D^{PM} = 2.08$) are obtained from Monte –Carlo simulation.

EV Battery SOC: The EVs battery capacity and its SOC determine the time required to charge the battery of each arriving vehicle. The battery capacity varies with the type of vehicle. The present work comprises of light EVs (motorbikes with 3.6KWh), small EVs (cars with 16KW), medium (large private cars with 25KWh) and large EVs (buses and trucks with 63KWh) [Chang *et al.*2013]. The SOC of an EV battery is given by:

$$SOC(S : \mu_{SOC}, \sigma_{SOC}) = \frac{1}{s\sigma_{SOC}\sqrt{2\Pi}} e^{-(\ln S - \mu_{SOC})^2 / 2\sigma_{SOC}^2} \quad (4)$$

where, deviation ($\sigma_{SOC} = 0.8$) and average ($\mu_{SOC} = 3$) with initial SOC as 'S' varies from 0 to 1 [Peng *et al.* 2012].

EV battery capacity: A set of random number is chosen from interval [0, 1] with the accumulated probability for obtaining the vehicle type arriving at the EVCS in order to obtain the maximum battery capacity. The battery capacity can be calculated by open circuit voltage method discussed in [Shen *et al.* 2014]. Another set of random number for every arrival of EV is introduced for parameter S of (4) for obtaining the battery SOC. With the obtained SOC, battery capacity (B_c) and charging power (P_c) of the EVs that are distributed to the EVCS, the charging time (T_c) can be computed and is given by: $$T_c = \frac{B_c \times (1 - SOC)}{P_c} \quad (5)$$

By considering the P_c and the chargers number (n) in use, the EVCS power demand is given by: $$P_{station}(t) = \sum_{m=1}^{n} P_{c,\mathrm{m}}(\mathrm{t}) \quad (6)$$

IV. GENERATED RES POWER:

Power Generated from PV: The solar or PV panels collect the heat energy from sun and convert to DC current which is stored in battery. Maximum solar power can be extracted by MPPT control of a converter. The hourly output power of the PV panels is given by (7) [Eldeeb *et al.* 2018].

$$P_{PV}(t) = \eta_{PV} A_{PV} G_T (1 - 0.005(T_a - 25)) \lim_{x \to \infty} \quad (7)$$

where, G_T is global solar irradiance, the installed PV array surface area of the (A_{PV}), η_{PV} is the efficiency and T_a is the air temperature.

Power Generated from Wind: Wind energy is generated from wind turbines through aerodynamic motion of rotor blades. The velocity of wind varies from (2-15) m/s and is used to generate electricity. Velocity of wind (v) depends on parameters such as scale (c), shape (k) and the location that are to be calculated and given by: $P(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} \times e^{-\left(\frac{v}{c}\right)^k}$ (8)

$$C = V_m \times \left(0.568 + \frac{0.433}{k}\right)^{-1/k} \quad (9)$$

Using Weibull distribution [Jayaraj *et al.* 2018] hourly wind speed is calculated by (p) and is given by: $v = -c\left[\ln(1 - p)\right]^{1/k}$ (10)

Power Generated Mini-Hydro: Hydro power is generated from water by passing it through hydraulic turbine at high speed. This turbine converts mechanical to electrical energy. The hydro generator consists of a Permanent Magnet synchronous generator with a cross flow water turbine and a DC-DC converter. The green energy produced from the mini- hydro power generator is used by the EVs for charging with an aim to convert the water pressure into electric power. The power equation of hydro turbine is given by (11) [Das *et al.* 2018]

$$P_{HT} = \frac{1}{2}\rho C_p S w^3 \quad (11)$$

where, density of the water is ρ, C_p is co-efficient of power, S is the swept surface area and w is the rate of water flow. The turbine shaft torque T_t with turbine shaft rotational speed (Ω_T) is given by: $T_t = \frac{P_{HT}}{\Omega_T}$ (12)

