# A Survey on Coordinated Charging Methods for Electric Vehicles

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***Abstract:*** ***Electric vehicles (EVs) is regarded as one of the most effective ways to reduce oil and gas use. EVs (electric vehicles) have many advantages over ICEVs (internal combustion engine vehicles), including zero pollution, little noise, and exceptional energy efficiency. Even though an EV is known to have a three times higher fuel efficiency than an ICEV, the driving range is often significantly lower because batteries have a lower energy density than gasoline or diesel. Over the next few decades, it is anticipated that the number of electric vehicles will increase significantly due to concerns about pollution and technological advancements in the sector. Utilizing a variety of energy sources will boost energy security while reducing emissions and fuel usage. A paradigm shift has been observed with the switch from internal combustion to electric car technology. For electric vehicles to become widely used, a charging infrastructure must be developed. However, there is a cap on the amount of electricity that can be used to charge the vehicles in a charging station. Rearranging charging times, specifically charging coordination can help optimize the distribution of the available power among the vehicles. In this paper, a review of the various coordinated charging methods has been presented. A detailed comparison of the methods has been done.***

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**Keywords:** Electric vehicle; Forecasting; Optimal discharge; Coordinating charging; State of Charge (SoC).


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## 1. Introduction

Electric vehicles (EVs), which provide hope for reducing the greenhouse effect, have undergone extensive study. Thanks to developments in power electrics, energy storage, and support, the plug-in hybrid electric vehicle (PHEV) offers a competitive driving range and fuel economy in comparison to internal combustion engine vehicles (ICEV). By fostering the establishment of innovative, high-tech businesses, increasing energy security through the diversification of energy sources, and—most importantly—protecting the environment by lowering tailpipe emissions, electric vehicles (EVs) have the potential to boost economic growth. Electric vehicles are particularly cost-effective to operate since they have fewer moving parts to maintain and use little to no fossil fuels (petrol or diesel). While some electric cars (EVs) used lead acid or nickel metal hydride batteries, lithium-ion batteries are now regarded as the industry standard for modern battery electric vehicles because of their greater energy retention and an increased lifetime (self-discharge rate of just 5% per month).

R.R. Kumar *et al.* [1] presented according to data, the number of academic studies on the subject of electric vehicles has significantly increased over the last 10 years. However, there haven't been any comprehensive studies that synthesize and integrate these findings. This study seeks to close that gap by employing an integrated review methodology. It includes an integrated assessment of 239 articles compiled from journals during the Scopus Q1 period utilizing an integrative review process. The five main types of variables included in this analysis are socio-demographics, mediators, moderators, consequences, and mediators. The research procedure produced a wide range of noteworthy results regarding research methodologies and local changes. The review highlights both relatively unstudied aspects like dealership experience, charging infrastructure resilience, and marketing strategies as well as extensively investigated ones like charging infrastructure development, the total cost of ownership, and purchase-based incentive schemes. Additionally, it highlights the mechanisms underpinning the adoption of electric vehicles by emphasizing crucial mediators and modifiers. The results would be valuable to both scholars and policymakers as there have been a few earlier evaluations that have concurrently and thoroughly explored all sustainable consequence variables. The development of a comprehensive nomological network of electric vehicle adoption gave this study a new perspective. Stakeholders have a lot of information to evaluate when it comes to electric mobility thanks to the segment-specific key policy recommendations.

This review paper is organized as follows. An approach from a few review papers of a survey for coordinating the charging of electric vehicles is presented in Section 4. The framework or model formulation for coordinating the charging of electric vehicles from a few review papers of a survey is described in Section 5. A Comparison between different Algorithms for the coordinated charging of EVs is defined in Table 1. The conclusion is defined in section 6.

## 2. Charging Station

As part of their future ambitions for smart cities, many countries will electrify their transportation infrastructure in an effort to increase environmental sustainability. As a result, there will be a dramatic rise in the number of electric vehicles (EVs) present in urban areas. The battery of an electric vehicle can be recharged in a variety of ways, but charging stations will be the main energy source. The locations of charging stations are essential; they should not only be widely dispersed so that an EV can easily access a charging station anywhere within its driving range, but also extensively dispersed so that EVs may travel the entire city after being recharged. An electric vehicle charging station is a piece of technology that can be used to refuel electric cars, neighborhood electric cars, and plug-in hybrids. While some charging stations are simpler than others, others have more advanced capabilities like Smart metering, cellular functionality, and network connectivity. The two primary types of charging stations are DC charging stations and AC charging stations. Batteries can only be charged using direct current (DC) electricity; the majority of electricity is delivered from the power grid as alternating current (AC). As a result, most electric vehicles have an "onboard charger," often known as an inbuilt AC-to-DC converter.

