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Review

A Review of Optimal Charging Strategy for Electric Vehicles under Dynamic Pricing Schemes in the Distribution Charging Network

Adil Amin [1], Wajahat Ullah Khan Tareen [2,*], Muhammad Usman [1], Haider Ali [3], Inam Bari [4], Ben Horan [5], Saad Mekhilef [6,7,8], Muhammad Asif [1], Saeed Ahmed [1] and Anzar Mahmood [1]

1 Department of Electrical Engineering, Mirpur University of Science & Technology, (MUST), AJ&K, Mirpur 10250, Pakistan; adil.pe@must.edu.pk (A.A.); usman.pe@must.edu.pk (M.U.); huzaf001@gmail.com (M.A.); saeed.ahmed@must.edu.pk (S.A.); anzar.ee@must.edu.pk (A.M.)
2 Department of Electrical and Electronic Engineering, College of Engineering, University of Jeddah, Jeddah 21589, Saudi Arabia
3 Department of Electrical and Electronic Engineering Technology, University of Technology Nowshera, Nowshera 24100, Pakistan; haider.ali@uotnowshera.edu.pk
4 Department of System Engineering, Military Technological College, Al Matar Street, Muscat 111, Oman; inam.bari@mtc.edu.om
5 School of Engineering, Deakin University, Waurn Ponds, VIC 3216, Australia; ben.horan@deakin.edu.au
6 Power Electronics and Renewable Energy Research Laboratory (PEARL), Department of Electrical Engineering, University of Malaya, Kuala Lumpur 50603, Malaysia; saad@um.edu.my
7 School of Software and Electrical Engineering, Swinburne University of Technology, Hawthorn, Melbourne, VIC 3122, Australia
8 Center of Research Excellence in Renewable Energy and Power Systems, King Abdulaziz University, Jeddah 21589, Saudi Arabia
* Correspondence: wajahattareen@gmail.com or wtareen@uj.edu.sa; Tel.: +92-332-574-4848 or +966-5907022392

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Abstract: This study summarizes a critical review on EVs' optimal charging and scheduling under dynamic pricing schemes. A detailed comparison of these schemes, namely, Real Time Pricing (RTP), Time of Use (ToU), Critical Peak Pricing (CPP), and Peak Time Rebates (PTR), is presented. Globally, the intention is to reduce the carbon emissions (CO_2) has motivated the extensive practice of Electric Vehicles (EVs). The uncoordinated charging and uncontrolled integration however of EVs to the distribution network deteriorates the system performance in terms of power quality issues. Therefore, the EVs' charging activity can be coordinated by dynamic electricity pricing, which can influence the charging activities of the EVs customers by offering flexible pricing at different demands. Recently, with developments in technology and control schemes, the RTP scheme offers more promise compared to the other types of tariff because of the greater flexibility for EVs' customers to adjust their demands. It however involves higher degree of billing instability, which may influence the customer's confidence. In addition, the RTP scheme needs a robust intelligent automation system to improve the customer's feedback to time varying prices. In addition, the review covers the main optimization methods employed in a dynamic pricing environment to achieve objectives such as power loss and electricity cost minimization, peak load reduction, voltage regulation, distribution infrastructure overloading minimization, etc.

Keywords: electric vehicle; distribution network; scheduled charging; optimal operation; dynamic pricing; power grid

1. Introduction

Global climate change, fossil fuel depletion, increasing prices, and energy security have carried the significant changes in power and mobility sector. The mobility sector consumes around one-fifth of global energy consumption [1]. The road transportation in European Union (EU) is recognized as one of the major sources of CO_2 emissions and it degrades the air quality level below EU standards. Therefore, it is estimated that if the economic growth of EU continues at the current rate, the emissions will increase up to 50% (compared to 1990) by 2020 [2]. Several steps are being commenced to accelerate the shift to decarbonize the transportation sector. In this direction, the EU has made legislation to achieve 30% reduction in CO_2 emissions up to 2030 by increasing the penetration of Electric Vehicles (EVs) in the transportation network [3]. However, in the coming days, EVs or Plug-In EVs (PEVs) are powered by rechargeable batteries and classified in the green technology vehicles, which will replace the Internal Combustion Engine (ICE). The transferring technologies from petroleum-based transportation to green transportation has a number of benefits in several areas like economic, environment, and technical support.

According to Eurostat [4], the transport sector marked up to 85% of total EU's oil imports by the end of 2015. This has stressed the EU economy by paying an ample amount on petroleum imports. The inclusion of EVs in the transportation sector will not only reduce oil consumption, but also saves millions of Euros financed to keep the environment healthy. This step will regulate the EU's economy. The additional economic benefits of EVs are in terms of new business avenues and employment opportunities in the manufacturing and service industries. In a study [5], it is projected that due to emergence of EVs, the European economy will be able to accommodate 206,000 people with jobs by the end of 2030. Thus, a sustainable technology will lead to sustainable economy. The carbonized vehicles on the roads are responsible for the 12% of EU carbon emissions and contribute to the global climate change [6]. The reduction in carbon emissions and other pollutants are the key drivers for EVs adoption in EU countries. The EU six-year plan targets the 18–40% CO_2 reduction (compare to 2007) in the transportation sector by encouraging more EVs on the road [6]. Besides making a mark in the economy and environment protection, the EVs also provide technical support to the electric grid. These services include voltage support to the grid, frequency regulations, energy storage for grid, peak shaving, and load flattening [7]. The voltage of the network may drop due to faults or feeding a suddenly introduced large load. The EVs equipped with voltage droop control system can maintain the system voltage quality. Similarly, frequency violation caused by mismatch of active power generation and demand can be avoided with its frequency droop control mechanism. Besides voltage and frequency regulation service, the EVs are also useful for managing the peak demand. The distribution system experiences a varying load and peak demand that can be managed by discharging the power stored in the vehicle's battery without network reinforcement. In conclusion, all the benefits stated above motivate EVs' adoption at large scale. In this race, the European countries look very active to promote the EVs through their policies including tax rebate and public subsidies. Therefore, the EV volume on the road will increase in coming years and will lead to achieving the benefits.

On the other hand, the wide spread adoption of the EVs is accompanied by numerous challenges such as in context from energy, transportation, and industries. The EV charging activities either performed at home or at a public charging station require the development of charging platforms and infrastructure for EVs. Additionally, the high penetration of EVs in the distribution network causes the high capital investment of smart grid technologies. Therefore, the charging operation of EVs consumes a relatively large amount of electricity due to the considerable size of EVs' battery charging time. Oppositely, the simultaneous or uncoordinated charging of EVs clusters considerably increases electricity consumption, which causes an unexpected peak on the system and leads to over loading of distribution network, resulting in the voltage quality degradation, power loss increment, and dispatch of uneconomical energy sources [8]. There exist two potential solutions to manage the growing charging demand of EVs without making a compromise on network operational performance, and each solution has its own operating domain. Firstly, the Supply Side Control Action (SSCA) is refers to increasing and managing the generation capacity of the system to meet the peak demand caused by simultaneous charging of electric vehicles. This is an expensive approach and needs modern gradation of grid infrastructure. Secondly, the Demand Side Control Action (DSCA), which is the alternate solution to control the charging demand of EVs, is concealed in demand response program. It refers to the steps taken by utilities and consumers with dynamic pricing to influence the electricity consumption for the sake of optimal billing [9]. Figure 1 shows the hierarchical flow of our survey, which mainly focuses on EVs charge scheduling environment, i.e., the pricing policies designed by the utilities and the optimization tools along with the optimization objectives require to accomplish an optimal EVs charging schedule.

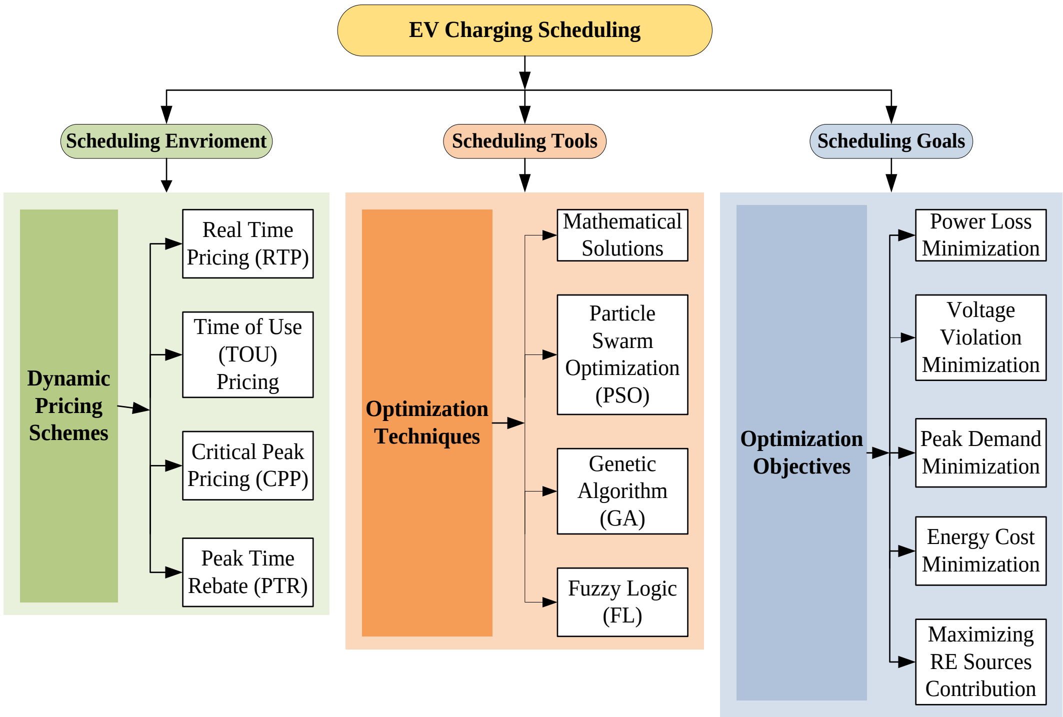

Figure 1. Order of literature survey on EV charging.

