energies

MDPI

Review

Electrical Vehicle Charging Services Planning and Operation with Interdependent Power Networks and Transportation Networks: A Review of the Current Scenario and Future Trends

Shafqat Jawad * and Junyong Liu

College of Electrical Engineering, Sichuan University, Chengdu 610065, China; liujy@scu.edu.cn
* Correspondence: jawadch92@yahoo.com; Tel.: +86-132-81232696

Received: 5 May 2020; Accepted: 15 June 2020; Published: 1 July 2020

Abstract: The growing trend in electrical vehicle (EV) deployment has transformed independent power network and transportation network studies into highly congested interdependent network performance evaluations assessing their impact on power and transportation systems. Electrified transportation is highly capable of intensifying the interdependent correlations across charging service, transportation, and power networks. However, the evaluation of the complex coupled relationship across charging services, transportation, and power networks poses several challenges, including an impact on charging scheduling, traffic congestion, charging loads on the power grid, and high costs. Therefore, this article presents comparative survey analytics of large-scale EV integration's impact on charging service network scheduling, transportation networks, and power networks. Moreover, price mechanism strategies to determine the charging fares, minimize investment profits, diminish traffic congestion, and reduce power distribution constraints under the influence of various factors were carried out. Additionally, the survey analysis stipulates the interdependent network performance index, ascertaining travel distance, route selection, long-term and short-term planning, and different infrastructure strategies. Finally, the limitations of the proposed study, potential research trends, and critical technologies are demonstrated for future inquiries.

Keywords: electrified transportation; charging service networks; load forecasting; route selection; interdependent network infrastructure; challenges; future research

1. Introduction

Electrical vehicles (EVs) are widely considered the most promising source of distributed energy in developed countries due to an increasing trend in climate change, with economic and political concerns. There were more than five million fleet EVs in 2018, which are expected to represent 57% of global car sales by 2040 [1]. Therefore, governments and private organizations around the world are intensively exploring to reduce greenhouse emissions from their operations with a robust initiative to expand the electric vehicle market and release market incentives to achieve their goals [2]. The prevalence of electric vehicles is due to their exceptional advantages over traditional vehicles: they are environmentally friendly, meet individual travel demands, and support vehicle-to-grid (V2G) programs as distributed load mobility in transportation networks. With the improvement in battery technology, the driving range of EV models has been significantly improved, where the standard EV models have a variety of 100–250 km, and some models can reach 300–500 km without charging or depletion of battery [3]. However, despite numerous advantages, the integration of highly congested interdependent networks may introduce several new challenges to electrified transportation from charging scheduling, traffic flow, charging load on power network, and cost perspectives. The deployment on the large scale of

EVs leads to an increase in power transportation network constraints [4]. The peak congestions hours increase overall social costs and reduce operational efficiency in urban areas. According to economist reports, the hidden congestion costs in developed countries, such as the United States, the United Kingdom, and Germany, are about USD $1000 per year, where the total costs were about USD $461 billion last year [5]. The growing trend of EV deployments in various regions is depicted in Figure 1.

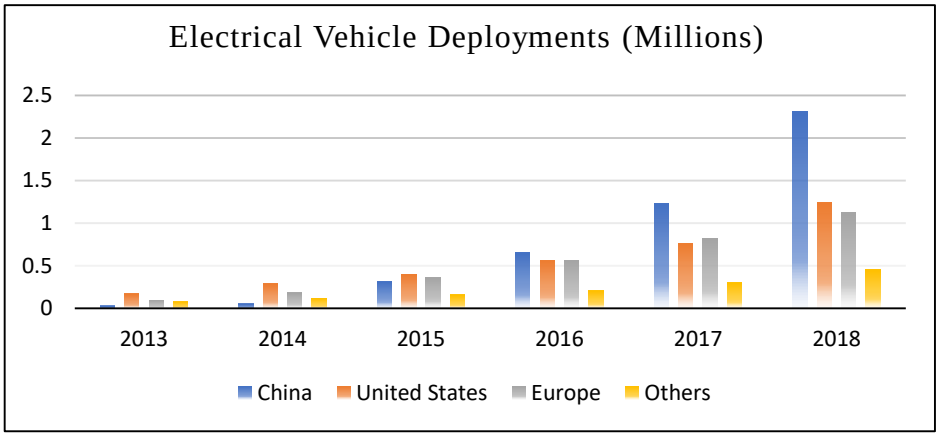

Figure 1. Global EV deployments 2013–2018 [Data from: International Energy Agency 2019].

The development of electric vehicles is influenced by many factors, such as economy, environment, policies, technology, and infrastructure construction. The planning process of charging service networks not only needs to analyze the characteristics of electric vehicles, such as battery charging requirements and the cruising range of electric vehicles, but also should consider the collaborative objectives and limitations of the distribution network and transportation network, such as distribution network capacity and safety constraints, and urban transportation system. A large amount of charging load is connected to the distribution network, which significantly influences the urban load shape compared with the traditional power grid, and also affects the transportation network. To promote the development of electric vehicles and support the charging service network infrastructure, the proposed survey demonstrates the cooperative coordination of interdependent networks across the charging service network, power distribution network, and transportation network. Consequently, the objective of the survey analysis can be summarized as follows:

(1) An extensive background study of power and transportation networks is provided to analyze the optimal operation and planning of an EV charging network infrastructure, including a performance index to predict the mobility of the vehicles and enhance the quality of service (QoS) and price strategies under the influence of multiple factors.
(2) Technical strategies for interdependent relationships across the charging service, transportation, and power networks were determined to devise charging load scheduling and traffic congestion constraints and to analyze driving range extension and power load constraints.
(3) Several potential research directions are highlighted that can add significant benefits to investigate interdependent charging service, power distribution, and transportation network expansion.

Based on the factors mentioned above, the study presents in-depth insights into interdependent networks that have not yet been adequately analyzed. Charging load forecasting, scale derivation, and customer comfort should be considered to evaluate the impact of purchasing decision behavior and travel behavior on the charging load. Additionally, there are complex coupling relationships among various factors that define the distribution of the charging load mobility. The EV is linked to the distribution network during charging in the form of a charging load. The uncertainty in the moving charging loads significantly alters the operating characteristics of the distribution network, resulting in a significant peak-to-valley difference in the distribution network. In the distribution

network, considering the impact of the moving loads' distribution uncertainty in the charging load on the charging service prices is inevitable. The traffic network also fails to consider the impact of traffic flow, traffic network structure, route selection, and robust traffic management strategies. The charging service network's element and cluster characteristics are the key factors for the planning and operation of the charging service network. Therefore, it is necessary to conduct an in-depth study on scale estimation and charging load prediction methods for electric vehicle clusters and improve quality of service if the charging demand is more than the charging station capacity under the influence of various factors.

The rest structure of the paper is generally distributed into categorical perspectives depicted in Figure 2. In Section 2, the operation and planning of the EV charging service network are established. The proposed study explicitly analyzed the EV charging schedule and allocation of charging stations to predict vehicle mobility, load management, and charging service price methods under the influence of multiple factors. Then, the different transportation network modeling approaches, driving range and traffic flow equilibrium constraints determining the shortest path, long-term and short-term planning, and their comparisons are highlighted in Section 3. Section 4 demonstrates the interdependent network technical challenges and their possible solutions to alleviate the system constraints. Section 5 provides some discussion and potential research directions for the further development of three-way networks. Finally, Section 6 concludes the proposed study.

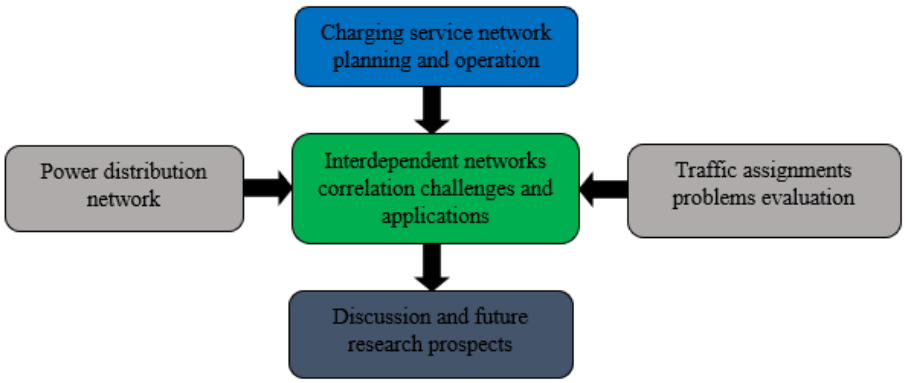

Figure 2. A study evaluation framework of interdependent networks.

2. Charging Service Networks' Planning and Operation

Interdependent network integration studies are a growing trend in electricity trading, which allows EV participants to purchase low-cost electricity from the grid and, during peak demand, sell it back to the grid. The applied linear programming model is introduced in [6] to maximize the energy available to all electric vehicles and determine the network constraints. Nevertheless, EV users are not considered adequately in the problem formulation. A decentralized coordinated charging method is developed to minimize the EVs costs in response to real-time electricity prices, and an aggregator is used to maximize profit and manage system security [7]. A similar problem is formulated by using a robust optimization approach [8], where the benefits of the aggregator in the worst-case market price situation are maximized. Reference [9] proposed siting and sizing of parking lots, where the distance between the parking lot and the EV allocation is examined to reduce the EV cost and maximize the profitability of the distribution system operator. The charging service network is generally a complicated network comprised of charging stations, charging piles, and different scales of charging machines, considering charging infrastructures and integrating multiple systems, such as distribution networks, transportation networks, and data network infrastructure. The main factors in EV charging services' network infrastructure operation modes are presented in Figure 3.

At the operational level, the service network can participate in the real-time scheduling of the grid to provide peaking and frequency modulation backup services. Additionally, it can consider investment

cost improvement and revenue to determine reasonable charging service rates, and further participate in the power market to compete with other entities. A comprehensive planning framework for the optimal location and sizing of EV charging stations in an urban area is studied in [10]. The charging demands are investigated by a forecasting method; however, the effect of traffic flow on EV charging demand is underrated. The interaction between parking lot investors and distribution system operators is presented in [11]. The investor parking lots select candidate buses to maximize their profits, and distribution system operators resolve the network losses. The relevant approaches for parking lot allocation constraints are suggested, where ancillary services such as uncertain electricity prices and time-varying profits are investigated [12,13].

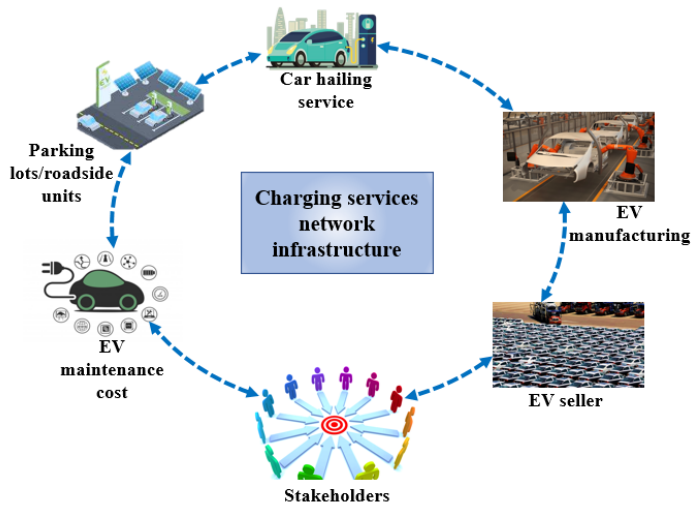

Figure 3. Charging service networks' operation modes.

At present, research on the planning and operation of charging service networks mainly focuses on the planning of individual charging and distribution networks. The planning and operation of the charging service network with coupled power distribution and transportation networks also requires dynamic adaptive updates. The time series mechanism and the correlation degree analysis method can be utilized for effective collaborative planning of the interdependent networks. Regarding the multi-network coupling state, the literature [14] introduced a multi-objective collaborative planning method based on vehicle–road-network coupling. The traffic network origin–destination matrix is employed to determine the trajectory data and traffic flows. The literature above individually considers the coupling-related characteristics of the charging service network, distribution network, and transportation network. However, three-network collaborative planning and operation mechanisms have not been analyzed adequately in the existing literature.