S. Acharya *et al.* [2] proposed that machine assiduity is edging away from conventional gasoline-powered vehicles as EVs grow in favor. As a result, the need for EV charging stations is growing., and they are being erected for both business and residential use in an effort to meet this demand. Intricate cyber-physical dependencies are created as a result of the interplay between EVs, EVCSs, and power grids. These dependencies can be cruelly exploited to negatively impact any of these components separately. This article outlines and examines the cyber risks that develop at this intersection and highlights existing and impending security holes in the EV charging ecosystem. These vulnerabilities need to be fixed as the number of EVs grows worldwide and their impact on the electrical system becomes more probable. The objective of this article is to compile and detail any backdoors that could be exploited to seriously degrade the power grid, EV and EVCS accessories, or both. The highlighted issues and challenges are intended to spur research on smart EV charging cybersecurity and enhancing power grid resilience generally against similar demand-side intrusions.

## 3. Coordinated Charging

The charging of EVs will create additional pressure on distribution networks, which were not initially designed to accommodate EVs. The current distribution system can support a small increase in EV use. However, it is projected that penetration levels will quickly rise over the next few years because of the price decrease, the availability of charging stations, and the wide spectrum of production. This added stress will have bad impacts if not managed properly. Increased system losses, increased operating expenses, and temperature limit violations brought on by overloading feeders and transformers are some of these repercussions. Distribution system operators must build smart EV coordination structures to manage EV load in order to rely on the infrastructure of upcoming smart grids. Because the power demand will exceed the capacities of the distribution transformers, phase unbalance may result in excessive current, and surplus power may lower the system's reserve capacity, uncoordinated charging will have a detrimental impact on the distribution network to meet the charging requirements of electric vehicles, it is necessary to establish a coordinated charging plan that maximizes the depth of discharge. a synchronized charge management strategy that incorporates offline optimization and online management. Power limit overages can be prevented by managing the combined regular load in residential areas and the charging load for electric vehicles using the power limit value collected from the non-control period.

G. A. Salvati *et al.* [3] proposed the idea of coordinating electric vehicle charging schedules. In order to account for the interdependence between the selection of stations, the charging options offered at each station, and the charging quantity settings, it formulates the EVCS problem as a hierarchical mixed-variable optimization problem. R. Jarvis *et al.* [4], in their research, presented a variety of network congestion scenarios, including

PEV charging at random locations and times, are investigated. A 24-hour load flow analysis is conducted using 5-minute time intervals, and the analysis is focused on the effects on distribution transformer performance. Investigation of PEV charger impacts on distribution transformers is required since they are essential components of the grid. The machine learning valley-filling (MLVF) technique is described in the publication by J. Garcia *et al*. [5] with the aim of enhancing plug-in electric vehicle (PEV) charging at the local power level while lowering the detrimental effects of uncontrolled PEV charging. In order to decide when to start charging a PEV, this study investigated whether a neural network algorithm could be trained to recognize low and high demand times in the anticipated baseload

## 4. An approach from a few review papers of a survey for coordinating the charging of electric vehicles

The following three points are the main contributions of the current study, according to a method offered by C. Zhou *et al*. [6]:

1. Calculations and simulations showed that disordered charging of EVs increases the peak-valley difference in the power grid and coal consumption for the power supply but decreases the utilization rate of coal, increasing carbon emissions.
2. The government cannot force the EV charging load to reduce the peak load and improve the valley load if it only relies on the economic means of peak valley price.
3. The proposed economic incentive technology controls orderly charging.

The following were suggested as the main contributions of the research by K. Zhou *et al*. [7]. The suggested technique starts by taking into account how urgently EV charging demand, as determined by a charging urgency indicator, must be met (CUI). Second, rather than being planned as a group, all EVs were scheduled in accordance with various charging requirements. Third, two different EV charging patterns were used in simulations to account for the uncertainty of EV charging behavior in order to show the usefulness of the suggested strategy applied in real circumstances. The findings shown that the suggested approach can transfer load demand from peak to valley periods and decrease the overall peak-valley load difference by scheduling EV charging in a coordinated manner, enhancing the safety and dependability of the microgrid. characteristics into account. To prevent the gassing of transformer insulation, the constraint function of a transformer operating limit is additionally applied.