From a utilities prospective, the EVs' charging is a typical demand side management subject and can be effectively realized by dynamic electricity pricing, which directly influences the charging activities. Electricity pricing policies can motivate the EV customers to shape their charging demand in response to the price signal, which could not only eradicate the adverse impacts on the distribution network, but also diminish the customer's electricity billing. The EVs' charging can be scheduled by dynamic electricity pricing policies such as Time of Use (ToU), Real Time Pricing (RTP), and Critical Peak Pricing (CPP). These pricing policies influence the charging behavior of EV customers, thus offering the coordination flexibility of charging activity.

There exist a number of surveys in the literature related to EVs' charge scheduling. The surveys [10–12] mainly focus on the optimization techniques and objectives employed for smart charging of EVs. In [10], the authors provide a comprehensive review on EV charging while covering the centralized, decentralized, and hybrid control frameworks that lack in [11–14]. In [13], the authors mainly focus on the objectives of EVs. The optimization tools to achieve these objectives are not part of this study. Our study mainly differs from [10–14] in terms of its focus on dynamic electricity pricing policies, which cannot be ignored when dealing with smart charging scheduling of electric vehicles. Concentrating on each pricing policy, we have presented a survey of optimization techniques and their objectives employed to achieve an optimal charging schedule. This study is mainly concerned with optimal scheduled charging of EVs in the context of dynamic electricity pricing policies including

RTP, CPP, and ToU. An optimal scheduled charging of electric vehicles involves the objectives and the optimization techniques used to achieve target. Within the domain of individual pricing policy, we have also explored various optimization techniques employed during EV charging to achieve objective functions such as charging cost minimization, profit maximization, power loss minimization, voltage profile improvement, and load leveling.

The key contributions discussed in this review paper are as follows:

1. In the electricity market, dynamic electric pricing policies have chief importance to influence the customer's electricity consumption. We have explored various pricing policies from the perspective of EV charging to highlight their effects on EV charging behavior.
2. In each pricing domain, we have explored various optimization techniques employed to schedule the charging demand of EVs.
3. The optimization objectives realized during this charge scheduling process are also featured in this study.

The paper is structured is as follows: Section 2 discusses the EV charging concept and two charging framework available in the smart grid environment, i.e., centralized and decentralized. Dynamic electricity pricing policies are presented in detail in Section 3, and Section 4 is about EV charging accomplished in dynamic pricing environment. Sections 5 and 6 discusses various optimization techniques and their computational performance for coordinated EV charging. Section 7 discusses the optimization objectives set for coordinated charging. In Section 8, an analysis of dynamic pricing policies and optimization techniques is presented. Lastly, conclusions and future work is presented in Section 9.

2. Smart Grid and EV Charging

The traditional electricity grid has been facing the challenge of managing the increasing electricity consumption effectively. With the development of technology, the existing grids are transforming into a self-regulated grid called Smart Grid (SG). The SG network is an intelligent electricity grid equipped with information and communication (ICT) facilities. The SG network provides a controlled environment to coordinate EVs' charging operation [15,16], enable large integration of renewable energy sources and flatten their variability [17], and support the vehicle to grid (V2G) feature for grid support services including frequency tuning and load regulation [18]. Various attributes of Smart Grid at different levels of electricity network are summarized in Figure 2. All these attributes are about smart grid technology, which sets an efficient and sustainable energy system to facilitate (1) individual customers regulating their electricity consumption against varying electricity prices and (2) utilities and grid operators monitoring and controlling their generation resources and network assets for optimized network operation. Smart grid has a comprehensive charging facility including advanced metering infrastructure, which allows the bidirectional communication between electricity customers and aggregator to schedule the charging/discharging activities. An aggregator is an intermediate entity that manages the communication and electricity distribution between the group of electricity users (EV charging customers) and utility, as highlighted in Figure 3. The major role of the aggregator is between load devices and dispatcher to establish and monitor market supply and demand [19]. In a cooperative set-up, an aggregator coordinates and schedules the EV charging to minimize the overall charging cost [20]. The EV aggregator persuades or allots the charging load to level the off-peak loading occurs at power grid and also improves the load curve by consuming the surplus power during the off-peak hours [21].

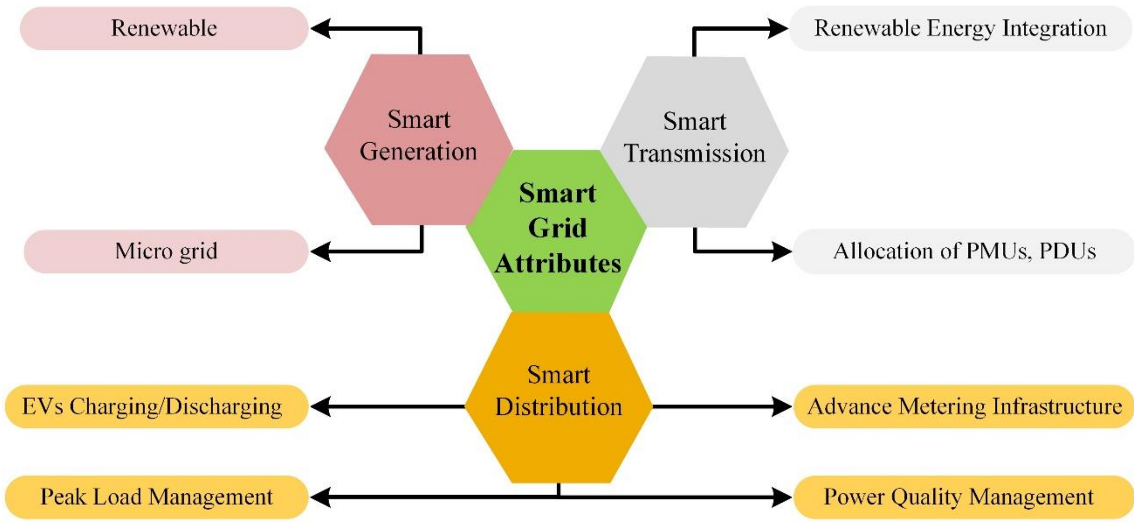

Figure 2. Various attributes of smart grid technology.

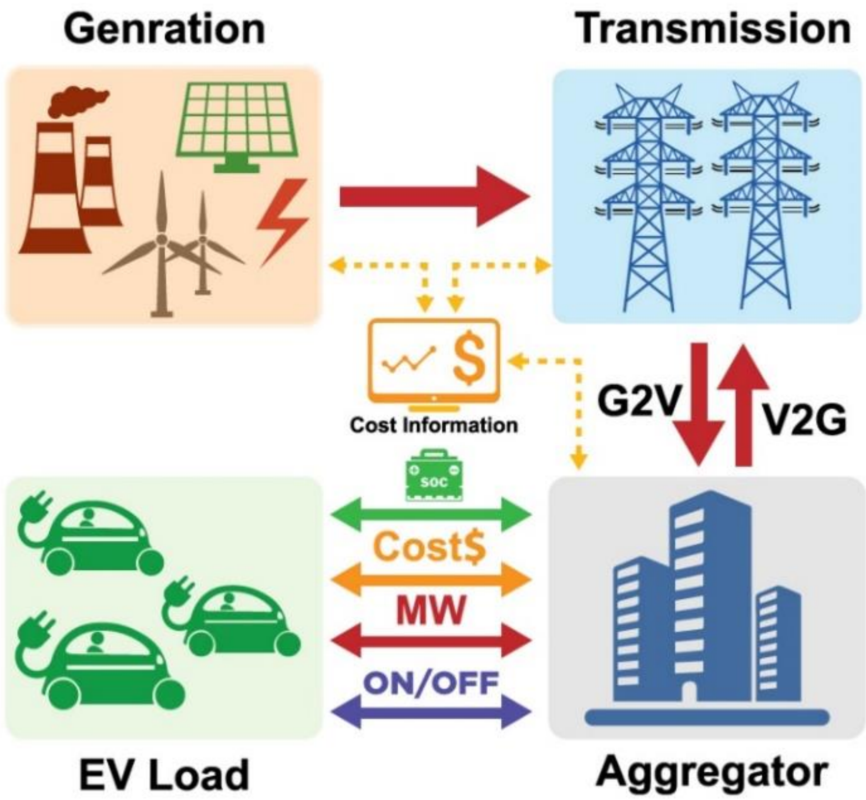

Figure 3. The EVs aggregators' role in the energy market.

The information shared by the EVs to the aggregator includes EVs' current location, battery's State of Charge (SOC), required SOC, maximum battery's charging capacity, and the time frame to achieve requested SOC level. The aggregator is an additional entity between utility and electricity customers who control the EVs' charging activities, keeping in view the interest of both parties: the customers and the utility [22]. The aggregator/grid operator and the customers share information with each other the following communication protocol defined by Society Automotive Engineer (SAE) J2836/1 and J2847/1 standards [23]. Different communication layers including ZigBee, Wi-Fi, Power Line Carrier (PLC), Digital Subscriber Line (DSL), and Cellular Network (CN) are used to communicate with the smart grid [24].