In practice, the charging station allocation difficulties are often two-stage decisions, due to uncertainty in size, while the second-stage decisions happen after uncertain demand response in the system. In the first stage, the location and sizing of charging infrastructure are established to determine the uncertainties in the system. In contrast, the second stage takes place to identify possible infeasibilities in the system. The proposed scenario analyzes the complex constraints, typically calculation of a proposed expansion plan concerning worst-case uncertainties, and optimal power flow is determined. The second scenario can transport information back until an ideal solution is accomplished. Based on the proposed method, multistage stochastic planning is portrayed in Figure 4. The constraints combine the market power of an aggregator formulated as a bilevel optimization suggested in [15], where the electricity price is confined by binary variables of the lower-level market-clearing constraints. At present, various power electronics converter topologies of DC fast charger mechanisms for EV fast-charging stations have been developed to determine the charging stations' loads, traffic congestion and travel behavior constraints, and investment costs, and to improve

system reliability [16–21]. EV charging scheduling constraints are optimized through a decentralized algorithm that can strongly determine the load profile and real-time implementation [22]. A detailed review of different charging schemes and their infrastructures is envisioned in [23].

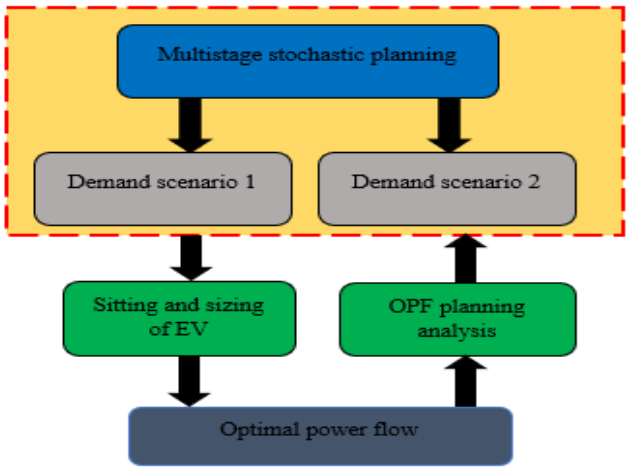

Figure 4. Multistage stochastic planning for EV charging and optimal power flow analysis.

2.1. Electrical Vehicles Charging Load Forecasting Evaluation

Charging load forecasting is one of the significant concerns of power system operation and is crucial to effective scheduling for economic dispatch at different timescales. Various electric vehicle charging studies consider only a few factors to determine a traffic flow prediction model, which may result in reduced flexibility and prediction accuracy. Therefore, to promote electric vehicle development and support charging network infrastructure, it is necessary to study the interaction and coupling relationship between interdependent networks. There are several approaches to predict mileage, which involve many factors that influence mileage predictions, but existing research cannot jointly consider accuracy and versatility. The impact analysis of electric vehicle charging load on the distribution network in the daily parking lot is presented in [24], where a decentralized algorithm is recommended to optimize the electric vehicle charging schedule. A real-time method is introduced to estimate the continuous driving distance while considering the driving behavior and the route. The trip chain concept has also been widely applied in travel demand forecasting [25] to a time-ordered trip sequence containing locations and route selection [26]. An overview of the electrical vehicle charging management network is shown in Figure 5.

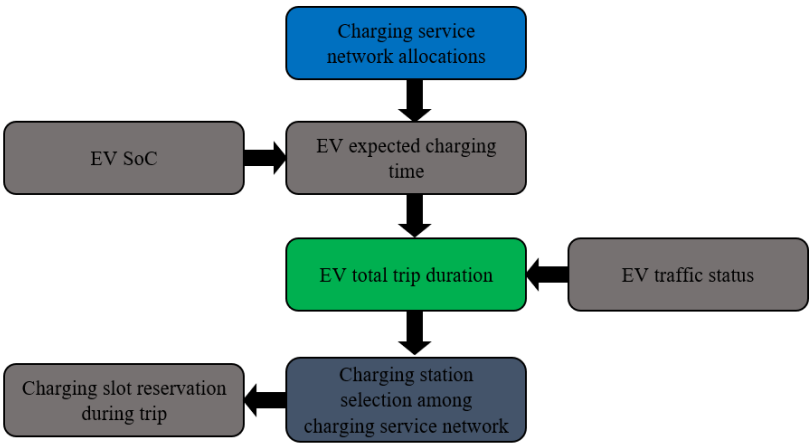

Figure 5. Overview of electric vehicle charging management network.

An EV charging load control strategy [27] for dispatching considerable moving loads is proposed to enhance the operating efficiency and reduce renewable energy source curtailments. The advancement of the Internet of Things (IoT) and cloud-based smart city technology deployments have enabled tracing of the EV traffic flow and congestion area information in a cloud server and the optimization of the entire process. A cloud computing real-time routing method for EV mobility compared on-road trip time, portrayed in [28]. The stochastic convex optimization method is practiced to minimize the average overall trip time for all customers relative to their actual trip time without in-route charging. Recently, stochastic EV charging navigation and charging fares studies have drawn some attention [29,30], to improve navigation accuracy and charging costs. EV charging routing navigation day-ahead scheduling constraints are optimized with a simplified charge-control (SCC) algorithm. An improved destination selection model is introduced in [31] to stimulate the EV operation system and determine the optimal charging station size based on charging demand prediction using real-time Beijing data. However, most studies have failed to manage random data and rely on statistical data to verify the effectiveness of the study.

In addition, a charging navigation architecture integrating grid information and traffic information load distribution on each fast-charging station is envisioned in [32]. The study simulates the dynamic driving process of EVs and specifies suitable charging stations for vehicles with low charge levels. On the other hand, a probabilistic model is proposed to simulate the spatial–temporal dynamics of large-scale EV moving loads based on a random trip chain and Markov decision process (MDP) to determine time-varying impact and space positioning [33]. A "vehicle–road–grid network" and power network nodes are mapped by the OD matrix to predict the grid charging load distribution and the traffic network flow status, presented in [34]. The reference [35] discussed the location and capacity of charging stations through the analysis of fast charging demand hotspots based on data on highway flow and vehicle travel mode. Besides, GIS-based probabilistic models employed to determine the charging load, trip-chain-related travel parameters with the integration of distributed generation, and the cost of electricity have been analyzed under uncontrolled and controlled charging scenarios [36,37]. This study confirmed that the probabilistic model is accurate in replicating observed travel patterns and suggested the model could further be utilized to predict the EV charging load for various regions. GIS distribution models based on an online ride-hailing trip approach for determining EV charging demand forecasting, traffic planning, and operation are also suggested to distinguish between regions charging demand and load transfer, and are intensively studied [38,39]. Nevertheless, most of the previous studies considered the EV load characteristics of EVs, but most of them neglected the mobility of loads, which is susceptible to traffic factors during traffic flow. Consequently, EV charging prediction considering spatial–temporal randomness with random data is still young.

In the present, different from traditional methods, experts have begun deploying various intelligent load forecasting approaches involving the Internet of Things (IoT) and big data to manage electric vehicles' smartness and complex decision-making and minimize system constraints [40]. The load prediction problem is a particular time series problem, which has a substantial similarity to natural language processing, and the deep learning method will make it possible to contribute effectively. More reliable predictions for such new types of loads may make a significant contribution to power system operators due to economic and security concerns, which require more robust mechanisms to resolve system constraints. However, the characteristics of new players, such as approaches considering more than one source power grid and renewable energy resources based on demand, have produced more complicated features and higher uncertainties, which challenge traditional approaches. Robust adaptive learning and generalization capabilities, artificial neural networks (ANN), and machine learning have become most effective in delivering load forecasting tasks [41]. The foundation of artificial intelligence and deep-learning-based design algorithms to minimize cost and avoid traffic congestion challenges by effective EV routing, charging point selection and integration of EVs into the smart grid are addressed in [42,43]. A new driving-based gradient-boosting decision tree (GBDT) traffic range prediction method has been investigated through machine learning for a large number

of feature data [44], to improve accuracy, battery status, and the traffic environment considering the real-world scenario. Besides, charging load operation prediction and operation data from the traffic side, employing a bottom-up analysis method with big data, are portrayed in [45]. However, this study only considers an architectural assumption rather than theoretical measurements.

Moreover, reference [46] proposed a machine learning EV driving accuracy prediction model, where the gradient-enhanced decision tree algorithm is applied to correctly predict the EV driving range and the driver's convenience. A deep learning method for predicting the charging load of short-term random electric vehicles is introduced to investigate fine-tuning and appropriate hyperparameters [47]. The proposed method can effectively reduce the prediction error, but the load forecasting features evaluation with random data required further analysis. An agent-based optimal routing decision making method for a PEV distributed model for interdependent networks is suggested in [48]. However, most of the load prediction approaches rarely consider the influence of traffic network characteristics, such as traffic congestion, on the spatial–temporal distribution of the charging load.

2.2. Charging Services Network Price Mechanism Analysis

Without proper deployments of demand response (DR), EV charging designs could create severe problems for distribution networks and minimize the environmental benefits of transportation electrification. Therefore, the charging service network can effectively realize the recovery and profitability of charging infrastructure construction and operation costs through the robust operation of the charging business and related services. In this section, an analysis of the main operating modes and price mechanism strategies of the charging service network are summarized.

The operating mode of the charging service network profitably provides energy supply for electric vehicles, and the central part of the charging business is the formulation of the charging price. The actual charging price of an electric vehicle is the sum of the charging price and the charging service fee, where the charging service fee is an additional fee charged by the charging service network to recover the investment cost and realize the operating profits. At present, the literature has few factors to contemplate when formulating charging service fees, and no uniform standards have been formed. In the context of the coupled networks, it is necessary to consider various factors to obtain the reasonable formulation of charging service fees. Against the background of three-way networks, the reasonable charging service fee strategy fails to consider the dual effects of traffic network congestion mitigation and the transition characteristics of the distribution network load to achieve a matching degree of traffic load, distribution network power capacity, and reliability. According to the influencing factors of quantitative analysis, the relationships between equipment utilization, transportation convenience, clean energy usage, uncertain oil price, charging service cost, and other factors are deeply analyzed to construct a causal relationship between multi-dimensional and complex components. Charging price mechanisms and critical factors influencing them are exhibited in Figure 6.

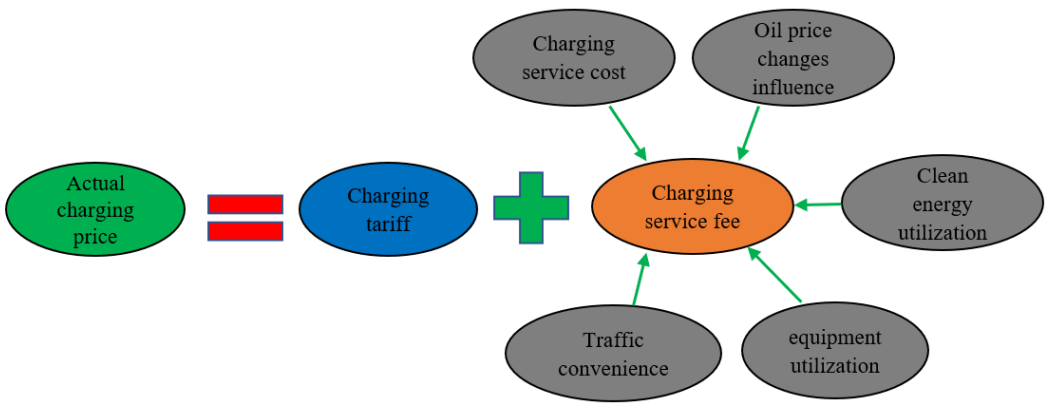

Figure 6. Charging service price mechanism and influencing factors.