A technique for distributing EV charging spaces in an urban village network was suggested by C. Srithapon *et al.* [8] that accounts for the battery price arbitrage gain for the EV owner as well as the operational expenses of the DSO network, which includes the cost of transformer loss of life. The main goal of this optimization effort is to achieve the following goals: minimization of the loss costs associated with energy arbitrage, peak demand, network power loss, and transformer aging. The cost of a transformer's loss of life takes its thermal. H. Suyono *et al.* [9] presented a minimal power loss and voltage deviation optimal charging coordination method for a random arrival of PEVs in a residential distribution network. To further enhance the voltage profile, the method also uses capacitor switching and on-load tap changer adjustment. Using a hierarchical decision-making (HDM) approach, A. Zahedmanesh *et al*. [10] proposed developing a charge control system (CCS). With only a few minor modifications, this CCS may be quickly implemented for the dependable and affordable charging of commercial EVs while enhancing PQ in the power grids. A crude energy management technique and an adaptive droop control are both included in the HDM approach for real-time operation. J. Hu et *al*. [11] suggested that this paper coordinate the beneficial services and operational constraints of three actors: the EV owner, the Fleet operator (FO), and the Distribution system operator (DSO), taking into account the individual EV owner's driving requirement, the cost of charging the EV, and the thermal limits of cables and transformers in the proposed market framework. The first step is the description of a theoretical market framework. Within this framework, FOs who represent their customers' (EV owners') interests will centrally ensure the EV owners' driving needs and more affordably secure the energy for their vehicles. By coordinating DSO and FOs through a distribution grid capacity market plan, the congested area problem will be resolved. The market strategy is then described mathematically. To solve the scheduling problem involving several vehicle types, E. Yao *et al*. [12] proposed a novel solution (MVT-E-VSP). First, the MVT-E-VSP—the scheduling problem of EBs for various vehicle types—is proposed. Second, an optimization model is created to reduce annual total scheduling expenses, which include the price of the EBs and chargers that are required, as well as the running costs of timetabled and deadheading journeys. The best answer is then discovered using a heuristic approach. R. Das *et al*. [13] suggested that multi-objective technological, economic, and environmental optimization be used to plan the charging and discharging of electric vehicles. For the first time in the context of a home microgrid, end-user energy costs, battery deterioration, grid interactions, and CO2 emissions are modeled and simultaneously optimized. S. Hussain *et al.* [14], proposed the charging cost optimization algorithm (CCOA) for electric vehicles (EVs) residential charging. By heuristically learning the real-time price trend and the EV's data, including the battery size, current state-of-charge, and arrival and departure schedules, the proposed CCOA organizes the charging of EVs.

## 5. Framework or model formulation for coordinating the charging of electric vehicles from a few review papers of a survey

Q. Deng *et al.* [16] studied the accommodation capability for electric vehicles of a distribution system considering coordinated charging strategies. Their model's primary goal is to increase ACE, while its secondary goal is to reduce the operational costs of the distribution system, which include the price of power purchased, the price of DG unit generation, the price of compensating loads for demand-side response, and the price of ESS compensation. Then, based on the linear combination, these two objective functions are normalized and integrated into one objective function.

$$O_1^{bj}=\sum_{t=1}^{T}\sum_{i=1}^{N_{EV}} P_{i,t}^{EV}$$

$$O_2^{bj}=\sum_{t=1}^{T}(\sum_{i=1}^{N_{node}} C_t^{S}\, P_{i,t}^{G}+\sum_{g=1}^{N_{DG}} C_{g,t}^{DG}\, P_{g.t}^{DG}+ \sum_{d=1}^{N_{IL}} C_{d,t}^{IL} P_{d.t}^{IL}+\sum_{r=1}^{N_{TL}} C_t^{TL}|P_{r,t}^{TL}|+ \sum_{m=1}^{N_{ESS}} C_t^{ESS}|\alpha_{m,t}^{d} P_{m,t}^{ESSD}-\alpha_{m,t}^{c} P_{m,t}^{ESSC}|)$$