2.1. EV Charging International Standards

The EV charging can be done either at home or at public charging station located at shopping malls, restaurants, workplaces, etc. There are three different modes of charging of EVs, as defined by the SAE standards. Two modes, namely mode 1 and mode 2, are for Alternating Current (AC) type charging, and mode 3 is for Direct Current (DC) type charging. These charging modes are being implemented in many European countries, Japan, and the United States [25]. The charging standards and different level charging stations are designed according to the charging characteristics modes stated in Table 1. For home-based charging, Mode 1, also called AC Charging Level 1, is used. It functions at 120 V AC voltage and is developed by making a small change in household wiring. It is a low cost charging setup but involves high charging time, i.e., 12–16 h to reach 100% SOC. Besides home based charging, EVs can also be charged at charging stations positioned at public places. The public charging stations use Mode 2 and offer a relatively fast charging rate. However, it is expensive to install Mode 2 charging infrastructure and has considerable impact on the utility. In addition to AC charging facility, a DC charging arrangement also exists commercially. The Mode 3 charging is the DC fast charging, which is accomplished with an off-board supply unit. It has power rating 80–200 kW and can charge the vehicles in short time of around 30 min; however, it significantly affects the utility's maximum demand rates and encompasses the highest cost of installation.

Table 1. Distinct charging modes and their characteristics.

Charging Mode	Charging Characteristics						Advantages	Disadvantages
	Charging Outlets	Voltage Rating (V)	Current Rating (A)	Power Rating (kW)	Supply Connection	Charging Period (Hour)		
Mode 1	Domestic	120 V_{AC}	12–16	1.4–1.9	Single phase	6–10	Low installation cost Less impact on utility	Slow charging rate Long charging period
Mode 2	Domestic, Public	240 V_{AC}	80	19.2	Single/Three phase	1–3	Fast charging time Energy efficient	High installation cost Impact on the utility
Mode 3	Public	480 V_{DC}	80–200	20–120	Three phase	0.5	Very fast charging time High energy efficient	High installation cost High impact on the utility

2.2. Coordinated EV Charging Framework

A random or uncoordinated EV charging approach imposes negative impacts on the distribution grid including real power loss increment, sever voltage variation, over loading of the network, grid reinforcement, and expensive charging operation [8,26,27]. The coordinated charging can improve a utility's operational performance by smartly managing EV charging load and can minimize the charging cost by adopting dynamic pricing policies. In a smart grid environment, the coordinated EV charging operation can be accomplished in two ways: 1) centralized framework and 2) decentralized framework. In either control framework, the charging activities are managed by an agent called an aggregator [22]. An aggregator is the interfacing body between EV customers and the distribution network operator, which optimally fulfills the charging demand of the customers without compromising on network constraints [18]. The aggregator involvement enables the customers to link with the electricity market and it upholds their financial interests. Similarly, the aggregator equally works for the network operators to optimize their network performance. Besides controlling charging operation of EVs, the aggregator also contributes in voltage and frequency support, load balancing, and power loss reduction by controlling discharging operation of EV batteries. The operation, i.e., charging/discharging, is controlled either centrally or in a distributed manner as discussed in the following sections.

The centralized EV charging control is also called the direct control charging architecture [14], as shown in Figure 4. The aggregator is exclusively responsible for ensuring coordinated process for EV charging, keeping in view the benefits of both the parties, i.e., network operator and the charging customers. The centralized framework offers full support to the ancillary services. However, it involves higher order complexity and can entertain a limited number of charging customers [28].

The computational complexity is more for this framework, as it involves large volume of data [29]. With reference to [30], this approach requires a large number of conditions to schedule the charging load, which results in lesser flexibility. In a decentralized charging control frame work, the power of making a decision about EV charging is distributed among individual EV customers [31], as shown in Figure 5. Although this control logic empowers the customers to take their charging decisions, this may not guarantee to optimal solution for distribution network, because the aggregators cannot directly regulate the charging activities. They can only change the customers' charging behavior by offering attractive incentives through dynamic electricity pricing schemes [32]. For real time coordination, EV arrival is considered as a random variable; therefore, a framework having higher degree of scalability is very important. The decentralized model offers greater scalability in this regard [33]. A comparison of centralized versus distributed logic used to control EV charging activities is presented in Table 2. Compared to centralized charging control, the distributed framework is more flexible, scale-able, and empowers the customers in decision-making process of EVs charging. Therefore, it is highly acknowledged in EV charging scheduling control design.

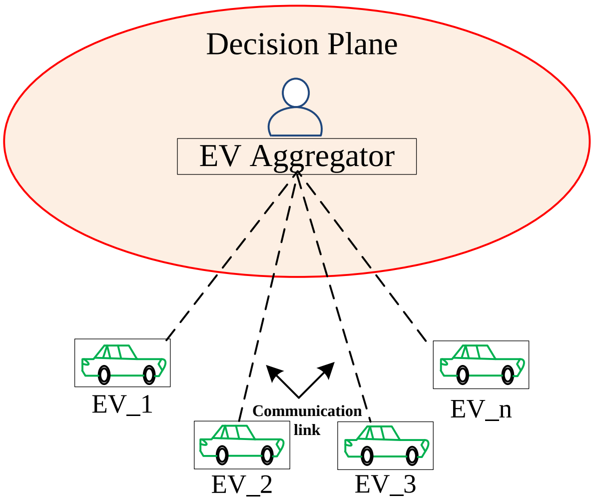

Figure 4. Centralized EV charging control.

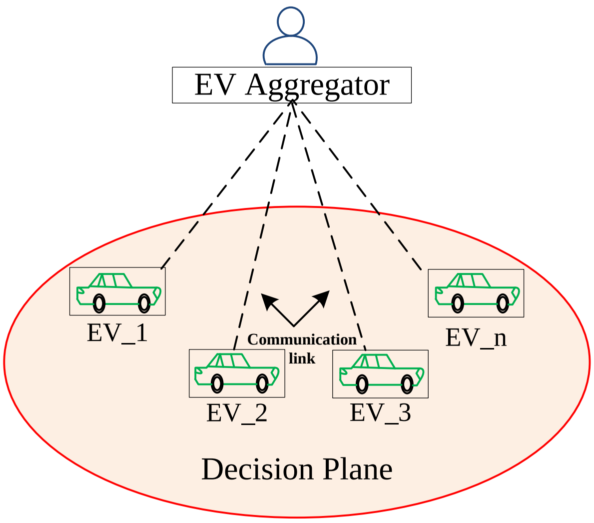

Figure 5. Decentralized EV charging control.

Table 2. Comparison of centralized and distributed EV charging control.

Characteristics	Charging Control Logic	
	Centralized	**Distributed**
Charging Decision	The aggregator	The EV customer
Control Action	Direct control	Price-Based Control
Ancillary Services	Fully supported	Partially supported
Computational Complexity	More	Less
Flexibility	Less	More
Scalability	Less	More

3. Dynamic Electricity Pricing Policies

Electricity billing recovers the cost of supplied electric energy and ensures the reasonable profit. This cost includes expenses by retailer or utility to provide electricity service (generation, transmission, and distribution) and fixed cost [34]. Each customer of electricity is charged with a certain amount based on usage of per kWh, known as a tariff, in order to recover this cost. Market-based cost of energy and administration-based price consist of tax, surcharge, and network charges (transmission and distribution), which are two major part of the tariff. The conventional tariffs, flat tariff, block rate tariff, simple tariff, two-part tariff, power factor tariff, and maximum demand tariff, are not sufficient for handling of modern complex network of smart grid and Intelligent Electronic Devices (IEDs) [35].

According to some recent surveys, residential building customers are responsible for 30% of carbon emissions and 40% of global energy consumption [20]. According to a US Department of Energy (DoE) survey in 2009, residential and commercial users consume 40% of total power consumption [36]. The world power consumption is growing rapidly, as it is expected this factor will rise by approximately 53% by 2035 [20]. According to International Energy Agency (IEA), this demand of electricity will increase up to 60% by 2040 [37]. In order to reduce these impacts, electricity suppliers provide customers with a different Demand Side Management (DSM) program. DSM is major part of smart pricing in order to operate the system efficiently by optimizing electricity usage and also cost minimization through modification of load curve shaped by six basic load shaping methods, which are load shifting, strategic conservation, peak clipping, strategic growth, and valley filling [20].

The demand response program is actually a change in usage of electricity by the end user from their regular load pattern in response to electricity price changing over time, or due to the incentive payments introduced to reduce electricity usage during the high wholesale market prices (market-driven DSM), or when network reliability is endangered (network-driven DSM) [34]. The important task of demand response (DR) management is to switch electricity consumers from a flat rate tariff to peak and off-peak pricing [35]. The DR is categorized into two parts: the interruptible program, which is Direct Control, and price based program which is the Indirect Control program. Load shedding, intended brown out, and Direct Load Control (DLC) are part of the controllable method engaged for reliable electricity supply. In order to maintain the system reliability, direct reduction of electricity consumption is practiced by scheduling load into different zones of a large area, known as load shedding. The second approach is DLC, which refers to direct control of operator to the load, which enables it to alternate load according to system requirements. Sometimes, the system operator marginally reduces voltage frequency within limitations to equate electricity generation and transport capacity, which is called brown out [36]. DLC is incentive-based DSM in which the electricity provider acquires control of electrical equipment installed in customer premises and schedules according to contractual terms to reduce the load on short announcement for peak duration, and in return, customers are rewarded with incentive money. It is very difficult to run DLC efficiently without creating trouble for the electricity customers. Although customers are incentivized for this inconvenience, restriction to utilize the facility at that moment when it is needed the most (e.g., urgent EVs charging) induces large discomfort. Another peak is again observed in the load demand, as large EVs fleets are connected simultaneously to recharge their EVs, when event is turned on, known as rebound effect or payback [36,37]. The indirect control type of DR, which is based on price, encourages customers to alternate their normal routine of electricity consumption as per the price signal. The time-based DR provides an opportunity to the customer to choose the time of use according to pricing signal. There are several dynamic pricing types based on usage and time [38], as highlighted in Figure 6. Our focus is on the non-dispatchable DR program, which is based on dynamic electricity pricing schemes.