V. PROBLEM FORMULATION

For modelling an EVCS, the network system parameters such as (i) number of chargers, (ii) chargers rating, (iii) installed RES power, (iv) power of storage units, (v) energy of the storage unit, (vi) grids contracted power to feed EVCS are taken into consideration. The EV chargers not only feed the batteries of EV but also fill the batteries of RES and storage units. The charging station behaviour is calculated for 8760 hours in a year. The main objective of this model is to maximize the profit of the EVCS, keeping the net cash inflows and outflows along with the maintenance cost, replacement cost, and the initial investment over 20 years is given by (13).

$$NPV = \sum_{t=1}^{n} \frac{\sum_{hr=1}^{8760} (\mathrm{Cinflow}_{hr} - Coutflow_{hr}) - (CRM_{t})}{(1+j)^{t}} - I_{initial} \quad (13)$$

where, the equations for cash inflow, cash outflow, CRM and investment (I) are given by (14 - 17) respectively

$$C\inf low_{hr} = Eev_{hr}.Cs_{hr} + Es2g_{hr}.Csale_{hr} \quad (14)$$

$$Coutflow_{hr} = Eg2s_{hr}.Cbuy_{hr} \quad (15)$$

$$CRM_{t} = \frac{\sum_{hr=1}^{8760} EDstorage_{hr}}{ETHstorage}.Cstorage.Estorage_{inst} + Cmstorage \quad (16)$$

$$I_{initial} = Ccharge.Ncharge.Pcharge_{inst} + \sum_{k=1}^{nw} (Cw_{k}.Qw_{k}.y_{k}) + \mathrm{Cpv.Spv}_{inst} + Cstorage.\mathrm{ECstorage}_{inst} \quad (17)$$

The Energy balance equation of the system is given by (18).

$$Epv_{hr} + Ew_{hr} + Eh_{hr} + Eg2s_{hr} + EDstorage_{hr} = Eev_{hr} + Es2g_{hr} + ECstorage_{hr} \quad (18)$$

The objective function is subjected to the following constraints and they is given from equation (19) to equation (27):

$$Esoc_{hr} = Esoc_{hr-1} + ECstorage_{hr} - EDstorage_{hr} \quad (19)$$

$$Pw_{hr} \le Pw_{inst},\ Ppv_{hr} \le Ppv_{inst},\ Ph_{hr} \le Ph_{inst} \quad (20)$$

$$PCstorage_{hr} \le Pstorage_{inst} \quad \text{and} \quad PDstorage_{hr} \le Pstorage_{inst} \quad (21)$$

$$EDstorage_{hr} \le Esoc_{hr-1} \quad \text{and} \quad ECstorage_{hr} \le Estorage_{inst} - Esoc_{hr-1} \quad (22)$$

$$Esoc_{hr} \le Estorage_{inst} \quad \text{and} \quad Esoc_{hr} \ge SOC_{\min}.Esto_{inst} \quad (23)$$

$$Ps2g_{hr} \le Pgc_{\max} \quad \text{and} \quad Pg2s_{hr} \le Pgc_{\max} \quad (24)$$

$$Pev_{hr} \le Pcharge_{inst} \quad \text{and} \quad Pev_{hr} \ge Pdischarge_{inst} \quad (25)$$

$$Eev_{hr} \le E\max ev_{hr} \quad (26)$$

The wait time limit is considered based on the arrival and departure time of an EV and is given by (27). The arrival time of EV in a day and number of EVs per hour is shown in Fig. 3(a) and 3(b), respectively.

$$tev_{k} \le tev_{\max} \quad (27)$$

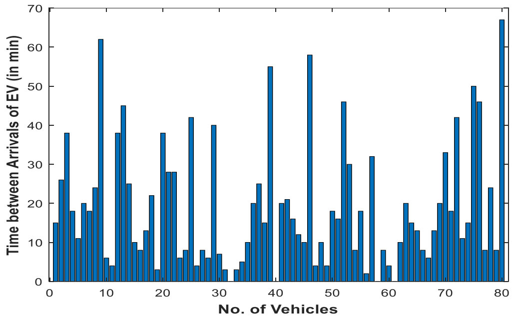


Fig.3(a)