$$O_{all}^{bj}=\omega_1 O_1^{bj}-\omega_2 O_2^{bj}$$

where T is the number of time periods in a day-ahead dispatch scheme and $O_1^{bj}$, $O_2^{bj}$, and $O_{all}^{bj}$ are the model's ACE, operating costs, and aggregative objectives, respectively. $P_{i,t}^{EV}$ represents the EV charging power at node i during time t. The number of nodes in the system that have EV charging stations is $N_{EV}$. $N_{node}$, $N_{DG}$, $N_{IL}$, $N_{TL}$ and $N_{ESS}$ are the numbers of nodes, DG units, interruptible loads, transferable loads, and the energy storage devices in the distribution system, respectively. $C_t^{s}$, $C_{g,t}^{DG}$, $C_{d,t}^{IL}$, $C_t^{TL}$, and $C_t^{ESS}$ stand for the cost of buying electricity from the upstream transmission system, the cost of producing one DG unit g, the cost of compensating for interruptible loads, the cost of compensating for transferable loads, and the cost of compensating for an energy storage device during the time period t, in that order. If node I is the slack bus, the upstream supply transformer will inject the necessary active power; otherwise, the injected active power at node I will be set to 0. $P_{i,t}^{G}$ is the active power injected at node I in time period t.$P_{g.t}^{DG}$ represents the actual output power of DG unit g (a photovoltaic or wind turbine unit) during time period t. $P_{d.t}^{IL}$ is the active power reduction of the interruptible load d during the course of time t. $P_{r,t}^{TL}$ is the active power that has been transfer from transferable load r over time t. Energy storage device m's active charging and discharging power are represented by $P_{m,t}^{ESSC}$ and $P_{m,t}^{ESSD}$, respectively, in time period t. Energy storage device m's charging and discharging states are represented, respectively, by the binary variables $\alpha_{m,t}^{c}$ and $\alpha_{m,t}^{d}$, which are both subject to the linear combination of the two normalised objective functions' weights $\alpha_{m,t}^{c}+\alpha_{m,t}^{d}\leq 1$ and $\omega_1$, $\omega_2$>0.

The coordinated charging optimization model's main goal is to reduce the load's peak-to-valley disparity during the system scheduling period.

Min $P^{cut}= P^{peak}- P^{valley}$

where $P^{cut}$ represents the difference between the system load's peak and valley, $P^{peak}$ and $P^{valley}$, respectively, represent the load's peak and valley during the system scheduling period.

F. L. D. Silva *et al.* [17] proposed a model to extend SGs (Stochastic Games) to the Multi-objective Partially Observable Stochastic Game (MOPOSG), which is made up of < S, U, D, P, $R_1^{01}$,..., $R_n^{0n}$ >, where the number of agents is n. S = $S_1 \times \cdots \times S_2$ is the state space made up of each agent's local state space. U= $A_1 \times \ldots \times A_n$ is the joint action space, which is made up of the individual action spaces of each agent. The joint observation space D = $Z_1 \times \ldots \times Z_n$ contains all potential arrangements of agent observations. P(sk, dk,uk, sk+1) signifies the probability of obtaining state sk+1 ∈ S and joint observation dk ∈ D after carrying out the joint action uk ∈ U in sk. P is the state and observation transition function. $R_i^{0i}$ : S × U × S → $R^{0i}$ is the agent Agi's reward function, and it represents a vector of oi rewards, one for each objective.

S. Ayyadi *et al.* [18] proposed While preserving the required charging conditions, the charger's maximum power, and the subscribed power, the method of charging EVs attempts to reduce energy expenses. Monte Carlo simulations have been utilised to address the uncertainty relating to the arrival and departure times as well as the initial state of charge. Equation could be used to solve this optimization problem.

$$\min\sum_{t=1}^{T}\sum_{i=1}^{N}(pr_t+\eta c_{bat})x_t^i\Delta t$$

K. Zhou *et al.* [19] presented the state variable $x_{i,j}$ is a binary variable in the optimization model. If $x_{i,j}$=0, the i-th electric vehicle (EV) is not charging during the j-th time slot; if $x_{i,j}$=1, the i-th electric vehicle (EV) is charging during the j-th time slot. Equation is given as

$$x_{i,j}=\begin{cases}1, & in\ charging\ state\\ 0, & not\ in\ charging\ state\end{cases}$$

The coordinated charging scheduling model's total load at the j th-time slot is given as

$$P_{T=c}^{j} = P_{con}^{j} + \sum_{i=1}^{N} x_{i,j}\ .P_{EV,i}$$

where,

$P_{con}^{j}$ = the basic load during j-th time slot.

$\sum_{i=1}^{N} x_{i,j}\ .P_{EV,i}$= Power that is provided for all the Evs in the j-th time slot.