The exploitation of V2G enabled ancillary services to support power system operations; EV involvement in the ramping market and additional frequency regulations are addressed in [49,50]. A virtual battery model was established in [51] to analyze EV fleet charging and discharging behavior, and the model simulates various driving patterns and wind power uncertainties. Furthermore, a real-time energy management solution for grid-connected charging parks is designed in [52], which functions to shift peak demand and alleviate the adverse effects of EV charging on the grid. A temperature-based smart charging method is suggested as a power generation plan for traditional units in [53]. Reference [54] examines the integration requirements, economic benefits, technical challenges, and charging strategies of the V2G interface, and analyzes its grid impact. An EV-based emergency power supply strategy for power system isolation, considering EVs' energy storage systems, vehicle-to-home (V2H) and vehicle-to-grid (V2G) scenarios and autonomous driving capability was analyzed in [55], where the genetic algorithm relaxed complex optimization constraints. Besides, several hierarchical V2G control strategies have been presented where uncertain scheduling is employed to track the automation frequency control and the state of charge (SoC) status, to reduce the operation costs of EV fleets and maximize ancillary services profit without any prior information on system uncertainties [56–59]. Vehicle-to-vehicle (V2V) energy offline and online scheduling of EV charging has been presented [60] to lessen the charging cost and enhance renewable energy sources (RES) utilization. EV charging management at peak load demand and V2G integration strategies are envisioned in [61].

The cost minimization and safe operation of EV battery swapping and charging strategies have been examined by differential evaluation algorithms [62], K-means clustering [63], and park-and-charge based approaches [64] to optimize system constraints. Wireless charging has also been introduced to determine the mobility of vehicles, reduce long charging times, and reduce high travel costs [65,66]. An optimal pricing scheme is studied in [67] to coordinate the charging process of electric vehicles and minimize the rate of service decline with the availability of alternating current (AC) and direct current (DC) dual charging modes. The proposed method confirms that the DC charging station is more accurate than the AC charging station. However, the cost of DC rechargeable battery life can affect the utilization of DC charging stations and requires further attention. Besides, a spatially and temporally based nodal impact assessment and the alleviation of moving EV loads in an integrated power and traffic system is suggested in [68]. Nodal time-of-use (NTOU) price and road traffic congestion (RTC) price methods are developed to shift the charging and movement of EV loads. A hierarchical game approach is described in [69], where a charging pricing strategy for EV fast-charging stations (FCSs) is established to determine the pricing scheme for the voltage control of electricity distribution networks. Besides, an EV mobility double-layer optimization model was developed to optimize the charging pricing scheme and minimize the total voltage magnitude deviation of distribution networks [70]. A fast-charging station demand-based optimal sizing solution has been established with a Markov chain considering profit of charging service, waiting times, and fast charging station constraints and economic benefits [71]. The costs of the EV station, distribution expansion, and a protection device cost model are portrayed in [72].

A hierarchical mixed-variable differential evolution strategy is formulated for EV charging station scheduling, considering factors such as charging station route construction, investment and total time cost, charging expenses, and SoC level [73]. Non-convex optimal pricing and routing [74], and online-based prior-free pricing [75] mechanisms are presented for the charging service network (CSN), considering charging decision constraints, travelers' routing preferences, and social welfare. A novel scheduled pricing policy (SPP) is proposed during peak traffic periods to reduce charging times and enhance profit margins for the fast-charging station operator [76]. In contrast, a dynamic charging network plan is analyzed to optimize charging station locations, the capacity of chargers in each station, and profit maximization with a large scale of EV penetration [77]. A charging pricing mechanism considering EVs self-charging behaviors and the flattering load for the grid is portrayed in [78], in a cooperative and non-cooperative scenario. A mixed-integer quadratic program (MIQP) has been formulated considering EV mobility and pricing mechanism to capture the spatial transportation

of energy [79]. A first-best congestion pricing approach is also presented in [80], to distinguish the price spatially and reduce travel fares. This study revealed that a hybrid pricing scheme is effective unless it compromises driver privacy. An EV charging schedule and pricing mechanisms are analyzed based on reinforcement learning algorithms in [81]. Besides, a system dynamics real-time charge pricing (RCP)-based mechanism for EVs, considering charging pricing, user response, benefit evaluation of all stakeholders and charging stations' lifecycle revenue has been presented to investigate the economic and environmental constraints [82]. Some authors [83–91] have suggested game-theoretic methods to determine EV charging scheduling, road traffic limitations and pricing mechanisms and impacts of the coupled power network and transportation network. However, most of the literature above relies on statistical data rather than considering the randomness of the analytic data.

Moreover, various RL-based approaches are suggested in the literature [92–96], in centralized and decentralized form, for day-ahead scheduling and EV fleet ride-hailing services, to minimize charging fares and waiting times. Fascinatingly, some studies have proposed Markov decision processes (MDP) and constrained Markov decision processes (CMDP) under the deep reinforcement learning (DRL) framework to determine the optimal strategies for EV charging and discharging scheduling, energy management issues, and price mechanisms [97–105]. The proposed studies demonstrate the effectiveness of the approach's solution relative to conventional theoretical approaches in terms of adaptivity and higher computation efficiency, without any prior knowledge of system uncertainties. Besides, multi-agent deep reinforcement learning methods, such as software-defined networking (SDN) communication and survey-based transfer learning, and energy management approaches for electric vehicle charging stations are analyzed in [106–108]. Unlike traditional methods, some advanced multi-agent approaches are presented for the cost minimization and optimization of charging scheduling, including multi-objective multi-agent selfish–collaborative architecture (MASCO) and hyperopia state action reward state action (SARSA)-based algorithms (HSA), considering the randomness of EV data [109,110]. A multi-agent multi-objective optimizing model has been designed to manage charging-demand-optimal charging station locations by considering the impact on travelers and passengers, the coupled transportation network and power network, and electricity costs [111]. Furthermore, a vehicle-to-vehicle (V2V) multi-agent-based EV charging and traffic management approach, considering charging selection and reservations and trip duration mechanisms through a vehicular ad hoc network (VANET), has been examined from a cost-minimizing perspective [112–115]. However, the proposed strategies ignore large-scale EV integration, and its impacts on the distribution network, EV owner perspectives, and real-world scenarios could represent more complex data. The charging service network introduces a new set of operating protocols to maximize the profitability of the charging infrastructure. An online internet platform can be useful for shared charging, flexible charging power control, charging navigation, charging status inquiry, charging reservations, and non-inductive payment. A fee-based service network can be developed while enhancing customer experience and satisfaction.

3. Transportation Network Traffic Assignments Problems Evaluation

The impact of EV charging on a distribution grid has been addressed in various studies, while the effects of EV charging service networks on transportation networks have received insufficient attention. Regarding increasing the share of EVs and enhancing traveler convenience, an appropriate charging infrastructure needs to be established so that each vehicle can receive charging services on time and within its driving range. Electrified transportation network research has begun to identify the appropriate advanced analytical tools, focused on analysis and possibly traffic flow congestion reduction. In 1952, Wardrop presented a scenario which manages a stable traffic flow pattern in a congested transportation network, named user equilibrium (UE), where no traveler has the incentive to change their route unilaterally.

The mathematical programming-based method for computing UEs originated in 1956, when Beckmann proved that the Wardrop equilibrium condition is equivalent to the optimality

condition in the strict convex traffic assignment problem (TAP) [116]. However, UEs are employed for practical applications due to travelers' selfish behavior. A comprehensive literature review of UE research and an introduction to the basic theory is addressed in [117]. To overcome the non-convexity, the most common function of the bureau of public roads (BPR) can be signified as follows [118]:

$$x_a\, t_a = t_a^0 \left[1 + 0.15 \left(\frac{\chi_a}{c_a}\right)^4\right], \forall\, a \in T_A^R \tag{1}$$

where $x_a\, t_a$ indicates the function increasing by vehicle x_a, t_a^0 is the free travel time, and capacity c_a, and $a \in T_A^R$ are a regular link without considering fast charging.

The Davidson function, based on the queueing theory, can be expressed as follows [119]:

$$x_a\, t_a = t_a^0 \left[1 + J\left(\frac{x_a}{c_a - x_a}\right)\right],\ \forall\, a \in T_A^R \tag{2}$$

where the charging link with an FCS is denoted $a \in T_A^R$, and parameter J controls the shape of the function. The smaller J is, the steeper $x_a\, t_a$ approaches to infinity when x_a tends to c_a.

Since the length of the bypass link is very short, the travel time on a bypass link can be neglected:

$$t_a\, x_a = 0,\ \forall_a \in T_A^B \tag{3}$$

In the UE pattern, the traffic flow common assumption is x_a, always less than the capacity link c_a; i.e., $x_a \geq c_a$ and the total travel time can be defined as $\Sigma_{a \in T_A} x_a\, t_a$.

The travel time t_a on the link a is equal to its free travel time t_a^0 when the traffic flow x_a is below its capacity c_a; the travel time t_a is equal to its free travel time plus a delay penalty λ_a^* when x_a reaches its capacity c_a [120]:

$$t_a = \begin{cases} t = t_{a,}^0\ x_a < c_a \\ t_a^0 + \lambda_a^*,\ x_a = c_a \end{cases} \tag{4}$$

where λ_a^* denotes a delay penalty for the link a which is equal to the value of the dual variable of link capacity.

The travel behavior, route selection, and traffic flow phenomena are long-standing and critically important topics in the area of smart cities. Early EV models were often limited by battery capacity and required to charge more frequently than gasoline vehicles (GV), which affected route selection. The UE model studied in [121] focused on the dependency of battery energy consumption and recharging time on traffic flows. Reference [122] also developed a UE model with length constraints for EV paths, which is further extended in [123]. A basic hybrid UE model with gasoline vehicles (GV) and electric vehicles (EV) was studied in [124], and a robust algorithm was introduced to resolve the problems. Based on the literature, reference [125] may be the first approach that conducted the equilibrium problem across the power distribution and transportation network based on charging station planning constraints, where direct current optimal power flow (DCOPF) is applied to determine the energy costs. In recent years, research has drawn some attention to the system-level interaction between urban-scale urban transportation networks and distribution networks [126]. In the proposed approach, travelers do not have accurate information to alter their routes, and they may not be capable of selecting the path to reach their destination independently. A multi-objective charging station planning model is studied in [127] to balance the number of destinations and transportation energy. Nevertheless, the detailed survey data may not accommodate other practical applications. A constrained fueling position model is introduced to evaluate the mobility of EV, which identified the optimal location of the transportation network charging station, and the EV charging demand was determined by considering the traffic in the origin–destination (O-D) pair [10,128,129]. A smart charging management system with a traffic assignment problem and alternating current-optimal power flow models is described in [130], considering the charging demand and pricing mechanism to determine the EVs' impact on

coupled transportation and power networks. However, in practice, detailed traffic assignment models describing traffic flow distributions analysis are neglected.

Vehicle Routing and Charging Operations Analysis

The vehicle routing and charging operation models were established based on the standard version of location theory and an initial flow-capturing location model (FCLM) developed in 1990 [131] to determine the retail facilities. The knowledge of traffic flow between origin–destination (O–D) pairs facilities maximizes the captured flow. The flow refueling location models were designed in [132,133], and an extended mathematical formulation for the capacitated flow refueling location model (CFRLM) was established in [134]. Besides, a capacitated flow refueling location model through mixed-integer programming has been suggested, considering coupled interactions among transportation and power networks under driving range constraints [135]. The proposed method provides a realistic solution for the coordinated planning of coupled traffic–electric networks. However, road capacity expansion, total travel vehicle time, and traffic flow distribution are not considered in CFRLM.