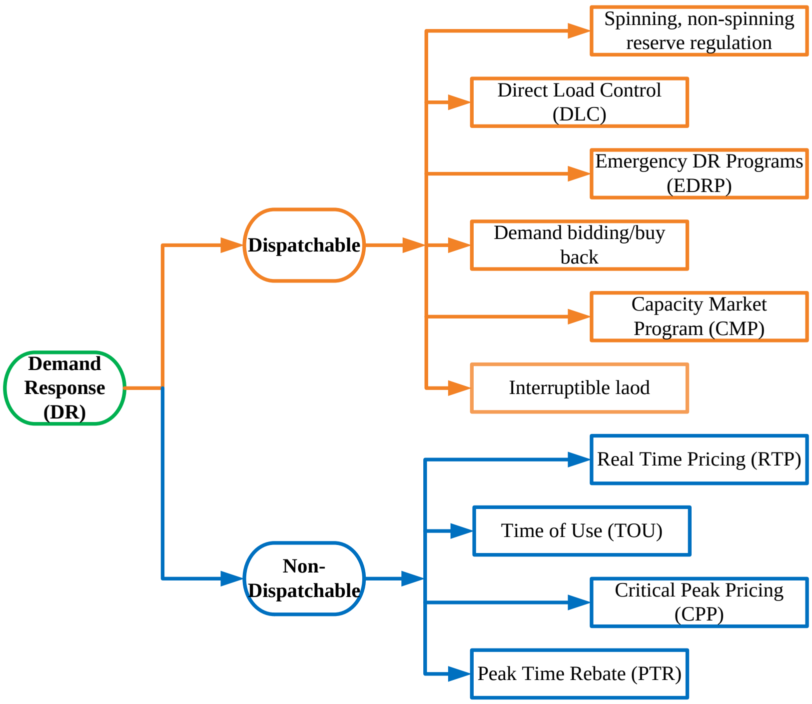

Figure 6. Classification of DR programs.

Most of the conventional tariff schemes are based on static pricing arrangements, which mean price does not change with the change in electricity demand, whereas modern tariff is based on dynamic pricing policies (e.g., CPP, RTP, ToU, PTR, etc.), which means prices vary according to demand [39,40]. A dynamic pricing scheme provides a chance to shrink their electricity bills by shifting load to off-peak hours. A dynamic pricing scheme is adopted to attain several goals listed in Figure 7. The response of domestic customers towards the dynamic pricing is negative, because it is possibly too difficult for an individual to respond according to changing price due to unawareness of billing. An International Business Machine (IBM) survey in 2011 reveals that 30% customers did not understand the basics of electricity billing [41]. Enabling automation technology helps customers significantly to respond quickly to pricing signal, as manually it's very difficult to manage loads for the uninformed individual. Study [35] presents a recent survey of 3863 residential electricity customers in China, and it shows that about 67% of energy users are ready to accept dynamic pricing. Recent research shows peak load reduction up to 30% by using dynamic pricing. Different experiment results are documented that show 4% reduction to 8% increment in electricity billing; however, more renewable energy (RE) integration in the grid can result in further reduction in electricity consumption cost [42]. From the perspective of willingness to pay for quality services, a customer may be willing to pay one and half times more than current billing [39]. In the following subsections, we will discuss major dynamic pricing schemes including Real Time Pricing (RTP), Time of Use (ToU), Critical Peak Pricing (CPP), and Peak Time Rebates (PTR). Every pricing scheme type has its own benefits and drawbacks; our study will highlight the objectives, optimization methods, and a comparison of different pricing schemes.

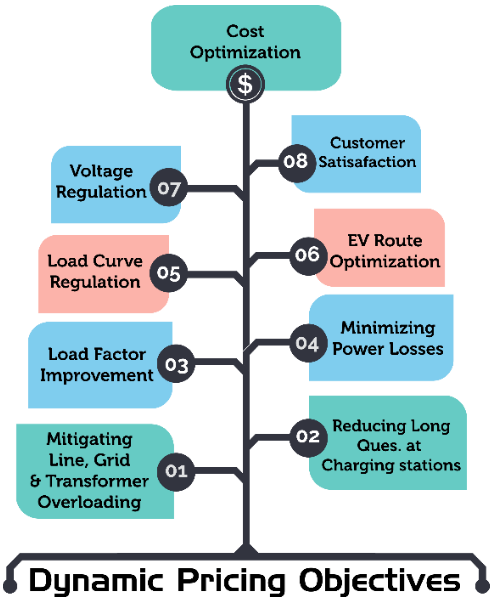

Figure 7. Various objectives of dynamic electricity pricing.

3.1. Real Time Pricing (RTP)

This dynamic pricing type, which seems superior to all other schemes, is RTP and is defined as "a varying rate that allows prices to be adjusted regularly in a consistent interval of hour or few minutes to reflect real time structure" [43]. The change in price in such a small interval of time makes this scheme most uncertain and risky for the customers; however, it is very beneficial for utilities. The efficiency of the pricing scheme is increased, because change in price in small intervals reflects the actual cost of supply [39]. In smart grid infrastructure, utility can obtain the desired load curve by adjusting the electricity price intelligently for an individual customer [44]. There are two major limitations of RTP deployment in the current grid system. Firstly, customers are not very educated about the billing, and they do not know how to deal with frequently changing rates. Secondly, the existing infrastructure and automation system of residential and commercial buildings is not effective to ride this new system [45]. In order to resolve these issues, RTP is used with Inclining Block Rate (IBR) and an automatic residential energy consumption scheduling framework [46]. RTP with feedback information of energy usage and saving devices proves beneficial to obtain optimal results. The installation of IHD (in home display) provides information to users of electricity consumption and market price, which can make customers more informed and decisive about their energy usage [47].

3.2. Time of Use (ToU)

The ToU is defined as "time block rates of electricity" and these rates are announced significantly in advance by utilities based on historical conditions rather than current load curve. The ToU pricing offers various electricity tariffs to customers with different time periods in the 24 h. The ToU is usually based on three time periods according to load: off peak, mid peak, and full peak. During the off-peak period, electric supply capacity is greater than demand, so ToU cost becomes low. At mid peak, capacity and demand are very close, which provides moderate pricing. Electric load becomes very high during peak hours. In order to meet this peak demand, utilities need to run less efficient and expensive peaking power plants such as diesel, coal, and petrol-based units, etc. Furthermore, in order to encounter peak demand, it requires development of the existing system and new power plants. As the electricity supply increases, technical losses of a system also increase, which cause higher peak rates [17,38]. Infrastructural variations and indirect control pricing seems advantageous to lessen the massive influence of EV charging on the power system. As the ToU has just high rates during the peak time and low rates in the off-peak period, only the ToU tariff is not capable of reducing the EV charging load. It may happen that simultaneously large fleets of EVs come into charging mode in the off-peak period, causing another peak or rebound effect [48]. Another variation of ToU is super-peak ToU, in which the peak window is much shorter, about 4 h, in order to give a strong price signal [39].

3.3. Critical Peak Pricing (CPP)

The CPP resembles to ToU pricing, but it is based on forecasting of high demand periods and advertised in a much shorter time as compared to ToU. CPP responds appropriately on the basis of present conditions, rather than relying on historic data. The comparative analysis of CPP and ToU shows that CPP has much higher prices than ToU, whereas the effectiveness of ToU at peak load reduction is lesser than CPP [49]. Days of CPP are divided into two categories: critical days and non-critical days. The critical days can be calculated using different algorithms like Particle Swarm Optimization (PSO), which helps to trigger the peak prices by CPP dynamic decision model. This model is very helpful in the improvement of load curve and electricity bills reduction [50].

3.4. Peak Time Rebates (PTR)

In this pricing scheme, customers are provided with rebates for using electricity under a certain preset limit in peak hours [39]. In the first three schemes, utilities charge more during peak hours as compared to the off-peak period; however, in PTR, customers are rewarded for load reduction during peak hours. The comparative analysis shows that in RTP, CPP, and ToU the customers view the peak load shifting to off-peak hours as loss, while in PTR, they view it as gain [51]. The cost-effectiveness of PTR is largely dependent on Customer Baseline Load (CBL) estimation. Therefore, PTR is costlier for electricity providers to implement, as it requires the development of appropriate precise CBL estimation [49]. Tariff representation of different dynamic pricing policies is summarized in Figure 8. The RTP scheme is highly unstable compared to other schemes, and it offers great flexibility to customers to regulate their consumption. Compared to the flat rate pricing policy, the dynamic pricing policies are a more attractive and economical choice for the customers. The comparative analysis of different pricing policies considering different aspects is presented in Table 3. The authors have analyzed the various dynamic policies based on different considerations. The analysis reveals that in all considerations, the RTP pricing scheme proves a more promising solution than other schemes, except in billing instability [52].