If the i-th Ev has an urgent charging demand, $P_{EV,i}$ is equal to $P_{EV}^{fast}$

If the i-th EV does not have an urgent charging demand, $P_{EV,i}$ is equal to $P_{EV}^{slow}$

The charge scheduling's goal is to lessen the microgrid's peak-valley load difference, and it is expressed as

Min $(P_{T=c}^{max} - P_{T=c}^{min})$

Where, $P_{T=c}^{max}$ and $P_{T=c}^{min}$ are the maximal and minimal load demand, respectively.

The model was proposed by K. Adetunji *et al.* [20]. In order to implement the Whale Optimization Algorithm (WOA) for intelligent control of EV charging, the proposed MOO model is evaluated. The MOO model is used to assess the fitness of each whale, and the best whale (final objective value) is updated as the leader and its position. The WOA method is used to update the locations further. The revised version makes use of the probabilistic model, which is described as

$$\overrightarrow{X_{t+1}} = \begin{cases}\vec{X}-A.\vec{D} & p<0.5\\ \vec{D}.e^{bl}.\cos(2\pi l)+\vec{X_t} & p\geq 0.5\end{cases}$$

where [0, 1] is a range of possible numbers for p. $\overrightarrow{X_{t+1}}$ and $X_t$ represent the next EV time slot and current best EV time slot respectively.

Equation's lower sub equation illustrates the spiral process, while the top sub equation depicts the shrinking mechanism. Applying a random vector $\vec{r}$ results in the optimal EV time slot using the shrinking technique. In the definitions of $\vec{A}$ and $\vec{C}$, this is evident. The formulas for them are $\vec{A}=2\vec{a}.\vec{r}$ and $\vec{C}=2.\vec{r}$. In order to approximate a spiral shape, the spiral search is obtained by a similar process but with an additional 2l factor.

where,

$$\overrightarrow{X_{t+1}} = \overrightarrow{X_{rand}} - A.\vec{D}$$

$$\vec{D} = \left|C.\overrightarrow{X_{rand}} - X_t\right|$$

Here, = $\overrightarrow{X_{rand}}$ and $X_t$ stand for the current iteration's random EV time slot, and current EV time slot $\vec{D}$ is the distance between the current whale's position, $X_t$ , and the positions of the whales that were randomly chosen.

Z. Yi *et al.* [21] presented the quadratic function shown is an example of an objective function that works well for valley filling in particular. This optimization framework can be expanded to satisfy various control requirements by developing the appropriate objective functions. For the purpose of choosing the control methods for PEV charging energy allocation for the following aggregator time step, the solution of the first time step, i.e., $e^{step}$ [p, 1], p = 1….,p, will be employed.

Min f($e^{step}$ [p, i]) = $\sum_{i=1}^{N}(\sum_{p=1}^{P} e^{step}[p.i] + D_{net}[i])^2$

$e^{step}$ [p, 1] is the energy to be allocated for PEV p in time step I within the prediction horizon.

V. S. Kasani *et al.* [22] presented the goal of this model is to maximize the number of vehicles that can be charged in a specific amount of time while meeting network and vehicle battery limits. equation is given by

$$\max \sum_{k=1}^{K}\sum_{i=1}^{L} V_{ik} * D_{ik} * C_{max} * \Delta h$$

The distribution transformer's capacity is $S_t$ with a power factor $\emptyset$ of the charging station has L charging slots, with $C_{max}$ as the maximum charging power for each slot. In the optimization, the slot charging power is handled as a continuous variable that can take on any value between zero and the maximum charging power $C_{max}$. The battery management system receives $SOC_t^A$ as the car arrives and starts charging. The PHEV owner enters the number of parking hours t, which establishes the number of coordinated charging time intervals, K = t/Δh, as well as the components of the charging station's slot matrix, $D^{l*k}$. If the slot is open for the car to charge, $D_{lk}$ is equal to 1; otherwise, it is equal to 0. $D_{lk}$ represents the condition of the slot l for time interval k. The optimization determines the charging power decision matrix $V^{l*k}$. and $b_{lk}$ = 1 denotes that the PHEV is permitted to charge with a charging power of $V_{lk} * C_{max}$ at slot l for time interval k, while 0 denotes the optimal battery condition.

M. H. Hemmatpour *et al.* [23] presented to simultaneously decrease the operation cost, a multi-objective optimization problem with four objective functions is given.