A modified single O-D path with a driving range of R=100 km comprised four nodes A, B, C, and D, respectively, illustrated in Figure 7. The majority of travelers prefer the nearest location and avoid peak hours; therefore, assume that the travelers find the charging station at node A, which is about 3–4 km away from their origin. The objective is to ensure the proper allocation of the charging network to capture traveler demand for the long journey. The driver can completely charge the vehicle at the charging station and can arrive at any point between nodes B and C, which indicates that there must be a station on node B or C. The gap between nodes A and C should be less than the driving range if the vehicle is sufficiently charged at the origin. If there is no charging station at C, the vehicle must reach the last station D, the destination, with at least half charge remaining, which can be a preferable choice for drivers, as they can do whatever they like, such as shopping, working, and so on, rather than waiting for a long time during charging. Consequently, the higher the vehicle range is, the fewer facilities are needed to cover the route.

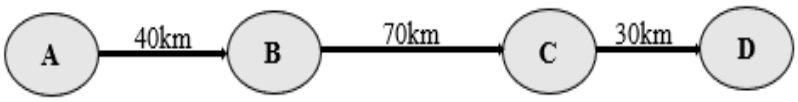

Figure 7. A simple example illustration of an origin–destination road network.

Several studies in this section were found in transportation network research. A general UE model which combines the destination, route, and parking choices of gasoline vehicles and EVs and limited driving range is portrayed in [136]. In addition, multi-objective long-term planning considering EV charging stations is introduced in [137]. A stochastic type-of-trip model suggested considering EV mobility, fuel consumption, and parking allocation to determine to charge load profiles and recharging price sensitivity based on traveler behavior [138]. Additionally, the optimal deployment of charging lanes under an energy-aware UE model is presented in [139]. According to the survey analysis, only a small amount of work is contemplated in the collaborative planning of electric vehicle charging stations, power networks, and transportation networks.

At present, various deep learning methods have drawn some attention to traffic flow predictions [140]. The literature presents [141] a new multivariate structural time-series (MST) model to predict traffic flow. The proposed study can effectively analyze the traffic flow status with higher prediction accuracy. A typical deep-learning-based approach for traffic flow prediction is suggested [142], where stacked autoencoders (SAEs) are built to learn generic traffic flow features with K layers. The fundamentals of vehicle routing and stochastic shortest path uncertainty constraints on travel time limitations are highlighted in [143], where Benders' decomposition is utilized to find the most optimal routing solution. The mixed-integer linear program (MILP) and quadratically constrained

formulations are represented in [144,145] to reduce traffic congestions and traffic management constraints effectively. Generally, the en-route charging flexibilities are more complicated to determine than the charging at the parking lots, due to charging scheduling constraints and travel behaviors. For instance, the charging event occurs when the car is parked at home or in the workplace. While in en-route charging, the vehicles charging rely on the load demand, and the charging time is considered as a time penalty. A heuristic approach is presented to extensively analyze the charging scheduling inconveniences and distinguish the SoC level and charging flexibility at different location scenarios [146]. However, most traffic flow prediction studies neglect the analysis of the integrated limitations of electrified transportation and power coupled networks.

4. Interdependent Networks Correlation Challenges and Applications

The charging service network supports electric vehicles as an energy source, and, further, has the coupled characteristics of a distribution network and a transportation network. With the prompt development of electric vehicles and their close ties to charging service networks, distribution networks and transportation networks have unfolded into highly integrated systems with mutual coupling and causal feedback.

4.1. Interdependent Networks Cooperative Planning and Operations Analysis

Charging service network infrastructure, as a significant support for electric vehicle charging, can effectively improve the economic, user and social benefits of electric vehicle charging services. Infrastructure planning of the traditional charging service network reflects the distribution network attributes and transportation network structure of electric vehicles but has not contemplated specific distribution network and transportation network characteristics. A general framework of independent-to-interdependent network transformation is depicted in Figure 8.

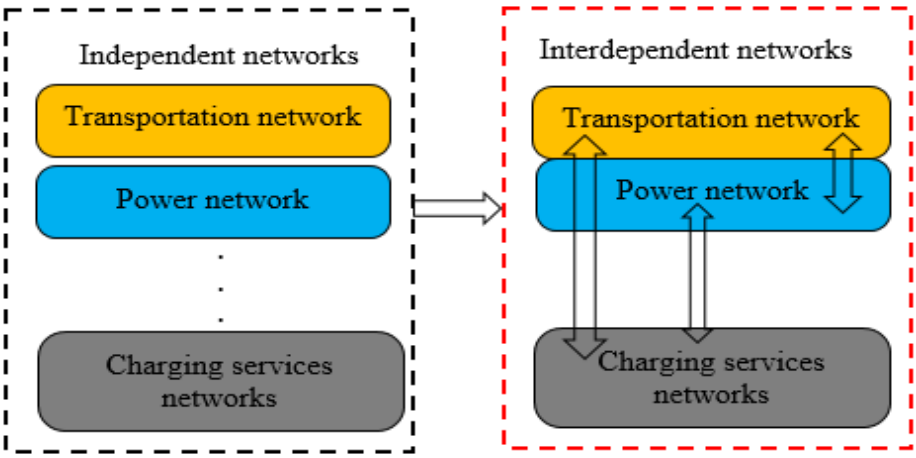

Figure 8. Development and formation of independent networks into interdependent networks.

An approach is introduced in [147] to evaluate the relationship between electric vehicle participants, transportation networks, and power networks. Additionally, an electrified transportation network, where the steady state distribution of the traffic flow is represented by a Wardrop user equilibrium to determine the travel behavior and operating status of the power grid, has been characterized by a linearized branch power flow model [148]. An extended transportation model has been developed to design the charging options of the virtual arc and EV user decisions [149]. A mixed-integer convex programming approach has been simulated [150] for road segments, power generation, charging facilities, and distribution line planning in a coupled infrastructure consisting of an optimal power flow and traffic flow balance.

In addition, interdependent power and transportation network analyses are extended in [151]. The authors suggest a Dijkstra algorithm to transfer data between electric vehicles and computing for charging stations to reduce electricity prices, energy demand, and electric vehicle routing constraints. Two-stage stochastic planning for the security-constrained unit commitment traffic assignment problem (SCUC-TAP), utilizing a heuristic algorithm and Benders' decompositions, is studied in [152] for flexible EV charging and discharging, power system delivery and cost reduction considering V2G. The coordination and planning strategy for an EV charging station in an electrified transportation network is addressed in [153]. An unconstrained traffic assignment model (UTAM) is established to seize the steady-state distribution of traffic flows in the transportation network, and a linearized DistFlow approach is applied to evaluate the distribution network conditions. Besides, the EV travel plan simplifies the complex traffic network using a UE mode [149,154,155]. In the coordinated planning and operation, the optimal expansion method of the transportation and distribution network constrained by the traffic UE is minimized. Most literature has analyzed two networks' performance. However, three interdependent networks' full-scale evaluation requires further attention in the future. The Interdependent network expansion model comparisons are illustrated in Table 1, where ✓ represents those considering, and ✗ those not considering, data.

Table 1. Interdependent network expansion models comparisons.

Network Modelling Approach	Charging Coordination	Traffic Conditions Model	Distribution Network Model	Three- Networks Performance Index	References
MILP	✓	CFRLM	Power flow	✗	[128]
mixed-integer SOCP	✓	CFRLM	Branch flow	✗	[135]
Multi-objective non-linear	✓	UE	Power flow	✗	[137]
Two-stage stochastic program	✓	UE	SCUC	✗	[152]
MILP	✓	UTAM	Linearized Distflow	✗	[153]

The EV driving patterns are known, which indicate the arrival rate and time, and charging requests have been determined either in a stochastic or deterministic manner, which can be learned from data-driven methods [156,157] and probabilistic models through a Markov decision process [33]. At present, smart driving strategy relocating operations adopting autonomous integer linear programs for autonomous vehicles and charging systems [158] are also recommended to minimize investment costs and operating costs and meet social welfare. Moreover, a distribution locational marginal pricing (DLMP) approach to mitigate EV load congestion for power systems is suggested in [159], where the distribution system operator (DSO) is utilized to determine the charging costs. A system dynamics model, considering electrical vehicle charging station (EVCS) allocations and distributed renewables integration, is examined using the k-means clustering method to determine user satisfaction levels [160]. The impact of electric vehicle integration and charging adaptability in terms of load flattening and load balancing against distribution generation and energy cost is investigated in [161,162]. The charging service network planning process considers a series of benefit indicators regarding distribution network reliability, power generation capacity, power quality, and economy. In the meantime, to consider route structure and traffic flow distribution based on the traffic network, traffic flow, convenience of user charging, economics of charging station construction, and investment profit is imperative. Besides, location and capacity optimization approaches to charging stations in the distribution network planning process can efficiently reduce the investment and operating costs of the distribution network.

4.2. Three-Ways Networks Modeling and Coupling Association

The charging service network is a diversified network comprising geographically dispersed charging infrastructures. There is a complicated relationship between charging stations and other types of charging infrastructure. The marginal location pricing (LMP) method is further practised to define the sites for a given number of charging facilities. A similar strategy was introduced in [163] to reduce electricity prices and traffic flow to enhance the overall operation of the coupled network. However, EVs are not effectively deployed in the above literature. A decentralized optimization model is extended based on wireless power transmission to extricate power distribution and transportation network coordination constraints, where the user equilibrium is utilized to minimize the traffic assignment problem (TAP) [65]. A coupled transportation and charging scheduling model are incorporated in [164], where the normalized Nash equilibrium problem is formulated to obtain the optimal solution.

Furthermore, spatial–temporal-distribution-based strategies have been suggested where the authors determine the uncertainties of the travelling behaviour and charging plan, and the impact of coupled power and transportation systems are analysed [165–169]. These approaches minimize the constraints of the transportation system, driving demand, and uncertain charging behaviour for user satisfaction. A multi-objective collaborative planning model has been proposed to manage EV charging schedules and the coupling constraints of power distribution and transportation networks to minimize the power losses and reduce costs [170,171]. This planning solution cannot provide an optimal solution for the different objectives but provides a reasonable trade-off solution. An EV charging management scheme with the integration of distributed generation is also proposed in [172,173], to minimize power losses and system costs. However, the proposed methods need further analysis to meet real-world demand. The current dynamic space–time probability model for the electric vehicle charging market has developed considering driving behaviour with a high penetration of electric vehicles [174]. However, the study lacks a smart charging infrastructure and V2G technology.

4.3. Three Networks Integration Technical Challenges Regarding Performance Evaluation

In the process of coordinated expansion of the three networks, ascertaining an extensive performance evaluation index system for the three coupled networks and mutual exclusion relationships between various factors in the planning and operation process are imperative. The matching degree between the three networks obtains the top-level layout mode of the interdependent network planning operation. The adaptability of the coupled systems for advanced events, where the dynamic UE model is used to capture the traffic flow scenario and achieve robust traffic flow management is presented in [175–177]. A two-layer approach coupled to power and traffic networks, peak load demand, and smooth load ramp is analysed in [178]. In [179], a similar method is proposed to determine the driving behaviour and charging flexibility of electric vehicles. The routing constraints on coupled systems are distinguished by the second-order cone program (SOCP) model under locational marginal prices and shortest-path algorithms to reduce the travelling costs, charging times, and power supply costs [180]. Transportation studies pay more attention to traffic flow; nevertheless, the operation of the charging services network and its impact on the power and transportation systems require further consideration. In the advanced power systems era, various tasks, such as planning and operation of the power system, involve different stakeholders. Therefore, EV charging flexibility also consolidates benefits to multiple participants. For instance, DSO is engaged in controlling EV charging and minimizing constraints. On the other hand, the electricity price of the fast-charging network also affects the travel plan of the EV. Hence, the uncertainty characteristics of the distributed behaviour make the generation and flow of power more complex.