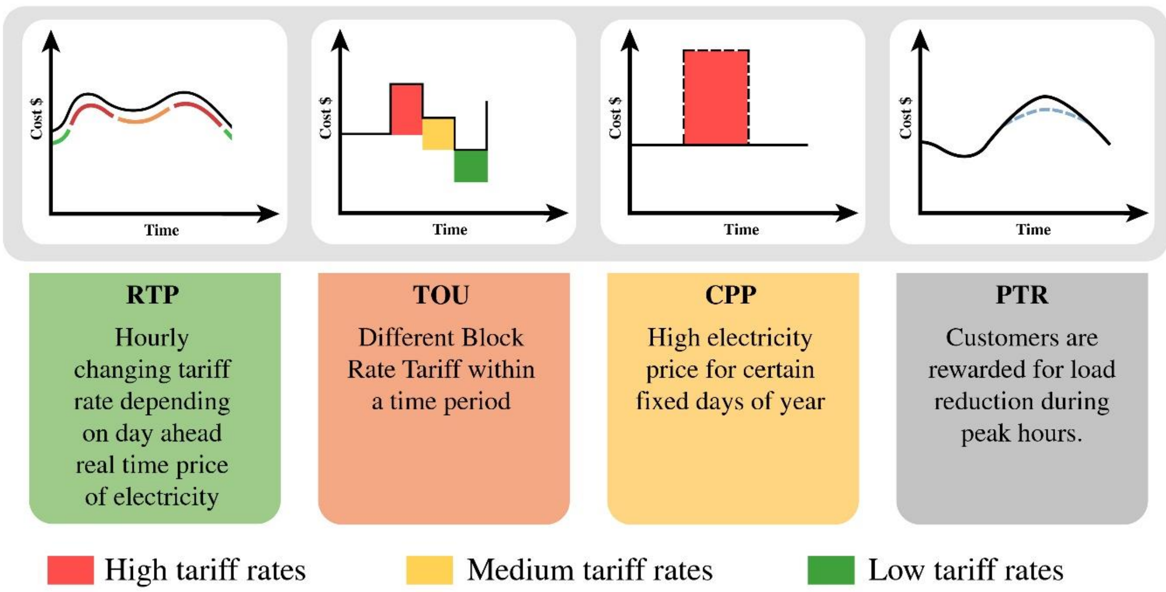

Figure 8. Tariff representation of different electricity pricing schemes.

Table 3. Comparison of different pricing schemes.

Considerations	RTP	ToU	CPP	PTR	Flat Rate
Economic efficiency	****	***	***	***	**
Bill steadiness	**	***	***	****	****
System complexity	****	***	***	***	**
Price uncertainty	****	**	***	***	**
Fairness	****	***	***	**	*
Risk incentive	****	***	****	**	*

***** Very High, **** High, *** Medium, ** Low, * Very Low.

4. Electric Vehicle Charging in Dynamic Electricity Pricing Environment

The non-renewable energy resource consumption is major concern of this era. Most of oil consumption is taken by transportation machinery. EVs have attained immense attention in the modern world due to their economical and emission control benefits. An EV can be defined as "a light weight vehicle powered by a rechargeable battery of 4 kW replacing conventional Internal Combustion Engine (ICE)". There are many advantages of EVs over internal combustion engine vehicles (ICEVs) [10]. Large penetration of EVs into the existing grid creates a high load profile. There are significant impacts of EV charging in terms of power grid load, distribution transformer overloading, voltage and frequency irregularity, and power losses. These effects increase drastically in the case of uncoordinated charging, as it loads heavily. EVs may increase the gap between peak load and valley load curve at rush hours [30]. The uncoordinated EV charging may increase power demand up to 5% during peak hours [48]. Dynamic pricing policies play a vital role in quenching peak load problems with uncertainty of changing price frequently, which is a new challenge. The study [53] proposed an energy management system for charging stations that combines Photo Voltaic (PV), Energy Storage Unit (ESU), and the power grid, with different operating modes. The ultimate goal of this proposed model is to diminish dynamic pricing uncertainty and to manage EV charging load on the power grid. EV charging stations face multiple challenges in the presence of RE and ESU such as charging demand volatility, the intermittent nature of RE, and electricity price fluctuation. In order to address these challenges, authors in [54] have adopted stochastic dynamic programming (SDP) and Greedy algorithm (GA).

4.1. *EV Charging under RTP*

The EV charging stations usually provide flat rate charging, which can create rush condition at stations. If the prices are frequently changing according to load on charging station, this will reduce the long queues. RTP will encourage the electric vehicle driver to go distant charging, which will less crowded and cheap. The study [55] proposes a notification system that provides details of charging station, their service fee, distance from user, possible queue delay time, and electricity prices. The results show that this proposed scheme can reduce the average delay time and raise the charging station by up to 40%. In study [56], the authors have proposed PV assisted charging stations and Automatic Demand Response (ADR) based on RTP. The proposed strategy has been divided in two models: Dynamic Price Vector Formation Model (DPVFM) and Dynamic Feasible Energy Demand Region (DFEDR). Fuzzy C Mean (FCM) and K Mean (KM) algorithms are applied to deal with RTP and comparative results show that proposed ADR reduces cost and reduces impact on grid voltage levels. The study [57] presents an RTP-based algorithm to control charging peaks by equating load and demand of large fleets of Plugin Electric Taxis (PETs). This scheme also modifies the drivers' charging decisions to overcome such unpleasant situations. The study [58] proposes a Real Time Charge Pricing (RCP) mechanism to mitigate adverse effects of uncoordinated charging on economic and environmental performance. The model includes four different charge pricing scenarios, which are RCP based on ToU, real time generation cost, marginal generation cost, and average generation cost.

4.2. EV Charging under ToU

The benefits of the ToU pricing scheme include EV route optimization, minimization of EV route cost, and battery optimization, etc. [59] has proposed an optimal route model for EVs by considering ToU electricity pricing policy. It has three characteristics of electricity demand, including peak, flat, and bottom. The other benefits of ToU include EV load shifting from peak hours to non-peak hours. The large intermittent EV charging load is growing immensely, which is an alarming situation for the existing grid system regarding demand and capacity equity [60]. A dynamic charging scheme based on the moving horizon principle with ToU is introduced. Each tier of ToU duration is obtained through using Gaussian-model-based clustering techniques [61]. Regional time of use (RToU) is a sub-category of ToU in where rates are applied by dividing the load into different regions. An optimal regional time of use (RToU) charging price model for EV is presented in [62], which considered urban area and categorized it into four different zones. These zones are the commercial zone, industrial zone, office zone, and residential zone. The results show the effectiveness of RToU over ToU from the perspective of minimization of peak valley difference and charging cost. A new Smart Load Management (SLM) control strategy determines the EV owner's preference for charging time zones. There are three time zones in 24 h of the day: red charging zone (18:00–22:00) high tariff, blue charging zone (18:00–1:00) medium tariff, and green charging zone (18:00–08:00) low tariff [63]. In study [64], a ToU policy is executed for charging scheduling of public electric buses by introducing an on-route fast charging strategy. The proposed model schedules the charging event of public electric buses in such a way that total charging cost is minimized. In another work [65], an optimal recharging schedule for electric buses is presented to minimize the net cost. The proposed approach is investigated on a real-world transit network. A summary of research work related to EV charging under various dynamic electricity pricing schemes is presented in Table 4.

Table 4. The EVs charging under various dynamic prices schemes and objectives.

Reference	Year	Major Objective Achieved	Pricing Scheme
Mohsenian et al. [46]	2010	Electricity cost minimization	RTP
Deilami et al. [8]	2011	Reducing potential stresses, performance degradations, and overloads in distribution system.	RTP
Masoum et al. [63]	2011	Power loss minimization, peak shaving, and voltage regulation	ToU
Cao et al. [60]	2012	Minimize charging cost and reduce peak and fill valley	ToU
Taheri et al. [19]	2013	EV load scheduling	CAP
Lian et al. [66]	2013	Optimized time based pricing schemes	UDP
Martinenes et al. [67]	2014	charging cost minimization	RTP
Andreson et al. [68]	2014	charging cost minimization	Two-tier policy
Yin et al. [50]	2015	resolving peak on peak	CPP
Misra et al. [69]	2015	Cost optimization and reduction of extra load during peak hours	RTP
Binitti et al. [70]	2015	Minimization of power losses, voltage deviation, load variance, operational cost, and emission control	Discrete charging rates
Soltani et al. [44]	2015	Reducing load peaks	RTP
Dubey et al. [71]	2015	Mitigating the impacts if EV load is on residential distribution circuit.	ToU
Yang et al. [59]	2015	EV route optimization	ToU

Table 4. *Cont.*

Reference	Year	Major Objective Achieved	Pricing Scheme
Soares et al. [34]	2016	Reducing distribution transformer overloading, voltage irregularities	UDP
Hajforoosh et al. [72]	2016	Reducing unwanted peaks, transformer over-loading	Variable charging rate
Crow et al. [61]	2017	Load factor improvement, electricity cost reduction, mitigating line overloading	ToU
Chen et al. [62]	2017	Solution of power congestion, under voltage, and grid instability	ToU
Xu et al. [55]	2017	Reducing imbalance usage and long charging delays at charging stations	RTP
Chen et al. [56]	2017	Electricity cost minimization and flattening peak power demand curve	RTP
Bitencourt et al. [48]	2017	Reducing peak load demand and transformer overloading	RTP
Korolko et al. [43]	2017	Reducing distribution transformer overloading, voltage irregularities, and uncontrolled charging effect	RTP
Yang et al. [57]	2017	Resolving large and unpredictable peaks	RTP
Latinopoulos et al. [41]	2017	EV load scheduling	Dynamic pricing (DP)
Zhang et al. [73]	2017	Minimize the peak–valley and economical improvements	ToU
Moon et al. [74]	2017	Balanced charging	ToU
Zhang et al. [58]	2017	Provides benefits to electricity supplier, charging station, EV user	RTP

5. Optimization Techniques for EV Charging Scheduling

Optimization is well-defined as mathematically finding the inputs of the inconsistent function (function which needs to maximize or minimize) under various constraints. In other words, optimization is process of finding the best possible values of function within the boundary of constraints to achieve desired goals. It is not possible to find out ideal solutions for a complex problem every time. It is quite possible that the optimum solution of some problems cannot be determined globally, and these types of problems come in the NP-hard problems category [10]. There is no polynomial algorithm existing for such problems; however, relatively difficult exponential time solution is considered for these problems. There are many estimated methods: heuristic method and artificial neural network (ANN). However, sometimes these methods are also unable to deliver satisfactory solutions for numerous complex problems [10]. In the modern era, advancement in computer technology and algorithms promotes computational optimization in today's research domains. Computational optimization is the set of methods that comprises crafting, execution, and then calculating the solution of the problem.