OF = $E_{cost} + TC_{cost} + SC_{cost} + VD_{cost}$

where $E_{cost}$ denotes the cost of energy used, $VD_{cost}$ is the cost of voltage variations, $SC_{cost}$ denotes the cost of switching shunt capacitors, and $TC_{cost}$ denotes the cost of changing transformer taps.

The cost of energy consumption is calculated as follows:

$E_{cost} = \delta^p E^p + \delta^q E^q$

Where, $E^p$ ($E^q$) is the total daily active (reactive) energy consumption, $\delta^p(\delta^q)$ is the cost of active (reactive) power per KWh (KVAr)

The cost due to voltage deviation at buses

$VD_{cost} = \sum_{h \in H} \sum_{i \in N} P_{i,h}^D \, UC_{i,h}^{VD}$

According to W.-L. Liu *et al.* [24], the EVCS problem is presented mathematically as follows::

Min f(S) (a)

Subject to

$\max|c_i| \leq J$ (b)

$\rho_i^t \in [0,1], \forall t, \forall I$ (c)

$\sum_i f_{status}^{charge} (i, j, o, t \leq \gamma_j^{0,max}, \forall j, \forall o, \forall t$ (d)

As a result, the problem model calls for the solution's fitness function, which aggregates the triple objectives of time cost, expense, and SoC gap, to be minimized. The number of charging stops for each EV within J is constrained by equation (a), both for the benefit of the actual driving experience and the effectiveness of the search process for schedule optimization. Equation (b) for the i-th EV gives relevant limitations for the range $\alpha_i^t$ and the energy level $\beta_i^t$ as well as the feasible value range of its SoC at the t-th time slot $\rho_i^t$. According to Equation (c), there can only be as many EVs charging at once at the j-th CS as there are $\gamma_j^{0,max}$ chargers accessible at any given time. Here, $\sum_i f_{status}^{charge} (i, j, o, t)$ stands for a charging status checking function. If the i-th EV is charged by a charger using the o-th charging option at its j-th CS stop at the t-th time slot, its value is set to 1; otherwise, it is set to 0.

M. Spitzer *et al.* [25] proposed two strategies:

1. Cost Optimized Strategy:
Charging schedules are designed to meet the needs of EV customers while using the least amount of energy possible. Constraints on the electrical grid need to be taken into account depending on the regulatory framework.

minimize x $\sum_{t=1}^{T} \sum_{n=1}^{N} x_{n,t} \cdot ce_t \cdot \Delta t$

The sum of all charging requirements for all vehicles at a time step is multiplied by the energy cost at the time step and the time step's length in equation, which represents the linear price objective function. The outcome is then total across all time steps.

2. Valley Filling (VF) Optimized Strategy:
This is the total variance over the optimization time horizon.

minimize x $\sum_{t=1}^{T} \frac{1}{N-1} \sum_{n=1}^{N} (x_{n,t} + b_t - \mu)^2 . \cdot \Delta t$

GHG Emission Optimized Strategy
The GHG emission function replaces the electricity price function in the objective function.