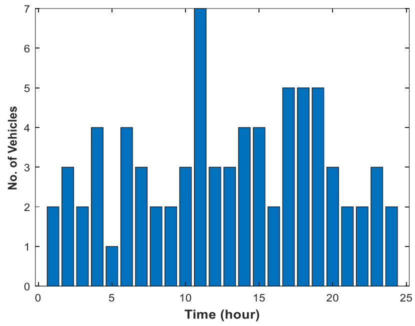


Fig.3(b)

Fig.3: Arrival of EVs in the EVCS (a) Time of arrival of EVs in a day (b) EVs per hour

Fig.4. shows the detailed model of the methodology, where the research hypothesis and the steps to reach the research objectives of the paper are completely visualized.

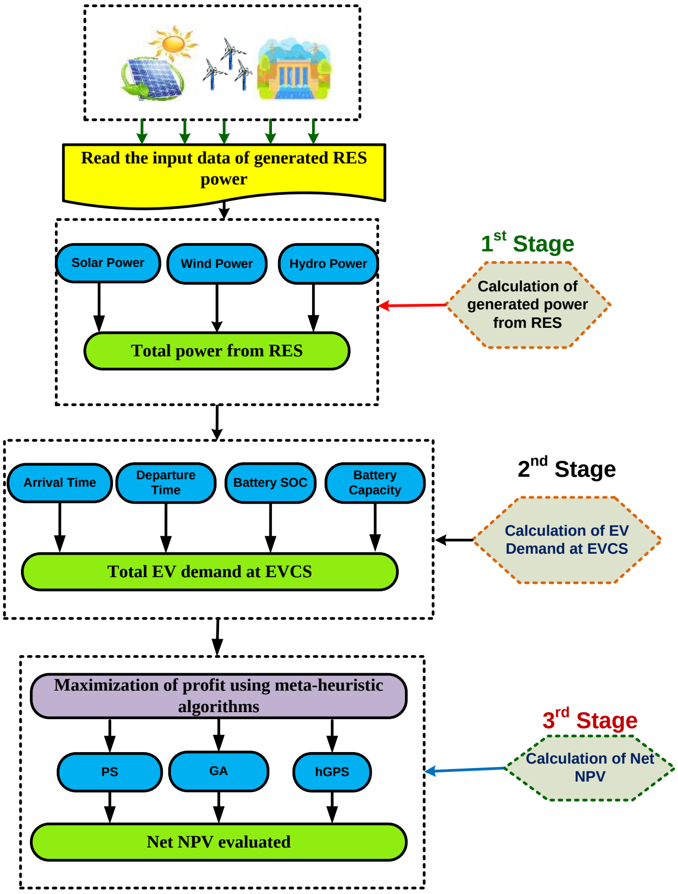


Fig.4. Three-layer energy management of EVCS framework

VI. OPTIMIZATION ALGORITHMS

Optimization algorithms are mainly used to solve real-time problems. In the present study, optimization techniques are required to maximize the net profit from the EVs and reduce the demand on the grid from equation (13). Further, they are also used to optimize the system parameters such as the number of EV chargers, power rating of EV chargers, number and type of wind generators, solar surface area, charger battery capacity, and power ratings of generating stations.

Genetic algorithm: Genetic Algorithms (GA's) are the evolutionary ideas of genetics and natural selection with the "survival of the fittest." They are flexible and robust in approach and are used in a wide range of optimization problems [McCall et al.]. The main components are encoding of the chromosome, fitness function, recombination, selection, and scheme of evolution. In this study, the initialization of the population is done using details of system parameters subjecting to constraints set from equation (14 - 27). Finally, the fitness function is calculated using equation (13), and the optimum parameters are saved.