EV charging scheduling is a complex optimization problem. An optimized charging schedule is necessary to boost up the efficiency of the grid, aggregator, distribution transformers, and EV itself. EVs charging scheduling problem involves several objectives including network power loss minimization, electricity cost minimization, voltage violation minimization, and distribution transformer overloading minimization. There are many optimization techniques used to attain single or multiple objectives during optimization of charging process of EVs. In various cases, more than one optimization technique is used to achieve these objectives. The optimization techniques employed for EV charging scheduling can be used in centralized or distributed approach. A comprehensive work has been done on EV charging scheduling in a dynamic pricing environment considering different optimization techniques. This work contains classical, mathematical, and intelligence based optimization techniques involved in EV charging optimization under dynamic pricing schemes.

5.1. Mathematical Optimization Techniques

EV charging using convex optimization is explained in [19,44,48,61,67,69]. There are many objectives that are achieved using this technique to boost up system efficiency. In study [19], a clustered linear program method was adopted to determine optimal charging, fueling, and generating schedules. The solving method of convex optimization is similar to least square or linear programming. Load peak reduction is achieved using online convex optimization under Conditional Random Field (CRF)-based Real Time Pricing (RTP) [44]. Electricity cost minimization and reduction of extra load during peak hours are achieved under RTP and ToU scheme using linear programming [48,67,69]. Dual Clustered Linear Programming (DCLP) is used for EV load scheduling under Constraint Adjusted Prices (CAP) [19]. Real time greedy (RTG) and enhanced scalable S-RTG algorithms are utilized with discrete charging rates for peak demand load reduction and minimizing transformer overloading [70]. Mixed Integer Nonlinear Programming (MINLP) is type of non-convex optimization. Using this type of optimization RTP and Usage Based Pricing (UDP) helps in reduction of distribution transformer overloading and voltage irregularities [43,55].

5.2. Computational Intelligence Techniques

Intelligence-based optimization techniques such as meta-heuristic techniques are used to solve non-linear non-convex solution spaces. These methods are called high level methods, in which a large set of solutions is compiled. Meta heuristic methods, used for EV charging scheduling, are given as follows.

5.2.1. Heuristic Method

Some heuristic methods for the EV charging optimization problem are elaborated in [31,60]. In [60], the authors have developed a heuristic algorithm to get minimum charging cost. The results obtained from the execution of the algorithm clearly lead the typical charging pattern. In study [31], a heuristic approach called graph search algorithm, which enables the customers to choose charging activity of EV, is presented. The algorithm was found to be efficient and involved less computation. In order to achieve immediate solution for optimization problem, heuristics is employed. However, it does not provide assurance of optimal solution. Mostly, it is employed practically for those problems whose solution seems impossible.

5.2.2. Particle Swarm Optimization (PSO)

Study [50,72,74–78] discussed EVs charging optimization with the Particle Swarm Optimization (PSO) approach. PSO is the stochastic method based optimization tactic motivated by the phenomena of fish schooling and bird flocking. It searches for global solutions, starting with random population of solutions and then updating them until it attains a final solution. For the optimal solution, PSO moves stepwise toward its ultimate goal. Particles hold a specific position in a search space, and their movement is refereed with respect to the position of other particles. This process to seek optimal solution moves iteratively. The best-found position is assigned to particle as personal best position. Coordinated aggregated Particle Swarm Optimization (CAPSO) is employed for balanced charging of electric vehicle under the ToU pricing scheme [74]. CAPSO is also helpful in order to minimize undesirable peaks in power consumption and transformer overloading under variable charge-rate [72]. PSO is employed with CPP to resolve the issue of peak during electric vehicle charging load [50]. An improved version of PSO is used with RTP to enhance the profit for electric vehicle parking lots [76]. Fuzzy genetic algorithm (FGA) and Fuzzy Discrete Particle Swarm Optimization (FDPSO) assist in profit improvement of vehicle parking lot under RTP [77]. In study [78], a PSO-based optimal charging schedule is presented, and its comparison with other priority based algorithms is investigated. The proposed method showed better performance for optimally allocating the charging power to EVs.

5.2.3. Genetic Algorithm (GA)

The Genetic algorithm (GA) is debated in study [59,79–82] for optimal EV charging. GA is a bio-inspired population-based optimization technique in which the searching of global optimal is executed by selection, recombination, and mutation process. As compared to other algorithms, the genetic algorithm is the most robust in seeking the optimized solution [10]. Each candidate in a solution space is known as a chromosome, and it has some fitness value. The fitness of each chromosome is evaluated and updated with the generation of new chromosomes. The process repeats until the optimal solution is traced [11]. The authors in study [79] developed a static GA model to define day-ahead charging schedule of EVs with other network control actions. In study [80], a multi-objective GA is proposed for the power strategy of hybrid electric vehicle. The validity of the proposed algorithm was realized through simulation results. GA is utilized for gratifying load profile, peak load shaving, and preventing power system elements by scheduling the EVs charging in Smart Grid [81]. Learnable Partheno Genetic Algorithm (LPGA) is helpful for EV route optimization under ToU pricing policy [59]. In study [82], a GA-based EV charging method is presented for a practical network, considering network operating cost. For the consistency of the results, the number trails of GA have been recorded.

5.2.4. Fuzzy Logic (FL)

Studies [13,28,56,62,83] discussed the fuzzy logic for solving optimization problem of EV charging. In a Boolean logic, there are two states, 0 and 1; however, fuzzy logic provides the degree of partial truth instead of 0 and 1. Basically, FL comprises the combination of different value logic between zero and one, which are developed to test the degree of truth. There are infinite-valued logic combinations, which are used to find the optimal solution of problem. Fuzzy logic is combination of many valued logics between 0 and 1 and used to test the degree of truth. It is considered as the infinite-valued logic for finding the optimal solution of the optimization problem. In order to diminish the peak–valley gap and charging cost of EVs, under regional time of use scheme (in which an area is divided into four regions) is adopted with Fuzzy C Mean (FCM) algorithm in [62]. Fuzzy C Mean (FCM) and Fuzzy K Mean (FKM) are utilized under the real time pricing (RTP) for electricity charging cost minimization and to flatten the peak–power demand curve [56]. In study [83], EV charging coordination is scheduled by fuzzy logic, which considers various factors such as the length between charging unit to substation, the delayed in EV charging process, and EVs' SOC. Study [84] determined the coordination of EVs with the grid from the V2G and G2V perspective. Each perspective is implemented with fuzzy logic controllers in a real time scenario. The fuzzy logic controller was able to responds the real time simulations.

6. Computational Performance of Optimization Techniques

The computational performance of an algorithm refers to the time taken by it to compute the objective function. EV charging scheduling is a complex real-time optimization problem, which challenges the computational performance of the algorithm. Therefore, the development of a robust optimization technique for EV charging scheduling is very important. There are a number of factors which influence the computational performance of EV charging scheduling problem, such as random arrival and departure of EVs, charging demand of EVs, scalability, etc. The selection of a suitable optimization technique that can handle the real time operations is a challenging task. The literature reported the work highlighting the computational performance of the algorithms used for EV scheduling. Referring to mathematical optimization procedures, the best performance is recorded in [19] using clustered linear programming (CLP), whereas among the computational intelligence techniques, the authors in [72] claimed that PSO is the most promising choice for the real time scheduling problem of EV charging. The computational time of various methods used for EV charging scheduling is listed in Table 5.

Table 5. Computational performance of various optimization methods.

Optimization Method	References	Time (Seconds)
Mathematical optimization techniques	[19]	40
	[43]	60
	[44]	Not given
	[48]	Not given
	[55]	Not given
	[61]	Not given
	[67]	Not given
	[69]	03
	[70]	10
Heuristic method	[60]	Not given
	[31]	Not given
Particle swarm optimization (PSO)	[50]	Not given
	[72]	0.035
	[74]	Not given
	[75]	02
	[76]	Not given
	[77]	0.054
	[78]	Not given
Fuzzy logic (FL)	[56]	Not given
	[62]	Not given
	[28]	Not given
	[83]	Not given
	[84]	0.5
Genetic algorithm	[59]	375
	[79]	Not given
	[80]	Not given
	[81]	Not given
	[82]	Not given

7. Optimization Objectives for EV Charging Scheduling

The EV owners are concerned about battery charging, as they want to have the desired State of Charge (SoC) at the time of departure, while on the other hand, the grid operator's intention is to maintain the operational efficiency of the grid. There are two major frameworks for EV charging, which are the centralized and distributed approach. These frameworks entertained either single or multiple objectives including charging cost minimization [61]; power loss minimization [70]; voltage stability [62]; peak load reduction [48]; long queue reduction at charging stations [55]; EV route optimization [59]; and mitigation of line, grid, and transformer overloading [34,43]. The summary of prominent optimization objectives used for EV charging scheduling and related constraints is presented in Figure 9. However, the detailed of numerous objectives achieved during EV charging under dynamic electricity pricing is given in subsequent sections.