minimize x $\sum_{t=1}^{T} \sum_{n=1}^{N} x_{n,t} \cdot co_t \cdot \Delta t$

### 5.1 Optimization Technique

Q. Deng *et al*. [16] proposed Mixed-integer linear programming is the basis of the ACE evaluation model. The issue is resolved using the CPLEX solver, which is a Simplex method implementation on the YALMIP platform. It is then decided to use the Particle Swarm Optimization (PSO) algorithm to resolve the coordinated charging optimization problem. F. L. D. Silva *et al*. [17] presented the use of a MOPOSG to represent the EV charging issue, with each agent having a local observation function in addition to a reward function for each objective. Given that MASCO is treated as a MOPOSG, it considers the partial observability and stochasticity that self-interested agents introduce. Unpredictable consumer behavior also raises the stochasticity of the environment. Like DWL, MASCO is a distributed solution. S. Ayyadi *et al.* [18] suggested ideal charging strategy used in this work has met the battery's lower and upper bounds, the maximum power charger for EVs, the SOC requirements, and the subscribed power. To deal with the arrival and departure times as well as the initial state of charge uncertainty, Monte Carlo simulations have been used. K. Zhou *et al.* [19] suggested model was created using MATLAB/YALMIP, and the CPLEX solver was used to resolve it. To imitate actual EV charging scenarios, the experiment's input data are produced at random using the probability density function. K. Adetunji *et al.* [20] proposed MOO model which is evaluated in order to implement the Whale Optimization Algorithm (WOA) for intelligent control of EV charging. The strategies are conceptualized from the way whales feed. To move between these techniques, a probabilistic model is used. Z. Yi *et al.* [21] proposed two distinct optimization routines- a one-stage direct optimization approach and a two-stage hierarchical optimization approach. In this paper, the optimization model for a centralized coordinated charge control framework is built using the one-stage approach as a base. A two-stage optimization method is created by conducting hierarchical operations on a one-stage approach to handle large-scale issues in a modest aggregate time step while using suitable computing resources. V. S. Kasani *et* *al*. [22] proposed two optimization models, one for the battery electric vehicle (BEV) routing algorithm and the other for the personal rapid transit (PRT) system in a college setting. The second optimization model focuses on charging as many PHEVs as possible through the American Electric Power (AEP) utility grid. To reduce power system overloading, PHEV charging schedules are chosen using Mixed Integer Linear Programming (MILP). The best BEV charging schedule to meet transportation system passenger demand is also discovered using MILP. The PRT routing algorithm makes use of real-time data. To demonstrate the viability of the suggested techniques, a time series simulation of a distribution feeder test system is carried out. M. H. Hemmatpour *et al.* [23] presented, to address the effects of EVs' coordination on energy and voltage regulation, an enhanced mixed real and binary vector-based swarm optimization technique is employed to optimize the distribution system's performance (EVC). W. L. Liu *et al*. [24] proposed to conduct the dynamic charging schedule for all considered EVs at a collection of CSs on a transportation network, they propose an EVCS system. To optimize the charging schedules of the EVs that are about to depart from their starting points or already visited CSs, this paper builds the dynamic EVCS system by calling Mixed-Variable Differentiate Evolution (MVDE) as a scheduling algorithm at every time slot. M. Spitzer *et al.* [25] presented a three-phase system is used to represent the semi-urban low voltage grid in MATLAB's Simp scape Electrical environment. Transient states are not included in the model because it runs as a quasi-steady model even though it operates in a time-domain context.

**Table 1:** Comparison between different Algorithms for coordinated charging of EVs

| Serial No. | Algorithm | Primary Objective | Test System | Reference No. |
|---|---|---|---|---|
| 1 | Multi Objective Particle Swarm Optimization (MOPSO) algorithm and Monte Carlo simulation. | The best scheduling of EV charging and discharging is developed with the goal of peak shaving, valley filling, and flattening the network load curve. | The 69-bus IEEE radial test system's 50-bus test case, which was created by removing one of the lengthy, lightly laden lateral feeders, is used to test the proposed approach in the study. | [15] |
| 2 | A mixed-integer linear programming problem and a constrained optimization problem are included in the model that is being presented, and they are each addressed using CPLEX (the Simplex method implemented in the C programming language). added to the particle swarm optimization (PSO) algorithm | An EV accommodation capability evaluation model of a distribution system is built and has large penetrations of flexible resources. | In order to illustrate the suggested approach, a real distribution system in a coastal region of China is used. In this system, there are seven 110 kV substations, 376 nodes, 368 branches, six photovoltaic units, two wind farms, and 51 nodes that are linked to EV charging stations. | [16] |

| | | | | |
|---|---|---|---|---|
| 3 | Q-Learning algorithm, in MASCO they used Reinforcement Learning (RL) | Three competing objectives are intended to be simultaneously optimized by a multiagent multi objective reinforcement learning system.<br>Battery Level - Agents strive to maximize it because customers need a high battery level before daily trip.<br>Price Paid - Agents work to keep consumers' overall energy costs as low as possible.<br>Transformer Overload - Agents specifically work to reduce the quantity of overloads. | For a neighborhood of 30 homes, each with one EV, a transformer safely supplies a maximum of 40kWh. The EV batteries have a 24kWh capacity, with the Nissan Leaf serving as a point of comparison. | [17] |
| 4 | The use of Monte Carlo Simulations (MCS). With the linear programming method, the optimization problem is solved. | An innovative method for reducing EV charging costs is presented and is based on the day-ahead electricity price (DAEP) and battery degradation cost subject to EV state of charge (SOC) limits, the maximum power charger, the EVs full charging at the end of the charging period, and the distribution feeder subscribed power. | The performance of the suggested method has been assessed using a single-phase distribution network. This network has 50 homes, and it is anticipated that each home has two electric vehicles, totaling a fleet of 100 EVs. | [18] |
| 5 | In order to implement the Whale Optimization Algorithm (WOA) for intelligent control of EV charging, the proposed MOO (Multi Objective Optimization) mode was evaluated. | Based on a unique multi-objective strategy, researchers concentrated on the best coordinated charging of electric vehicles in a centralized charging paradigm. Charger cost reduction, load variance reduction, and power loss reduction are the objectives. | An IEEE 33-bus distribution network with a total capacity of 3.72 MW and 2.3 MVAR was used to test the suggested model. The apparent power and voltage's base case values are 100 MVA and 12.66 KV, respectively. The maximum number of EVs the smart parking lot can hold is 500, and a maximum power of 8.90 KW is taken into account. | [20] |