5. Discussion and Future Research Prospects

An interdependent charging service, power distribution, and transportation network is a modern trend in the smart power and transportation sectors. The integration of electric vehicles into the grid

(V2G), implementing them with smart grid technology, can provide great benefits for all stakeholders. The present study focused on the EV charging service, power, and transportation networks at the distribution level, and assigned network planning challenges and opportunities. Transportation costs are route-specific features that can be managed through the EV fleet transportation plan. More robust network strategies are required to mitigate traffic congestion constraints. As discussed earlier, the development of electric vehicles is affected by various factors. Therefore, the influence of adverse weather on traffic conditions and traveler behavior is also required to be incorporated [181]. The effective prediction of electric vehicles' scale evaluation should consider the multiple influencing factors on electric vehicles in various development periods. In the future, charging load forecasting and scale derivation and the individual factors of the user should be studied to evaluate the impact of purchasing decision behavior and driving behavior on the charging load. Data mining and peer-to-peer exchange strategies can be utilized to investigate price mechanisms, multi-factor coupling features, and impact mechanisms to enhance the performance of interdependent networks [182–185]. Private EVs and fast charging stations can also participate in demand–response plans with robust economic enticements. On the other hand, the advancement of battery technologies requires further development to enhance the state of charge level and battery lifespan. Charging fares also need further study where the charging stations have low-load supplies, and the EV batteries are not fully depleted, respectively. In the past, the traditional charging mode required 7 to 9 hours to fully charge the EV [186], but the latest research states that the EV battery can be fully charged in 5 to 10 minutes, which is equivalent to 6 to 12 EV per hour [187,188]. Further, specific constraint analysis of EVs' battery management can be found in [189]. In the future, EV charging mechanisms, both at the pick-up locations and in-route charging, require further investigation. Notably, during peak demand, there is still some concern to capture the traffic flow scenario and to determine the relative location and optimal number of stations.

6. Conclusions

Increasing interest in economics and climate change have driven alleviation of the adverse effects of interdependent networks in the broader deployment of electrified transportation in recent years. The transformation from independent networks to interdependent networks may help to expand electric vehicle infrastructure, minimize costs, and continue the trend in modern power system and transportation system developments. Therefore, based on a comprehensive survey and analysis, the current study provides a comparative analysis of the developments required for EV charging service network implementation with coupled power distribution network and transportation network constraints. Additionally, it classifies the limitations of existing research on charging scheduling, load forecasting, cost minimization, travel behaviour and traffic congestion, and various strategies are distinguished. In particular, traditional electric vehicle strategies face severe problems in solving interdependent network constraints, such as large-scale EV charging scheduling, cost minimization, and traffic congestion constraints. Therefore, in the future, to investigate the distinct interactive, heterogeneous mode rather than individual EV routing, autonomous vehicles and deployment of smart strategies under the framework of three interdependent networks should be adequately interpreted. In the future, with the collaborative efforts of the power system and transportation stakeholders, the integration of the interdependent network infrastructures may add significant benefits to multiple stakeholders in minimizing environmental constraints and ensuring the economic benefits of electrified transportation.

Author Contributions: Conceptualization, S.J. and J.L.; Writing—original draft, S.J.; Writing—review and editing, S.J. and J.L. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the National Natural Science Foundation of China (51807127).

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Outlook, IEA Global EV. *To Electric Mobility*; IEA: Paris, France, 2019. Available online: https://www.iea.org/reports/global-ev-outlook-2019 (accessed on 15 October 2019).
2. Motors, Tesla. Tesla Motors-High Performance Electric Vehicles. 2010. Available online: http://www.teslamotors.com (accessed on 28 April 2019).
3. Grunditz, E.A.; Thiringer, T. Performance analysis of current BEVs based on a comprehensive review of Specifications. *IEEE Trans. Transp. Electr.* **2016**, *2*, 270–289. [CrossRef]
4. Marmaras, C.; Xydas, E.; Cipcigan, L. Simulation of electric vehicle driver behaviour in road transport and electric power networks. *Transp. Res. Part C Emerg. Technol.* **2017**, *80*, 239–256. [CrossRef]
5. The Economist. The Hidden Cost of Congestion. 2018. Available online: https://www.economist.com/graphic-detail/2018/02/28/the-hidden-cost-of-congestion (accessed on 16 February 2019).
6. Richardson, P.; Flynn, D.; Keane, A. Optimal charging of electric vehicles in low-voltage distribution systems. *IEEE Trans. Power Syst.* **2011**, *27*, 268–279. [CrossRef]
7. Sarker, M.; Ortega-Vazquez, M.A.; Kirschen, D.S. Optimal coordination and scheduling of demand response via monetary incentives. *IEEE Trans. Smart Grid* **2015**, *6*, 1341–1352. [CrossRef]
8. Wei, W.; Liu, F.; Mei, S. Energy pricing and dispatch for smart grid retailers under demand response and market price uncertainty. *IEEE Trans. Smart Grid* **2015**, *6*, 1364–1374. [CrossRef]
9. Kazemi, M.A.; Sedighizadeh, M.; Mirzaei, M.J.; Homaee, O. Optimal siting and sizing of distribution system operator owned EV parking lots. *Appl. Energy* **2016**, *179*, 1176–1184. [CrossRef]
10. Zhang, H.; Hu, Z.; Xu, Z.; Song, Y. An integrated planning framework for different types of PEV charging facilities in urban area. *IEEE Trans. Smart Grid* **2015**, *7*, 1. [CrossRef]
11. Amini, M.H.; Moghaddam, M.P.; Karabasoglu, O. Simultaneous allocation of electric vehicles' parking lots and distributed renewable resources in smart power distribution networks. *Sustain. Cities Soc.* **2017**, *28*, 332–342. [CrossRef]
12. Mohammadi-Hosseininejad, S.M.; Fereidunian, A.; Lesani, H.; Nezhad, S.M.H. Reliability improvement considering plug-in hybrid electric vehicles parking lots ancillary services: A stochastic multi-criteria approach. *IET Gener. Transm. Distrib.* **2018**, *12*, 824–833. [CrossRef]
13. Yang, Z.; Sun, L.; Chen, J.; Yang, Q.; Chen, X.; Xing, K. Profit maximization for plug-in electric taxi with uncertain future electricity prices. *IEEE Trans. Power Syst.* **2014**, *29*, 3058–3068. [CrossRef]
14. Xiang, Y.; Yang, W.; Liu, J.; Li, F. Multi-objective distribution network expansion incorporating electric vehicle charging stations. *Energies* **2016**, *9*, 909. [CrossRef]
15. Vayá, M.G.; Andersson, G. Optimal bidding of plug-in electric vehicle aggregator in day-ahead and regulation markets. *Int. J. Electr. Hybrid Veh.* **2015**, *7*, 209. [CrossRef]
16. Tan, L.; Wu, B.; Rivera, S.; Yaramasu, V. Comprehensive DC power balance management in high-power three-level dc–dc converter for electric vehicle fast charging. *IEEE Trans. Power Electron.* **2015**, *31*, 89–100. [CrossRef]
17. Tu, H.; Feng, H.; Srdic, S.; Lukic, S.M. Extreme fast charging of electric vehicles: A technology overview. *IEEE Trans. Transp. Electr.* **2019**, *5*, 861–878. [CrossRef]
18. Ronanki, D.; Kelkar, A.; Williamson, S. Extreme fast charging technology—Prospects to enhance sustainable electric transportation. *Energies* **2019**, *12*, 3721. [CrossRef]
19. Lee, M.; Yeh, C.-S.; Yu, O.; Kim, J.-W.; Choe, J.-M.; Lai, J.-S. Modeling and control of three-level boost rectifier based medium-voltage solid-state transformer for dc fast charger application. *IEEE Trans. Transp. Electr.* **2019**, *5*, 890–902. [CrossRef]
20. Viana, C.; Lehn, P.W. A drivetrain integrated DC fast charger with buck and boost functionality and simultaneous drive/charge capability. *IEEE Trans. Transp. Electr.* **2019**, *5*, 903–911. [CrossRef]
21. Ucer, E.; Koyuncu, I.; Kisacikoglu, M.; Yavuz, M.; Meintz, A.L.; Rames, C. Modeling and analysis of a fast charging station and evaluation of service quality for electric vehicles. *IEEE Trans. Transp. Electr.* **2019**, *5*, 215–225. [CrossRef]
22. Gan, L.; Topcu, U.; Low, S.H. Optimal decentralized protocol for electric vehicle charging. *IEEE Trans. Power Syst.* **2012**, *28*, 940–951. [CrossRef]
23. Shuai, W.; Maille, P.; Pelov, A. Charging electric vehicles in the smart city: A survey of economy-driven approaches. *IEEE Trans. Intell. Transp. Syst.* **2016**, *17*, 2089–2106. [CrossRef]

24. Rezaee, S.; Farjah, E.; Khorramdel, B. Probabilistic analysis of plug-in electric vehicles impact on electrical grid through homes and parking lots. *IEEE Trans. Sustain. Energy* **2013**, *4*, 1024–1033. [CrossRef]
25. Qian, K.; Allan, M.; Zhou, C.; Yuan, Y. Modeling of load demand due to ev battery charging in distribution systems. *IEEE Trans. Power Syst.* **2010**, *26*, 802–810. [CrossRef]
26. Wai, C.K.; Rong, Y.Y.; Morris, S. Simulation of a distance estimator for battery electric vehicle. *Alex. Eng. J.* **2015**, *54*, 359–371. [CrossRef]
27. Shao, C.; Wang, X.; Wang, X.; Du, C.; Wang, B. Hierarchical charge control of large populations of EVs. *IEEE Trans. Smart Grid* **2015**, *7*, 1. [CrossRef]
28. Ammous, M.; Belakaria, S.; Sorour, S.; Abdel-Rahim, A. Optimal cloud-based routing with in-route charging of mobility-on-demand electric vehicles. *IEEE Trans. Intell. Transp. Syst.* **2019**, *20*, 2510–2522. [CrossRef]
29. Cerna, F.V.; Kasmaei, M.P.; Romero, R.; Rider, M.J.; Pourakbhari-Kasmaei, M. Optimal delivery scheduling and charging of evs in the navigation of a city map. *IEEE Trans. Smart Grid* **2017**, *9*, 4815–4827. [CrossRef]
30. Liu, C.; Zhou, M.; Wu, J.; Long, C.; Wang, Y. Electric vehicles en-route charging navigation systems: Joint charging and routing optimization. *IEEE Trans. Control. Syst. Technol.* **2017**, *27*, 906–914. [CrossRef]
31. Shi, R.; Liu, J.; Liao, Z.; Niu, L.; Ibrahim, E.; Fu, F. An electric taxi charging station planning scheme based on an improved destination choice method. *Energies* **2019**, *12*, 3781. [CrossRef]
32. Guo, Q.; Xin, S.; Sun, H.; Li, Z.; Zhang, B. Rapid-charging navigation of electric vehicles based on real-time power systems and traffic data. *IEEE Trans. Smart Grid* **2014**, *5*, 1969–1979. [CrossRef]
33. Tang, D.; Wang, P. Probabilistic modeling of nodal charging demand based on spatial-temporal dynamics of moving electric vehicles. *IEEE Trans. Smart Grid* **2015**, *7*, 1. [CrossRef]
34. Luo, Y.; Zhu, T.; Wan, S.; Zhang, S.; Li, K. Optimal charging scheduling for large-scale EV (electric vehicle) deployment based on the interaction of the smart-grid and intelligent-transport systems. *Energy* **2016**, *97*, 359–368. [CrossRef]
35. Hilton, G.; Kiaee, M.; Bryden, T.S.; Dimitrov, B.; Cruden, A.; Mortimer, A. A stochastic method for prediction of the power demand at high rate ev chargers. *IEEE Trans. Transp. Electr.* **2018**, *4*, 744–756. [CrossRef]
36. Li, M.; Lenzen, M.; Keck, F.; McBain, B.; Rey-Lescure, O.; Li, B.; Jiang, C. GIS-based probabilistic modeling of bev charging load for Australia. *IEEE Trans. Smart Grid* **2018**, *10*, 3525–3534. [CrossRef]
37. Li, M.; Lenzen, M.; Wang, D.; Nansai, K. GIS-based modelling of electric-vehicle–grid integration in a 100% renewable electricity grid. *Appl. Energy* **2020**, *262*, 114577. [CrossRef]
38. Xing, Q.; Chen, Z.; Zhang, Z.; Huang, X.; Leng, Z.; Sun, K.; Chen, Y.; Wang, H. Charging demand forecasting model for electric vehicles based on online ride-hailing trip data. *IEEE Access* **2019**, *7*, 137390–137409. [CrossRef]
39. Chiou, S.-Y.; Tu, T.-Y. A trusted mobile ride-hailing evaluation system with privacy and authentication. *IEEE Access* **2020**, *8*, 61929–61942. [CrossRef]
40. Park, D.; El-Sharkawi, M.; Marks, R.; Atlas, L.; Damborg, M. Electric load forecasting using an artificial neural network. *IEEE Trans. Power Syst.* **1991**, *6*, 442–449. [CrossRef]
41. Hippert, H.S.; Pedreira, C.E.; Souza, R.C. Neural networks for short-term load forecasting: A review and evaluation. *IEEE Trans. Power Syst.* **2001**, *16*, 44–55. [CrossRef]
42. Rigas, E.S.; Ramchurn, S.D.; Bassiliades, N. Managing electric vehicles in the smart grid using artificial intelligence: A survey. *IEEE Trans. Intell. Transp. Syst.* **2014**, *16*, 1619–1635. [CrossRef]
43. Vázquez-Canteli, J.R.; Nagy, Z. Reinforcement learning for demand response: A review of algorithms and modeling techniques. *Appl. Energy* **2019**, *235*, 1072–1089. [CrossRef]
44. Zhang, Y.; Haghani, A. A gradient boosting method to improve travel time prediction. *Transp. Res. Part C Emerg. Technol.* **2015**, *58*, 308–324. [CrossRef]
45. Huang, X.; Chen, J.; Chen, Y.; Yang, H.; Cao, Y.; Jiang, L. Load forecasting method for electric vehicle charging station based on big data. *Autom. Electr. Power Syst.* **2016**, *12*, 68–74.
46. Sun, S.; Zhang, J.; Bi, J.; Wang, Y. A machine learning method for predicting driving range of battery electric vehicles. *J. Adv. Transp.* **2019**, *2019*, 1–14. [CrossRef]
47. Zhu, J.; Yang, Z.; Mourshed, M.; Li, K.; Zhou, Y.; Chang, Y.; Wei, Y.; Feng, S. Electric vehicle charging load forecasting: A comparative study of deep learning approaches. *Energies* **2019**, *12*, 2692. [CrossRef]
48. Amini, M.H.; Mohammadi, J.; Kar, S. Distributed holistic framework for smart city infrastructures: Tale of interdependent electrified transportation network and power grid. *IEEE Access* **2019**, *7*, 157535–157554. [CrossRef]