Pattern search algorithm: [Dolan *et. al*] has proposed a pattern search (PS) algorithm for solving various optimization problems whose scope lies outside the optimization. It consists of a balanced and flexible operator that helps inculcate global optima values so that local optima values can be tuned. It selects a path of points in a series that may or may not lie in the optimum range. In this algorithm, the initialized points in the mesh are given byY_0 [0, 1], Y_0 [1, 0], Y_0 [−1, 0], and Y_0 [0, −1] subjected to constraints set from equation (14 – 27). Then, the fitness of the population is evaluated using equation (13) and sorted accordingly. Finally, updating the current point with the best fitness solution saved the obtained optimum parameters.

Hybrid genetic with Pattern search algorithm: This algorithm is implemented by taking the best output solution by the genetic algorithm (GA) and feeding it into the pattern search (PS) algorithm [Lok *et al.* 2017]. The computation steps in Hybrid genetic with Pattern search algorithm (hGPS) are shown by the flowchart in Fig.5.

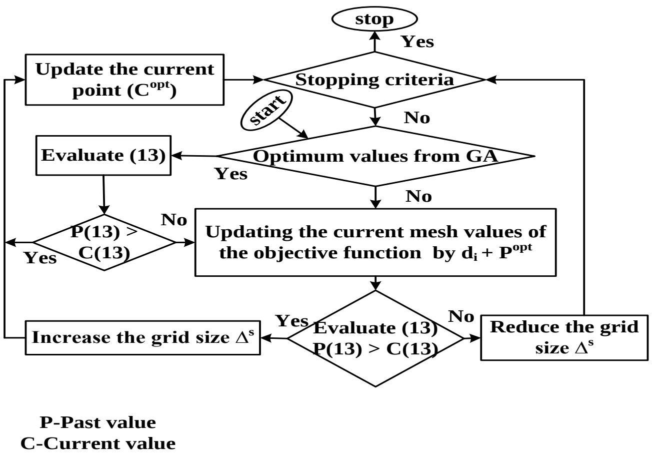


Fig.5. Flow chart of hGPS algorithm

VII. RESULTS AND DISCUSSION

The proposed research presents a model that optimizes the design of EVs. The EV data modelling with RES (wind, mini-hydro, and solar) and BSS. A battery system like Li-ion batteries with a SOC of 10% is considered. The parameters for optimization variables subjecting to a set of constraints given in equation (14 - 27) with objective function given by equation (13) considering various algorithms like Genetic Algorithm (GA), Pattern Search (PS) algorithm, and hybrid genetic with pattern search (hGPS) are tabulated in Table-1. The investigations are conducted at an hourly interval for a year. The simulations are performed in Matlab-2020a software.

Case study I: when grid feeding the EV station only: In this study, EVCS is connected with the grid (Fig.1(a)-Case-1), i.e., the energy required for the EVs are asserted from the grid only, and its energy prices are taken from Fig.6. The investigation results of genetic algorithm (GA), pattern search (PS) algorithm, and hybrid genetic with pattern search (hGPS) are listed in Table-2, and it is observed that the NPV with hybrid genetic with pattern search (hGPS) algorithm earns a maximum profit.