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| 6 | In this study, two distinct optimization routines—a one-stage direct optimization approach and a two-stage hierarchical optimization approach—are presented. | A very effective receding horizon control technique is presented to enable dynamic charging coordination for sizable plug-in electric vehicle (PEV) populations. The individual PEV charging flexibility is aggregated using a two-stage hierarchical optimization method to lessen the computing complexity of the optimization process. | The planned home PEV charging control framework has been developed by INL (Idaho National Laboratories) on a high-fidelity demonstration platform. In the control framework, a desktop acts as the aggregator to carry out centralized control techniques, such as one-stage direct and two-stage hierarchical optimization. The Raspberry Pi card can mimic each household PEV based on information about its parking and charging requirements. | [21] |
| 7 | PHEV charging schedules are chosen using Mixed Integer Linear Programming (MILP). The PRT routing algorithm makes use of real-time data and a time series simulation of a distribution feeder test system is carried out. | This develops a novel scheduling technique based on the scheduled mode of operation from the data provided by the West Virginia University's Department of Transportation and Parking, and proposes a concept of converting the guideway power rail propelling vehicles to battery-driven vehicles. The coordinated charging strategy for a charging station is designed to maximize the number of PHEVs charged. | The AEP (American Electric Power) system's Feeder 2 is used to test the charging strategy because it has a mix of residential and commercial consumers as load types. Five charging stations are taken into account in this feeder. These stations are portrayed as price-responsive customers who can take part in demand-response initiatives. | [22] |
| 8 | Improved Mixed Real and Binary Vector-Based Swarm Optimization Algorithm. | A solution to assess the effects of EVs and controllable loads on the EVC performance in power distribution networks is put forth.<br>The suggested methodology in order to as closely as possible match the reality of distribution systems with the solution that was found.<br>The capacitor switches and transformer taps can be chosen in accordance with the optimization model's ideal design while also minimizing the operation cost. | The suggested method is tested using the seven-lateral IEEE 69-bus test system and the IEEE 119-bus test system. These systems' combined active (reactive) power outputs are 22709.7 kW (17041.1 kVAr) and 3801.5 kW (2694.6 kVAr), respectively. | [23] |

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| 9 | Receding Horizon Optimization (RHO) based Network-aware EV charging (and Discharging) N-EVC(D) | Network-aware EV Charging (and Discharging) N-EVC(D), a centrally coordinated EV charge-discharge scheduling technique that considers both EV customer economics and distribution grid restrictions, is proposed. | According to the method used, the performance of the suggested EV charge-discharge scheduling system is assessed on a modified IEEE 13 node test feeder. In particular, a single-phase model of the IEEE 13 node test feeder is used, eliminating all capacitor banks as well as the transformer between nodes 2 and 3. | [26] |

## 6. Conclusion

This study will analyze and compare the applications of EV demand management for coordinating transportation systems and creating an infrastructure based on the existing research. Both the electricity distribution network and the transportation network are impacted by EV charging requirements. Numerous investigations into the coordinated operation of interconnected networks have been made to identify the most effective individual EV routing, traffic flow directing, etc. Although the main study interests are modeling and methods for dealing with issues involving coordinated activities, economic aspects, and social behaviors should also be taken into consideration. The majority of the current study on the subject of designing the infrastructure for EV charging focuses on the optimal location and sizing of different types of EVCS, including FCS, BSS, and WCS. The secure operation of the power distribution network, constraints on traffic flow, or even the interaction between connected networks may be added as extra considerations. Future work will require taking into account a variety of uncertainties from the coordinating approach, user behavior, and system model combined. These risks must be taken into account together with the coordinated charging of electric vehicles due to the rapid expansion of renewable energies in the distribution systems.

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