49. Zhang, B.; Kezunovic, M. Impact on power system flexibility by electric vehicle participation in ramp market. *IEEE Trans. Smart Grid* **2015**, *7*, 1. [CrossRef]
50. Liu, H.; Hu, Z.; Song, Y.; Wang, J.; Xie, X. Vehicle-to-grid control for supplementary frequency regulation considering charging demands. *IEEE Trans. Power Syst.* **2014**, *30*, 1–10. [CrossRef]
51. Vaya, M.G.; Andersson, G. Self scheduling of plug-in electric vehicle aggregator to provide balancing services for wind power. *IEEE Trans. Sustain. Energy* **2015**, *7*, 886–899. [CrossRef]
52. Mohamed, A.; Salehi, V.; Ma, T.; Mohammed, O.A. Real-time energy management algorithm for plug-in hybrid electric vehicle charging parks involving sustainable energy. *IEEE Trans. Sustain. Energy* **2014**, *5*, 577–586. [CrossRef]
53. Khodayar, M.E.; Wu, L.; Li, Z. Electric vehicle mobility in transmission-constrained hourly power generation scheduling. *IEEE Trans. Smart Grid* **2013**, *4*, 779–788. [CrossRef]
54. Yilmaz, M.; Krein, P.T. Review of the impact of vehicle-to-grid technologies on distribution systems and utility interfaces. *IEEE Trans. Power Electron.* **2013**, *28*, 5673–5689. [CrossRef]
55. Xu, N.Z.; Chan, K.W.; Chung, C.Y.; Niu, M. Enhancing adequacy of isolated systems with electric vehicle-based emergency strategy. *IEEE Trans. Intell. Transp. Syst.* **2019**, 1–7. [CrossRef]
56. Liu, H.; Qi, J.; Wang, J.; Li, P.; Li, C.; Wei, H. EV dispatch control for supplementary frequency regulation considering the expectation of ev owners. *IEEE Trans. Smart Grid* **2018**, *9*, 3763–3772. [CrossRef]
57. Wenzel, G.; Negrete-Pincetic, M.; Olivares, D.E.; Macdonald, J.; Callaway, D.S. Real-time charging strategies for an electric vehicle aggregator to provide ancillary services. *IEEE Trans. Smart Grid* **2018**, *9*, 5141–5151. [CrossRef]
58. Liu, H.; Huang, K.; Wang, N.; Liu, H.; Wu, Q.; Ma, S.; Li, C. Optimal dispatch for participation of electric vehicles in frequency regulation based on area control error and area regulation requirement. *Appl. Energy* **2019**, *240*, 46–55. [CrossRef]
59. Deforest, N.; Macdonald, J.; Black, D.R. Day ahead optimization of an electric vehicle fleet providing ancillary services in the Los Angeles air force base vehicle-to-grid demonstration. *Appl. Energy* **2018**, *210*, 987–1001. [CrossRef]
60. Koufakis, A.-M.; Rigas, E.S.; Bassiliades, N.; Ramchurn, S.D. Offline and online electric vehicle charging scheduling with V2V energy transfer. *IEEE Trans. Intell. Transp. Syst.* **2020**, *21*, 2128–2138. [CrossRef]
61. Saldaña, G.; Martin, J.I.S.; Zamora, I.; Asensio, F.J.; Oñederra, O. Electric vehicle into the grid: Charging methodologies aimed at providing ancillary services considering battery degradation. *Energies* **2019**, *12*, 2443. [CrossRef]
62. Zheng, Y.; Dong, Z.Y.; Xu, Y.; Meng, K.; Zhao, J.H.; Qiu, J. Electric vehicle battery charging/swap stations in distribution systems: Comparison study and optimal planning. *IEEE Trans. Power Syst.* **2013**, *29*, 221–229. [CrossRef]
63. Infante, W.; Ma, J.; Han, X.; Liebman, A. Optimal recourse strategy for battery swapping stations considering electric vehicle uncertainty. *IEEE Trans. Intell. Transp. Syst.* **2020**, *21*, 1369–1379. [CrossRef]
64. Wei, Z.; Li, Y.; Cai, L. Electric vehicle charging scheme for a park-and-charge system considering battery degradation costs. *IEEE Trans. Intell. Veh.* **2018**, *3*, 361–373. [CrossRef]
65. Manshadi, S.D.; Khodayar, M.E.; Abdelghany, K.; Uster, H. wireless charging of electric vehicles in electricity and transportation networks. *IEEE Trans. Smart Grid* **2018**, *9*, 4503–4512. [CrossRef]
66. Ou, C.-H.; Liang, H.; Zhuang, W. Investigating wireless charging and mobility of electric vehicles on electricity market. *IEEE Trans. Ind. Electron.* **2014**, *62*, 3123–3133. [CrossRef]
67. Zhang, Y.; You, P.; Cai, L. Optimal charging scheduling by pricing for EV charging station with dual charging modes. *IEEE Trans. Intell. Transp. Syst.* **2019**, *20*, 3386–3396. [CrossRef]
68. Tang, D.; Wang, P. Nodal impact assessment and alleviation of moving electric vehicle loads: From traffic flow to power flow. *IEEE Trans. Power Syst.* **2016**, *31*, 4231–4242. [CrossRef]
69. Tan, J.; Wang, L. Real-time charging navigation of electric vehicles to fast charging stations: A hierarchical game approach. *IEEE Trans. Smart Grid* **2015**, *8*, 1. [CrossRef]
70. Dong, X.; Mu, Y.; Xu, X.; Jia, H.; Wu, J.; Yu, X.; Qi, Y. A charging pricing strategy of electric vehicle fast charging stations for the voltage control of electricity distribution networks. *Appl. Energy* **2018**, *225*, 857–868. [CrossRef]
71. Yang, Q.; Sun, S.; Deng, S.; Zhao, Q.; Zhou, M. optimal sizing of PEV fast charging stations with markovian demand characterization. *IEEE Trans. Smart Grid* **2019**, *10*, 4457–4466. [CrossRef]

72. Cui, Q.; Weng, Y.; Tan, C.-W. Electric vehicle charging station placement method for urban areas. *IEEE Trans. Smart Grid* **2019**, *10*, 6552–6565. [CrossRef]
73. Liu, W.-L.; Gong, Y.-J.; Chen, W.-N.; Liu, Z.; Wang, H.; Zhang, J. Coordinated charging scheduling of electric vehicles: A mixed-variable differential evolution approach. *IEEE Trans. Intell. Transp. Syst.* **2019**, 1–16. [CrossRef]
74. Moradipari, A.; Alizadeh, M. Pricing and routing mechanisms for differentiated services in an electric vehicle public charging station network. *IEEE Trans. Smart Grid* **2020**, *11*, 1489–1499. [CrossRef]
75. Ghosh, A.; Aggarwal, V. Control of charging of electric vehicles through menu-based pricing under uncertainty. In Proceedings of the 2017 IEEE International Conference on Communications (ICC), Paris, France, 21–25 May 2017; Volume 9, pp. 1–6.
76. Zenginis, I.; Vardakas, J.; Zorba, N.; Verikoukis, C. Performance evaluation of a multi-standard fast charging station for electric vehicles. *IEEE Trans. Smart Grid* **2017**, *9*, 4480–4489. [CrossRef]
77. Zhang, Y.; Chen, J.; Cai, L.; Pan, J. Expanding EV charging networks considering transportation pattern and power supply limit. *IEEE Trans. Smart Grid* **2019**, *10*, 6332–6342. [CrossRef]
78. Hu, Z.; Zhan, K.; Zhang, H.; Song, Y. Pricing mechanisms design for guiding electric vehicle charging to fill load valley. *Appl. Energy* **2016**, *178*, 155–163. [CrossRef]
79. Xie, R.; Wei, W.; Wu, Q.; Ding, T.; Mei, S. Optimal service pricing and charging scheduling of an electric vehicle sharing system. *IEEE Trans. Veh. Technol.* **2020**, *69*, 78–89. [CrossRef]
80. Ren, T.; Huang, H.-J.; Liu, T.-L.; Nie, Y. (Marco) Some analytical results on spatial price differentiation in first–best congestion pricing schemes. *Transp. Res. Part C Emerg. Technol.* **2020**, *114*, 425–445. [CrossRef]
81. Arif, A.; Babar, M.; Ahamed, T.I.; Al-Ammar, E.; Nguyen, P.; Kamphuis, I.R.; Malik, N. Online scheduling of plug-in vehicles in dynamic pricing schemes. *Sustain. Energy Grids Netw.* **2016**, *7*, 25–36. [CrossRef]
82. Zhang, X.; Liang, Y.; Liu, W. Pricing model for the charging of electric vehicles based on system dynamics in Beijing. *Energy* **2017**, *119*, 218–234. [CrossRef]
83. Zhang, K.; Mao, Y.; Leng, S.; He, Y.; Maharjan, S.; Gjessing, S.; Zhang, Y.; Tsang, D.H.K. Optimal charging schemes for electric vehicles in smart grid: A contract theoretic approach. *IEEE Trans. Intell. Transp. Syst.* **2018**, *19*, 3046–3058. [CrossRef]
84. Ding, Q.; Zeng, X.; Zhang, X.; Sung, D.K. A public goods game theory-based approach to cooperation in vanets under a high vehicle density condition. *IEEE Trans. Intell. Transp. Syst.* **2019**, *20*, 3995–4005. [CrossRef]
85. Shokri, M.; Kebriaei, H. Mean field optimal energy management of plug-in hybrid electric vehicles. *IEEE Trans. Veh. Technol.* **2018**, *68*, 113–120. [CrossRef]
86. Zhou, Y.; Kumar, R.; Tang, S. Incentive-based distributed scheduling of electric vehicle charging under uncertainty. *IEEE Trans. Power Syst.* **2018**, *34*, 3–11. [CrossRef]
87. Laha, A.; Yin, B.; Cheng, Y.; Cai, L.X.; Wang, Y. Game theory based charging solution for networked electric vehicles: A location-aware approach. *IEEE Trans. Veh. Technol.* **2019**, *68*, 6352–6364. [CrossRef]
88. Hou, L.; Wang, C.; Yan, J. Bidding for preferred timing: An auction design for electric vehicle charging station scheduling. *IEEE Trans. Intell. Transp. Syst.* **2019**, 1–12. [CrossRef]
89. Cui, Y.; Hu, Z.; Luo, H. Optimal day-ahead charging and frequency reserve scheduling of electric vehicles considering the regulation signal uncertainty. *IEEE Trans. Ind. Appl.* **2020**, 1. [CrossRef]
90. Chen, S.; Guo, Z.; Yang, Z.; Xu, Y.; Cheng, R.S. A game theoretic approach to phase balancing by plug-in electric vehicles in the smart grid. *IEEE Trans. Power Syst.* **2020**, *35*, 2232–2244. [CrossRef]
91. Shakerighadi, B.; Anvari-Moghaddam, A.; Ebrahimzadeh, E.; Blaabjerg, F.; Bak, C.L. A hierarchical game theoretical approach for energy management of electric vehicles and charging stations in smart grids. *IEEE Access* **2018**, *6*, 67223–67234. [CrossRef]
92. Chis, A.; Lundén, J.; Koivunen, V. Reinforcement learning-based plug-in electric vehicle charging with forecasted price. *IEEE Trans. Veh. Technol.* **2016**, *66*, 1. [CrossRef]
93. Vandael, S.; Claessens, B.; Ernst, D.; Holvoet, T.; Deconinck, G. reinforcement learning of heuristic EV Fleet charging in a day-ahead electricity market. *IEEE Trans. Smart Grid* **2015**, *6*, 1. [CrossRef]
94. Claessens, B.J.; Vrancx, P.; Ruelens, F. Convolutional neural networks for automatic state-time feature extraction in reinforcement learning applied to residential load control. *IEEE Trans. Smart Grid* **2016**, *9*, 3259–3269. [CrossRef]