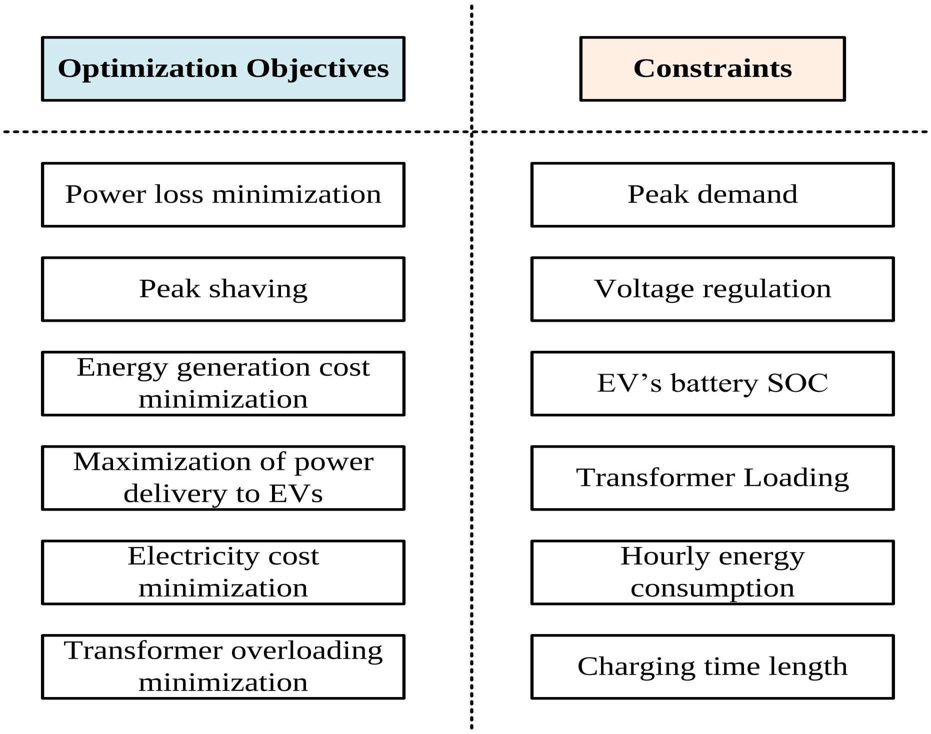

Figure 9. Optimization objectives and related constraints.

7.1. Power Loss Minimization

The EV charging under dynamic pricing is explored for distribution network power loss minimization in [16,63,70,77]. An optimized charging schedule shrinks power losses with boosting the battery life and efficiency of distribution network. Study [63] proposes a multi objective based smart charging strategy in which network power and system voltage profile are optimized to have a coordinated charging schedule of EV charging activities. They have developed realistic charging by considering the charging priorities of the EV customers. The authors in [70] also successfully proposed a coordinated charging schedule of EVs by considering customers' easiness of desired SOC level at the time of departure. The undesirable impacts of random charging of EVs, such as poor voltage quality and high power loss, are reduced by proposing an online schedule of EV charging [77].

7.2. Electricity Cost Minimization

The authors in research [46,56,61,62,67,69,72] have discussed the electricity cost minimization considering dynamic pricing policies for coordinated operation of schedule. In [46], the authors proposed an optimal scheduling framework thata aimed to minimize the electricity cost minimization in a real time pricing environment. In another study [56], a real time pricing model is considered to schedule the EV charging process. The cost of electricity is minimized by implementing a dynamic feasible energy demand model. The focus of [61] was also on electricity cost reduction for EV charging by considering static and dynamic models. The aim of [62] was to propose a charging model for EVs that could contribute to electricity cost reduction. A regional time of use model, which comprised four sub-regions, was adopted, and performance of the individual zone was realized. The electricity cost minimization was achieved by implementing a real time charging strategy [67]. Study [69] has proposed a cost effective charging mechanism for PHEVs by adopting distributed dynamic pricing policy in a multiple micro grid infrastructure. A set of rules was introduced for energy utilization and its trading with other energy deficient micro-grids. A cost effective online charging mechanism is developed for EV charging by taking customers' satisfaction into account [72]. There is an important role of charging cost in terms of selection of an EV for its charging either in station or in residential premises. An economical solution for the customers can be found by considering charging cost minimization as an objective function for the EV charging process for the interval of on-peak and off-peak hours".

7.3. Peak Load Minimization

Electric vehicle load elevates new peaks of power demand at the power grid, which needs to be minimized. EV charging coordination with dynamic pricing plays a vital role in peak load reduction. Authors in [8,44,48,50,56,57,62,69,73] have discussed the peak load minimization techniques. In [8], the authors have managed to minimize the peak load by introducing preferred charging time slots while considering time varying electricity pricing. The peak demand in [44] is controlled by an optimal price adjustment mechanism. Study [48] proposed an instantaneous real time pricing policy peak shaving. A dynamic decision model was proposed in [50] to effectively reduce the peak demand. The authors in [56] formulated a clustering-algorithm-based dynamic price vector of RTP. The model has successfully reduced the cost of electricity and peak load demand. A new peak due to charging load of EVs is avoided in [57] by a real time pricing method, which has provision of adjustment of charging action. Ref. [62] has proposed a RTOU pricing model for EV charging. An incentive program was introduced to analyze the reaction of the charging customers. The aim of this program was to reduce the system's peak demand. In [69], the authors considered the multiple micro grid infrastructure for the EV charging scheduling problem. In this framework, they proposed a distributed dynamic pricing policy aimed at reducing peak charging demand within the individual micro grid. Similarly, in study [73], the effect of EV charging on the total system demand is investigated and therefore a charging price model is proposed that showed that a peak–valley TOU pricing mechanism can help to minimize peak demand. There could be a deteriorating effect on the electric grid if the charging activities are performed for the period of peak hours. Therefore, peak load should be minimized so that the performance of the grid cannot be challenged during EV charging activities.

7.4. Voltage Regulation

The voltage regulation or voltage instability minimization in circumstances of EV charging under dynamic pricing is discussed in studies [44,62,63,70,72,74,85]. The utilities have shown their concern about voltage variations and overloading of the system due to growing charging activities without any controlled mechanism. Uncoordinated EV charging practice can significantly violate system voltage profile, and the customers feeding from the same network face power quality issues [86]. In the stated references, an optimal charging strategy for EVs was developed by keeping in view the system voltage as key parameter. The utilities are aimed at providing quality of service to their customers. An optimal charging strategy can provide voltage regulation to the utilities for smooth operation; therefore, it is deliberated as an important objective function in EV charging scheduling.

7.5. Distribution Transformer and Distribution Lines Overloading Minimization

One of the leading worries that the utilities experience is the overloading of distribution transformer and distribution lines under simultaneous or uncontrolled charging of electric vehicles. [8,48,61,70–72] have discussed mitigation and minimization of overloading of network assets including distribution transformer and distribution lines by coordinating electric vehicles [87]. The overloading of a transformer is avoided in [8] by introducing a maximum system demand limit. A real time load controlled mechanism was developed to manage the charging demand of EVs without system overloading. In [48], the authors proposed a coordinated charging mechanism considering distribution transformer overloading under RTP and TOU pricing schemes. It was found that transformer load factor and peak shaving increases with charging activities. Study [61] addressed the overloading of transformers due to EV charging by proposing static and dynamic framework. In order to reduce peak demand and hence overloading of the system, a real time decentralized greedy approach was established in [70]. A method to schedule the EV charging process was introduced by [71] with the aim to reduce the peak demand and transformer overloading and heating. The authors in [72] proposed an online method for optimal scheduling of EVs. The proposed method ensured that the transformer is not overloaded. In the stated work, the EV scheduling is either treated as a single objective optimization or multi-objective optimization problem. In a single objective framework, either customer of the electricity grid interests is focused on, whereas on the multi-objective platform, the welfare of both stakeholders are taken into account. Practically, it is not possible to achieve 100% satisfaction of both stockholders in a constrained environment. However, an acceptable compromised solution could be determined by the optimization algorithms.

8. Discussion

The EV deployment in the electric power grid introduces new challenges such as power congestion, voltage instability, and peak loading for the distribution network operators. Uncontrolled and uncoordinated EV charging in a deregulated electricity market has a devastating impact on grid steady state operation. Usually the burden of EV charging is managed by handing overload to off peak periods. However, it may be possible that large fleets of EVs can simultaneously access the grid in uncoordinated fashion, which leads to rise of peak on peak. EV charging activity can be synchronized with the price based programs, as the EV charging load management is a typical DSM subject where the charging behavior can be directly influenced by various pricing schemes. Compared to flat tariff, the dynamic pricing attracts the customers to manage their charging load according to the price signal. This paper reviews the EV charging under dynamic pricing policies including RTP, ToU, CPP, and PTR, along with the optimization techniques employed to achieve different objectives. By the analysis of surveyed work, it can be established that most of the work related to EV charging has been done in the RTP environment, as summarized in Table 6. RTP is a supreme form of dynamic pricing in which electricity price changes frequently in a regular interval of time according to the load on grid; thus, it provides great flexibility to EV customers to manage their charging activities at a low cost. However, a sophisticated communication infrastructure is required for real time information between EV customers and the aggregator so that charging activities can be monitored and controlled. Moreover, the uncertainty arises due to frequently varying prices and lack of awareness among users, which are also major challenges of RTP charging policy. Under ToU, prices are high for the duration of peak period and low in the course of off peak hours. It's not possible to handle EV load using only ToU, because it may happen that majority of EV customers may move to off-peak period and can create another peak on the system. In a comparison with ToU, CPP is more effective, but comparative price forecasting for CPP is really challenging. The PTR scheme can be introduced to incentivize the EV customers to not overload the grid during peak hours.