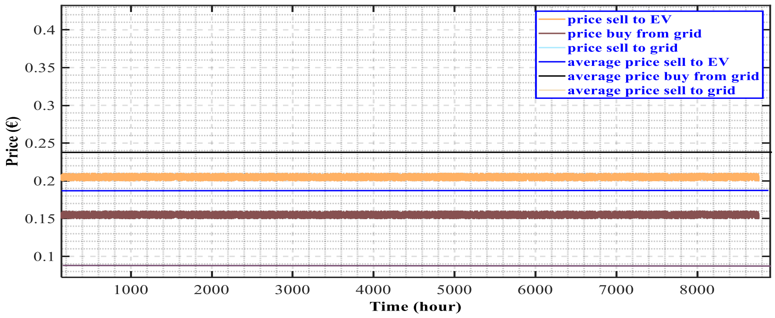


Fig.6. Pricing structure of hybrid grid-RES system

Table-1 Optimal parameter configuration of wind, solar and mini-hydro stations

Case	Wind generators		EV Chargers		Battery rating (KWh)	Hydro Power (KW	Surface of solar (m^2)	Grid Power (KW)
	Number	Type	Number	Power rating				
I	0	0	4	44.00	0	0	0	128.33
II	4	3	5	44.50	380.56	211.12	1500.38	0
III	4	3	5	45.85	350.65	225.69	1901.65	330.50
IV	4	3	5	46.10	150.95	233.54	1906.79	300.65
V	4	3	5	46.78	145.18	238.20	1907.05	280.54
VI	4	3	5	45.98	155.49	221.60	1901.98	108..32

Table-2 The optimum NPV considering various algorithms like GA, PS and hGPS when grid feeding the EV station

Algorithm	PIR (p.u)	Investment (€)	Maintenance (€/year)	IRR (years)	Income from energy selling to EV (€/year)	Energy buying price from grid (€/year)	NPV (€)
GA	2.879	88532.09	1000	5	79027.52	60829.29	168502.18
PS					79056.67	60851.72	168564.34
hGPS					79077.90	60868.06	168609.98

Case study II: RES along with BSS feeding the EV station: Fig.1(a)-Case-II shows the investigated system with the EV station fed by RES (solar, mini-hydro, and wind) and is isolated from the grid. Now, the energy for EVs in the charging station is purchased from the RES station only, and its hourly pricing is taken from Fig.6. Due to the intermittent nature of RES, BSS (Li-ion batteries) with 0.01 p.u SOC are included. The obtained economic results from the genetic algorithm (GA), pattern search (PS), and hybrid genetic with pattern search (hGPS) algorithm are listed in Table-3, and it is observed that the NPV with hGPS algorithm gives better results.

Table-3 The optimum NPV considering various algorithms like GA, PS and hGPS when RES feeding the EV station

Algorithm	PIR (p.u)	Maintenance (€/year)	IRR (years)	Investment (€)	Battery replacement (€)	Income from energy selling to EV (€/year)	NPV (€)
GA	3.234	1000	4	352215.83	43662.11	79528.45	800100.64
PS						79543.68	800150.64
hGPS						79558.36	800201.89

Case III: Integration of grid with RES and BSS for feeding EV station: In this study, Fig.1(a)- Case III shows that the EVs feed from the grid integrated with RES (wind, mini-hydro and solar) and BSS. This hybrid grid-RES system extracts the benefits of utilizing cheap energy from RES and provides flexibility over the grid system. EVs are allowed to sell their excess energy to the grid during peak hours. Simulations of hybrid grid-RES system are carried by considering grid power, wind generators type, solar panels surface, battery capacity, chargers installed (N). Further, power ratings of wind, solar and mini-hydro stations are also considered and are listed in Table-4. The economic values of the proposed hybrid system using genetic algorithm (GA), pattern search (PS) algorithm, and hybrid genetic with pattern search (hGPS) algorithm are tabulated in Table-4. It is observed that hybrid genetic with pattern search (hGPS) algorithm extracts maximum profits as compared to others

Table-4 The optimum NPV considering algorithms like GA, PS and hGPS when hybrid grid-RES feeding the EV station

Algorithm	PIR (p.u)	Maintenance (€/year)	Investment (€)	IRR (years)	Battery replacement (€)	Income of energy selling to grid (€/year)	Energy buying price from grid (€/year)	Income of energy selling to EV (€/year)	NPV (€)
GA	3.533	1000	390897.26	4	37903.48	15245.52	4162.75	84123.80	1002050.07
PS						15253.57	4173.43	84134.64	1002105.85
hGPS						15265.58	4187.50	84150.43	1002154.05

From the above case studies I, II, and III, the optimal simulated results with proposed hybrid genetic with pattern search (hGPS) algorithm outperform over genetic algorithm (GA) and pattern search (PS) algorithms. Hence, the proposed hGPS algorithm is considered for the rest of the studies.