95. Shi, J.; Gao, Y.; Wang, W.; Yu, N.; Ioannou, P.A. Operating electric vehicle fleet for ride-hailing services with reinforcement learning. *IEEE Trans. Intell. Transp. Syst.* **2019**, 1–13. [CrossRef]
96. Sadeghianpourhamami, N.; Deleu, J.; Develder, C. Definition and evaluation of model-free coordination of electrical vehicle charging with reinforcement learning. *IEEE Trans. Smart Grid* **2020**, *11*, 203–214. [CrossRef]
97. Qian, T.; Shao, C.; Wang, X.; Shahidehpour, M. Deep reinforcement learning for EV charging navigation by coordinating smart grid and intelligent transportation system. *IEEE Trans. Smart Grid* **2020**, *11*, 1714–1723. [CrossRef]
98. Wan, Z.; Li, H.; He, H.; Prokhorov, D.; He, H.L.H. Model-free real-time EV charging scheduling based on deep reinforcement learning. *IEEE Trans. Smart Grid* **2019**, *10*, 5246–5257. [CrossRef]
99. Li, H.; Wan, Z.; He, H. Constrained EV charging scheduling based on safe deep reinforcement learning. *IEEE Trans. Smart Grid* **2020**, *11*, 2427–2439. [CrossRef]
100. Lu, R.; Hong, S.H.; Zhang, X. A Dynamic pricing demand response algorithm for smart grid: Reinforcement learning approach. *Appl. Energy* **2018**, *220*, 220–230. [CrossRef]
101. Xu, X.; Jia, Y.; Xu, Y.; Xu, Z.; Chai, S.; Lai, C.S. A Multi-agent reinforcement learning based data-driven method for home energy management. *IEEE Trans. Smart Grid* **2020**, 1. [CrossRef]
102. Qi, X.; Luo, Y.; Wu, G.; Boriboonsomsin, K.; Barth, M. Deep reinforcement learning enabled self-learning control for energy efficient driving. *Transp. Res. Part C Emerg. Technol.* **2019**, *99*, 67–81. [CrossRef]
103. Zhou, Q.; Li, J.; Shuai, B.; Williams, H.; He, Y.; Li, Z.; Xu, H.; Yan, F. Multi-step reinforcement learning for model-free predictive energy management of an electrified off-highway vehicle. *Appl. Energy* **2019**, *255*, 113755. [CrossRef]
104. Zhang, C.; Yu, J.J.Q.; Liu, Y. Spatial-temporal graph attention networks: A deep learning approach for traffic forecasting. *IEEE Access* **2019**, *7*, 166246–166256. [CrossRef]
105. Yu, J.J.Q.; Yu, W.; Gu, J. Online vehicle routing with neural combinatorial optimization and deep reinforcement learning. *IEEE Trans. Intell. Transp. Syst.* **2019**, *20*, 3806–3817. [CrossRef]
106. Shin, M.; Choi, D.-H.; Kim, J. Cooperative management for PV/ESS-enabled electric vehicle charging stations: A multiagent deep reinforcement learning approach. *IEEE Trans. Ind. Inform.* **2020**, *16*, 3493–3503. [CrossRef]
107. Liu, J.; Guo, H.; Xiong, J.; Kato, N.; Zhang, J.; Zhang, Y. Smart and resilient EV charging in SDN-enhanced vehicular edge computing networks. *IEEE J. Sel. Areas Commun.* **2020**, *38*, 217–228. [CrossRef]
108. da Silva, F.L.; Costa, A.H.R. A survey on transfer learning for multiagent reinforcement learning systems. *J. Artif. Intell. Res.* **2019**, *64*, 645–703. [CrossRef]
109. da Silva, F.L.; Nishida, C.E.H.; Roijers, D.M.; Costa, A.H.R. Coordination of electric vehicle charging through multiagent reinforcement learning. *IEEE Trans. Smart Grid* **2020**, *11*, 2347–2356. [CrossRef]
110. Wang, S.; Bi, S.; Zhang, Y.J.A. Reinforcement learning for real-time pricing and scheduling control in EV charging stations. *IEEE Trans. Ind. Inform.* **2019**, 1. [CrossRef]
111. Pan, A.; Zhao, T.; Yu, H.; Zhang, Y. Deploying public charging stations for electric taxis: A charging demand simulation embedded approach. *IEEE Access* **2019**, *7*, 17412–17424. [CrossRef]
112. Bautista, P.A.B.; Cárdenas, L.L.; Urquiza-Aguiar, L.; Igartua, M.A. A traffic-aware electric vehicle charging management system for smart cities. *Veh. Commun.* **2019**, *20*, 100188. [CrossRef]
113. Li, G.; Sun, Q.; Boukhatem, L.; Wu, J.; Yang, J. intelligent vehicle-to-vehicle charging navigation for mobile electric vehicles via vanet-based communication. *IEEE Access* **2019**, *7*, 170888–170906. [CrossRef]
114. García-Magariño, I.; Palacios-Navarro, G.; Lacuesta, R.; Mauri, J.L. ABSCEV: An agent-based simulation framework about smart transportation for reducing waiting times in charging electric vehicles. *Comput. Netw.* **2018**, *138*, 119–135. [CrossRef]
115. Li, G.; Boukhatem, L.; Zhao, L.; Wu, J. Direct vehicle-to-vehicle charging strategy in vehicular ad-hoc networks. In Proceedings of the 2018 9th IFIP International Conference on New Technologies, Mobility and Security (NTMS), Institute of Electrical and Electronics Engineers (IEEE), Paris, France, 26–28 Februry 2018; pp. 1–5.
116. Beckman, M.; McGuire, C.B.; Winsten, C.B.; Koopmans, T.C. Studies in the economics of transportation. *OR* **1956**, *7*, 146. [CrossRef]
117. Sheffi, Y. *Urban Transportation Networks: Equilibrium Analysis with Mathematical Programming Methods*; Prentice-Hall: Upper Saddle River, NJ, USA, 1984; pp. 463–466.

118. United States. *Bureau of Public Roads. Traffic Assignment Manual for Application with a Large, High Speed Computer*; US Department of Commerce, Bureau of Public Roads, Office of Planning, Urban Planning Division: Washington, DC, USA, 1964; Volume 37.
119. Davidson, K.B. A flow travel time relationship for use in transportation planning. In Proceedings of the 3rd Australian Road Research Board (ARRB) Conference, Sydney, Australia; 1966; Volume 3. Available online: https://trid.trb.org/View/1209266 (accessed on 24 October 2019).
120. Wei, W.; Wu, Q.; Shafie-Khah, M.; Catalào, J.P.S. Transportation system and power system interdependence: A comprehensive review on models and applications. *J. Mod. Power Syst. Clean Energy* **2019**. [CrossRef]
121. He, F.; Yin, Y.; Lawphongpanich, S. Network equilibrium models with battery electric vehicles. *Transp. Res. Part B Methodol.* **2014**, *67*, 306–319. [CrossRef]
122. Jiang, N.; Xie, C.; Waller, S.T. Path-constrained traffic assignment. *Transp. Res. Rec. J. Transp. Res. Board* **2012**, *2283*, 25–33. [CrossRef]
123. Wang, T.-G.; Xie, C.; Xie, J.; Waller, S.T. Path-constrained traffic assignment: A trip chain analysis under range anxiety. *Transp. Res. Part C Emerg. Technol.* **2016**, *68*, 447–461. [CrossRef]
124. Jiang, N.; Xie, C. Computing and analyzing mixed equilibrium network flows with gasoline and electric vehicles. *Comput. Civ. Infrastruct. Eng.* **2014**, *29*, 626–641. [CrossRef]
125. He, F.; Wu, D.; Yin, Y.; Guan, Y. Optimal deployment of public charging stations for plug-in hybrid electric vehicles. *Transp. Res. Part B Methodol.* **2013**, *47*, 87–101. [CrossRef]
126. Abousleiman, R.; Scholer, R. Smart charging: System design and implementation for interaction between plug-in electric vehicles and the power grid. *IEEE Trans. Transp. Electrif.* **2015**, *1*, 18–25. [CrossRef]
127. Yi, Z.; Bauer, P.H. Optimization models for placement of an energy-aware electric vehicle charging infrastructure. *Transp. Res. Part E Logist. Transp. Rev.* **2016**, *91*, 227–244. [CrossRef]
128. Zhang, H.; Moura, S.J.; Hu, Z.; Song, Y. PEV Fast-charging station siting and sizing on coupled transportation and power networks. *IEEE Trans. Smart Grid* **2018**, *9*, 2595–2605. [CrossRef]
129. Wang, Y.; Shi, J.; Wang, R.; Liu, Z.; Wang, L. Siting and sizing of fast charging stations in highway network with budget constraint. *Appl. Energy* **2018**, *228*, 1255–1271. [CrossRef]
130. Geng, L.; Lu, Z.; He, L.; Zhang, J.; Li, X.; Guo, X. Smart charging management system for electric vehicles in coupled transportation and power distribution systems. *Energy* **2019**, *189*, 116275. [CrossRef]
131. Hodgson, M.J. A flow-capturing location-allocation model. *Geogr. Anal.* **2010**, *22*, 270–279. [CrossRef]
132. Kuby, M.; Lim, S. The flow-refueling location problem for alternative-fuel vehicles. *Socio. Econ. Plan. Sci.* **2005**, *39*, 125–145. [CrossRef]
133. Capar, I.; Kuby, M. An efficient formulation of the flow refueling location model for alternative-fuel stations. *IIE Trans.* **2012**, *44*, 622–636. [CrossRef]
134. Upchurch, C.; Kuby, M.; Lim, S. A Model for location of capacitated alternative-fuel stations. *Geogr. Anal.* **2009**, *41*, 85–106. [CrossRef]
135. Zhang, H.; Moura, S.J.; Hu, Z.; Qi, W.; Song, Y. A second-order cone programming model for planning pev fast-charging stations. *IEEE Trans. Power Syst.* **2018**, *33*, 2763–2777. [CrossRef]
136. Luo, C.; Huang, Y.-F.; Gupta, V. Placement of EV charging stations–balancing benefits among multiple entities. *IEEE Trans. Smart Grid* **2015**, *8*, 1–10. [CrossRef]
137. Yao, W.; Zhao, J.; Wen, F.; Dong, Z.; Xue, Y.; Xu, Y.; Meng, K. A multi-objective collaborative planning strategy for integrated power distribution and electric vehicle charging systems. *IEEE Trans. Power Syst.* **2014**, *29*, 1811–1821. [CrossRef]
138. Grahn, P.; Alvehag, K.; Soder, L. PHEV utilization model considering type-of-trip and recharging flexibility. *IEEE Trans. Smart Grid* **2013**, *5*, 139–148. [CrossRef]
139. Chen, Z.; He, F.; Yin, Y. Optimal deployment of charging lanes for electric vehicles in transportation networks. *Transp. Res. Part B Methodol.* **2016**, *91*, 344–365. [CrossRef]
140. Polson, N.G.; Sokolov, V.O. Deep learning for short-term traffic flow prediction. *Transp. Res. Part C Emerg. Technol.* **2017**, *79*, 1–17. [CrossRef]
141. Ghosh, B.; Basu, B.; O'Mahony, M. Multivariate Short-term traffic flow forecasting using time-series analysis. *IEEE Trans. Intell. Transp. Syst.* **2009**, *10*, 246–254. [CrossRef]