Table 6. Summary of optimization techniques and objectives accomplished in a dynamic pricing environment.

Ref.	Year	Research Focus	Optimization Technique	Objective	Pricing Schemes
Deilami et al. [8]	2011	Real-Time Coordination of Electric Vehicle Charging in Smart Grids	Maximum sensitivities selection (MSS)	Cost Minimization and Load Management	RTP
Taheri et al. [19]	2013	A dynamic algorithm for EV charging of	Dual clustered linear programming (DCLP)	EV load scheduling	Constraint-adjusted prices (CAP)
Soares et al. [34]	2016	Dynamic electricity pricing for electric vehicles	Mixed integer nonlinear optimization formulation (MINLP)	Reducing distribution transformer overloading, voltage irregularities	Usage Based Dynamic Pricing (UDP)
Korolko et al. [43]	2017	Robust optimization of EV charging schedules	Mixed integer nonlinear optimization formulation (MINLP)	Reducing distribution transformer overloading, voltage irregularities, and uncontrolled charging effect	RTP
Sultani et al. [44]	2015	Real-time load elasticity tracking and pricing for EV	Online convex optimization	Reducing load peaks	Conditional random field CRF based RTP
Mohsenain et al. [46]	2010	Optimal Residential Load Control with Price Prediction	Mixed integer linear programming (MILP)	Electricity cost minimization	RTP
Bitencourt et al. [48]	2017	Optimal EV charging and discharging under dynamic pricing	Linear Programming	Reducing peak load demand and transformer overloading	RTP & ToU
Yin et al. [50]	2015	Dynamic decision model of CPP considering electric vehicles' charging load	Particle swarm optimization algorithm (PSO)	Resolving peak on peak	Critical Peak Pricing (CPP)
Xu et al. [55]	2017	Dynamic Pricing at Electric Vehicle Charging Stations for Queuing Delay Reduction	Poisson process	To reduce the long delay at the crowded charging station, load balancing	Dynamic pricing policy
Chen et al. [56]	2017	Dynamic Price Vector Formation Model-Based Automatic DR Strategy for PV-integrated EV Charging Stations	Fuzzy C-means (FCM) Fuzzy K-means (FKM) algorithm.	Electricity cost minimization and flatten peak power demand curve	RTP
Yang et al. [57]	2017	Regulating Load of Electric Taxi Fleet via Real-Time Pricing	Probabilistic decision model	Resolving large and unpredictable peaks	RTP
Zahang et al. [58]	2017	Pricing model for the charging of electric vehicles	SD modelling technique	Balancing the benefits of electricity supplier, charging station, EV user	RTP
Yang et al. [59]	2015	Electric Vehicle Route Optimization	learnable partheno genetic algorithm (LPGA)	EV route optimization	ToU
Cao et al. [60]	2012	An Optimized EV Charging Model	Heuristic algorithm	Minimize charging cost and reduce peak and fill valley	ToU

Table 6. *Cont.*

Ref.	Year	Research Focus	Optimization Technique	Objective	Pricing Schemes
Crow et al. [61]	2017	Cost-constrained dynamic optimal electric vehicle charging	Linear, quadratic, and quadratic constrained formulations moving horizon optimization	Load factor improvement, Electricity cost reduction, mitigating line overloading	RTP & ToU
Chen et al. [62]	2017	Optimal regional time-of-use charging price model for electric vehicles	Membership function, Fuzzy C mean. FCM	Minimizing the peak valley difference and charging cost	Regional ToU
Martinenas et al. [67]	2014	Electric vehicle smart charging using dynamic price signal	Linear programming	Charging cost minimization	RTP
Misra et al. [69]	2015	Distributed dynamic pricing policy	Linear optimization	Cost optimization and reduction of extra load during peak hours	RTP
Binetti et al. [70]	2015	Charging with discrete charging rates	Real-time greedy (RTG) and the enhanced scale able S-RTG algorithms	Minimization of power losses, voltage deviation, load variance, operational cost, and emission control	Discrete Pricing
Dubey et al. [71]	2015	EV Charging on Residential Distribution Systems	Dynamic Programming	Mitigating the impacts if EV load on residential distribution circuit.	ToU
Hajforoosh et al. [72]	2016	Online optimal variable charge-rate coordination of EV	Coordinated aggregated particle swarm optimization (CAPSO).	Reducing undesirable peaks in power consumption, transformer over-loading	variable charge-rate
Moon et al. [74]	2017	Balanced charging strategies for EV	Coordinated aggregated particle swarm optimization (CAPSO).	Balanced charging	ToU
Xu et al. [76]	2016	Dynamic Optimization of Charging Strategies for EV	Improved particle swarm optimization (PSO)	Great profit improvement for the vehicle parking lot	RTP
Arif et al. [29]	2016	Online scheduling of EV in dynamic pricing schemes	Learning Automata, Reinforcement Learning, Online Algorithm,	Cost minimization, Customer satisfaction	RTP

If we analyze the optimization solution employed for the EV charging scheduling problem in a dynamic pricing environment, most of the work focuses on mathematical or conventional optimization techniques, as they are easy to implement and have low computational cost. However, they are less flexible for multi-objective problems due to number of solution dimensions and complex non-linear constraints. The EV charging scheduling problem is mostly formulated as a multi objective problem, and it is mostly treated as a real time optimization problem, which requires a quick solution. It is very hard for the conventional optimization techniques to give a precise solution in quickly while handling the stochastic nature of EV charging in a multidimensional solution space. In contrast to conventional optimization techniques, computational intelligence techniques are more flexible for solving multi-dimensional solution spaces with a number of non-linear constraints; however, they are a computationally expensive choice. The application of meta-heuristic algorithms deals with the EV charging scheduling problem for the optimization of different objectives. Each optimization group, i.e., conventional and intelligent techniques, has its own merits and demerits. Therefore, the EV charging pattern and load prediction proves to be a significant aspect in order to enrich the charging structure and to optimize charging cost. The forecasting of EVs' charging pattern can play a vital role for selection of optimal charging time and duration. Similarly, the electricity price forecasting is a branch of energy forecasting that mainly focuses on prediction of future prices in the wholesale electricity market. On the basis of time, the price forecasting is divided into three categories, i.e., "short, medium, and long term forecasting". There are many factors affecting price forecasting such as weather, demand, supply, and fuel market. A number of techniques have been developed to forecast the price signal, such as ARMA, GARCH, Jump diffusion, Fuzzy model, Simulation model, and Neural network [88]. This survey lacks the techniques required to predict future electricity price. However, the V2G is an important key feature of smart gird. Bidirectional power flow allows EVs to communicate and discharge energy into grid. The major challenges for researchers are to reduce the greater degree of uncertainty in scheduling process, frequent discharging of EVs' batteries, and proper integration of EVs. The study includes a grid to vehicle (G2V) feature; however, for future work, we will consider V2G characteristics of EVs in a same pricing environment [89].

9. Conclusions and Future Research Directions

In recent years, the EV charging scheduling problem has been widely explored from various perspectives. However, the EV charging considering dynamic electricity pricing has not been reviewed so far. EV charging activity and electricity pricing are directly linked with each other, as changes in electricity price directly influences the customer's charging behavior. Therefore, this study mainly focuses on optimized scheduling of EV charging under dynamic electricity pricing schemes including Real Time Pricing (RTP), Time of Use (ToU), Critical Peak Pricing (CPP), and Peak Time Rebates (PTR). Each pricing policy has been discussed with prominent attributes. The comparison of all the schemes with respect to their economics, fairness, and risk incentive illustrates the superiority of RTP among all pricing schemes. However, RTP has billing instability and system complexity, which needs technical provision. An incentive programs to overcome the billing risk can be introduced in connection with dynamic pricing to gain the customer's confidence. The survey has also focused on the main optimization methods followed to achieve various EV charging objectives including power loss minimization, electricity cost minimization, peak load reduction, voltage regulation, and distribution infrastructure overloading minimization. The future research avenues are listed below.

1. It is important to recognize the EV customers' readiness to accept dynamic pricing for further advancement.
2. A detailed research contribution is required to estimate the charging demand and electricity price relationship at domestic level. Besides the electricity price, there exist a number of factors that impact the electricity demand of one EV customer to another. In a dynamic pricing environment, the recognition of these aspects is an impending research area.

3. In execution of dynamic electricity pricing from EVs charging perspective, a research on electricity market is a potential area to consider.
4. Considering flexible charging demand of EVs optimization of electricity prices, incorporation of renewable energy system and storage units is a potential research direction.
5. Locational incentive plans can be introduced in future research work to facilitate the charging activities.
6. Although the RTP offers a flexibility to EV customers to manage their demand, a sophisticated communication infrastructure is required for real time information between EV customer and aggregator so that charging activities can be monitored and controlled. Although there exist several research studies on the communication system, a privacy improvement needs further attentions.
7. The EVs arrival and departure pattern is a significant aspect to consider while executing charging activities. Therefore, forecasting the arrival and departure behavior of EVs is important for selection of optimal charging time and duration and it is a potential research topic.

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