Case IV: EVs feed with hybrid gird-RES system considering arrival time: The study system of case-III (Fig.1(a)-Case IV) along with the arrival time constraint of EVs, which helps in coordinated charge scheduling in order to avoid charging during load shedding. The hourly average arrival time is simulated with SMC using equation (1). Considering the arrival time of SMC, simulations are carried with a hybrid genetic with pattern search (hGPS) algorithm. The economic values are listed in Table-5 and compared with the Case-III results, it is observed that the system with arrival time earns maximum NPV over others.

Case V: EVs feed with hybrid gird-RES system considering flow of the EV's into the station: The investigated system in (Fig.1(a)-Case V) is provided with more detailed data of EV considering departure time from equations (2) and (3) along with arrival time. With the prior information regarding arrival, departure, and SOC of an EV, the parking time of EVs in the station can be estimated in order to gain a controlled scheduled charging. It also helps prioritize the EVs to be allowed in the charging station. Considering SOC, arrival, and departure time, investigations are performed with the hGPS algorithm, and their optimum values are listed in Table-5. The obtained economic values are compared with Case-IV. Critical observations explore that the system with detailed data of EV outperforms others.

Table-5 The optimum NPV using algorithms like GA, PS and hGPS when hybrid grid-RES feeding the EV station

Case	IRR (year)	Maintenance (€/year)	PIR (p.u)	Investment (€)	Battery replacement (€)	Income of energy selling to grid (€/year)	Energy buying price from grid (€/year)	Income of energy selling to EV (€/year)	NPV (€)
I	5	1000	2.879	88532.09	0	0	60868.06	79077.90	168609.98
II	4	1000	3.234	353215.83	43999.11	0	0	80558.36	800201.89
III	4	1000	3.533	391897.26	38500.48	15965.58	4187.50	82845.40	1002154.05
IV	4	1000	3.852	360692.62	14001.84	16832.44	16762.83	83102.56	1108004.48
V	4	1000	3.821	360692.62	26001.62	16311.19	17512.99	84560.43	1108264.23
VI	5	1000	3.718	371218.69	13092.59	12550.47	16380.71	76941.43	1100045.85

Case VI: Case-V with the limitation on power transfer capacity: For a stable and steady-state operation of the system network, a power transfer capacity constraint is imposed on the grid and the system network shown in Fig.1(a)-Case-VI helps to limit the impact of the grid on the system network, which reduces the energy transferred from the grid to the network. The optimum Economic results are obtained with hybrid genetic with pattern search (hGPS) algorithm and are listed in Table-5. From Table-5, it is observed that the energy price from the grid to customers and vice versa are reduced.

VIII. CONCLUSION

In In this research work, a realistic hybrid grid-RES (solar, mini-hydro, and wind) based EV fast-charging station considering EV demand characteristics are proposed. The investigation is carried out by considering the detailed modelling of EV demand characteristics, including hourly distribution of EVs in the charging station during a day, arrival time, departure time, battery capacity, and SOC as performance indices. The parameters for detailed modelling of EV are optimized using a hybrid genetic with pattern search (hGPS) algorithm. Comparisons of system economic considerations with hybrid genetic with pattern search (hGPS) algorithm and it extracts maximum profitable values over genetic algorithm (GA) and pattern search (PS) algorithm. The case studies confirmed that the NPV is maximum on feeding the EV charging station with hybrid grid-RES. The investigation shows that the detailed modelling of EV stations gives better economic results over the EV system fed with hybrid-RES. Further investigations are performed by imposing a limit to the power transferred capacity among the grid and system network reduces the impact on the grid. The impact of EVCS on distribution network and its power quality issue will be an important area for future research.

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