142. Lv, Y.; Duan, Y.; Kang, W.; Li, Z.; Wang, F.-Y. Traffic flow prediction with big data: A deep learning approach. *IEEE Trans. Intell. Transp. Syst.* **2014**, *16*, 1–9. [CrossRef]
143. Jaillet, P.; Qi, J.; Sim, M. Routing optimization under uncertainty. *Oper. Res.* **2016**, *64*, 186–200. [CrossRef]
144. Menelaou, C.; Timotheou, S.; Kolios, P.; Panayiotou, C.; Polycarpou, M.M. Minimizing traffic congestion through continuous-time route reservations with travel time predictions. *IEEE Trans. Intell. Veh.* **2018**, *4*, 141–153. [CrossRef]
145. Arslan, O.; Yıldız, B.; Karasan, O.E.; Yıldız, B.D. Minimum cost path problem for plug-in hybrid electric vehicles. *Transp. Res. Part E Logist. Transp. Rev.* **2015**, *80*, 123–141. [CrossRef]
146. Dixon, J.; Andersen, P.B.; Bell, K.; Træholt, C. On the ease of being green: An investigation of the inconvenience of electric vehicle charging. *Appl. Energy* **2020**, *258*, 114090. [CrossRef]
147. Alizadeh, M.; Wai, H.-T.; Chowdhury, M.; Goldsmith, A.J.; Scaglione, A.; Javidi, T. Optimal pricing to manage electric vehicles in coupled power and transportation networks. *IEEE Trans. Control. Netw. Syst.* **2017**, *4*, 863–875. [CrossRef]
148. Wei, W.; Wang, J.; Wu, L. Quantifying the impact of road capacity loss on urban electrified transportation networks: An optimization based approach. *Int. J. Transp. Sci. Technol.* **2016**, *5*, 268–288. [CrossRef]
149. Wei, W.; Mei, S.; Wu, L.; Shahidehpour, M.; Fang, Y. Optimal traffic-power flow in urban electrified transportation networks. *IEEE Trans. Smart Grid* **2016**, *8*, 84–95. [CrossRef]
150. Wei, W.; Wu, L.; Wang, J.; Mei, S. Expansion planning of urban electrified transportation networks: A mixed-integer convex programming approach. *IEEE Trans. Transp. Electr.* **2017**, *3*, 210–224. [CrossRef]
151. Amini, M.H.; Karabasoglu, O. Optimal operation of interdependent power systems and electrified transportation networks. *Energies* **2018**, *11*, 196. [CrossRef]
152. Sun, Y.; Chen, Z.; Li, Z.; Tian, W.; Shahidehpour, M. EV charging schedule in coupled constrained networks of transportation and power system. *IEEE Trans. Smart Grid* **2019**, *10*, 4706–4716. [CrossRef]
153. Wang, X.; Shahidehpour, M.; Jiang, C.; Li, Z. Coordinated planning strategy for electric vehicle charging stations and coupled traffic-electric networks. *IEEE Trans. Power Syst.* **2018**, *34*, 268–279. [CrossRef]
154. Li, M.; Lin, X.; He, F.; Jiang, H. Optimal locations and travel time display for variable message signs. *Transp. Res. Part C Emerg. Technol.* **2016**, *69*, 418–435. [CrossRef]
155. Wei, W.; Wu, L.; Wang, J.; Mei, S. Network equilibrium of coupled transportation and power distribution systems. *IEEE Trans. Smart Grid* **2018**, *9*, 6764–6779. [CrossRef]
156. Gong, Q.; Li, Y.; Peng, Z.-R. Trip-based optimal power management of plug-in hybrid electric vehicles. *IEEE Trans. Veh. Technol.* **2008**, *57*, 3393–3401. [CrossRef]
157. Wu, Q.; Arne, H.; Nielsen, J.O.; Seung, T.C.; Francesco, M.; Yu, C.; Chresten, T. Driving pattern analysis for electric vehicle (EV) grid integration study. In Proceedings of the 2010 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT Europe), Gothenburg, Sweden, 11–13 October 2010; pp. 1–6.
158. Zhang, H.; Sheppard, C.J.R.; Lipman, T.E.; Moura, S.J. joint fleet sizing and charging system planning for autonomous electric vehicles. *IEEE Trans. Intell. Transp. Syst.* **2019**, 1–14. [CrossRef]
159. Li, R.; Wu, Q.; Oren, S. distribution locational marginal pricing for optimal electric vehicle charging management. *IEEE Trans. Power Syst.* **2013**, *29*, 203–211. [CrossRef]
160. Liu, J.-P.; Zhang, T.-X.; Zhu, J.; Ma, T.-N. Allocation optimization of electric vehicle charging station (EVCS) considering with charging satisfaction and distributed renewables integration. *Energy* **2018**, *164*, 560–574. [CrossRef]
161. Vagropoulos, S.; Balaskas, G.; Bakirtzis, A. An investigation of plug-in electric vehicles charging impact on power systems scheduling and energy costs. *IEEE Trans. Power Syst.* **2016**, *32*, 1. [CrossRef]
162. Sadeghianpourhamami, N.; Refa, N.; Strobbe, M.; Develder, C. Quantitive analysis of electric vehicle flexibility: A data-driven approach. *Int. J. Electr. Power Energy Syst.* **2018**, *95*, 451–462. [CrossRef]
163. He, F.; Yin, Y.; Wang, J.; Yang, Y. Sustainability SI: Optimal prices of electricity at public charging stations for plug-in electric vehicles. *Netw. Spat. Econ.* **2013**, *16*, 131–154. [CrossRef]
164. Zhu, M.; Liu, X.-Y.; Wang, X. Joint transportation and charging scheduling in public vehicle systems—A game theoretic approach. *IEEE Trans. Intell. Transp. Syst.* **2018**, *19*, 2407–2419. [CrossRef]
165. Yang, X.; Li, Y.; Cai, Y.; Cao, Y.; Lee, K.Y.; Jia, Z. Impact of road-block on peak-load of coupled traffic and energy transportation networks. *Energies* **2018**, *11*, 1776. [CrossRef]

166. Xiang, Y.; Jiang, Z.; Gu, C.; Teng, F.; Wei, X.; Wang, Y. Electric vehicle charging in smart grid: A spatial-temporal simulation method. *Energy* **2019**, *189*, 116221. [CrossRef]
167. Sun, W.; Zhang, J.; Yang, J.; Liu, W.; Zhang, W. Probabilistic evaluation and improvement measures of power supply capability considering massive ev integration. *Electronics* **2019**, *8*, 1158. [CrossRef]
168. Lv, S.; Wei, Z.; Sun, G.; Chen, S.; Zang, H. Optimal power and semi-dynamic traffic flow in urban electrified transportation networks. *IEEE Trans. Smart Grid* **2020**, *11*, 1854–1865. [CrossRef]
169. Wang, H.; Fang, Y.-P.; Zio, E. Risk assessment of an electrical power system considering the influence of traffic congestion on a hypothetical scenario of electrified transportation system in New York state. *IEEE Trans. Intell. Transp. Syst.* **2019**, 1–14. [CrossRef]
170. Shukla, A.; Verma, K.; Kumar, R. Multi-objective synergistic planning of EV fast-charging stations in the distribution system coupled with the transportation network. *IET Gener. Transm. Distrib.* **2019**, *13*, 3421–3432. [CrossRef]
171. Gajani, G.S.; Bascetta, L.; Gruosso, G. Data-driven approach to model electrical vehicle charging profile for simulation of grid integration scenarios. *IET Electr. Syst. Transp.* **2019**, *9*, 168–175. [CrossRef]
172. Kikusato, H.; Fujimoto, Y.; Hanada, S.-I.; Isogawa, D.; Yoshizawa, S.; Ohashi, H.; Hayashi, Y. Electric vehicle charging management using auction mechanism for reducing PV curtailment in distribution systems. *IEEE Trans. Sustain. Energy* **2019**, 1. [CrossRef]
173. Battapothula, G.; Yammani, C.; Sydulu, M. Multi-objective optimal planning of FCSs and DGs in distribution system with future EV load enhancement. *IET Electr. Syst. Transp.* **2019**, *9*, 128–139. [CrossRef]
174. Xia, Y.; Hu, B.; Xie, K.; Tang, J.; Tai, H.-M. An EV charging demand model for the distribution system using traffic property. *IEEE Access* **2019**, *7*, 28089–28099. [CrossRef]
175. Wang, X.; Shahidehpour, M.; Jiang, C.; Li, Z. Resilience enhancement strategies for power distribution network coupled with urban transportation system. *IEEE Trans. Smart Grid* **2019**, *10*, 4068–4079. [CrossRef]
176. Li, Z.; Shahidehpour, M.; Bahramirad, S.; Khodaei, A. Optimizing traffic signal settings in smart cities. *IEEE Trans. Smart Grid* **2017**, *8*, 2382–2393. [CrossRef]
177. Li, Z.; Al Hassan, R.; Shahidehpour, M.; Bahramirad, S.; Khodaei, A. A hierarchical framework for intelligent traffic management in smart cities. *IEEE Trans. Smart Grid* **2017**, *10*, 691–701. [CrossRef]
178. Jiang, H.; Zhang, Y.; Chen, Y.; Zhao, C.; Tan, J. Power-traffic coordinated operation for bi-peak shaving and bi-ramp smoothing—A hierarchical data-driven approach. *Appl. Energy* **2018**, *229*, 756–766. [CrossRef]
179. Sterchele, P.; Kersten, K.; Palzer, A.; Hentschel, J.; Henning, H.-M. Assessment of flexible electric vehicle charging in a sector coupling energy system model—Modelling approach and case study. *Appl. Energy* **2020**, *258*, 114101. [CrossRef]
180. Zhang, H.; Hu, Z.; Song, Y. Power and transport nexus: Routing electric vehicles to promote renewable power integration. *IEEE Trans. Smart Grid* **2020**, 1. [CrossRef]
181. Kilpeläinen, M.; Summala, H. Effects of weather and weather forecasts on driver behaviour. *Transp. Res. Part F Traffic Psychol. Behav.* **2007**, *10*, 288–299. [CrossRef]
182. Zhao, J.H.; Dong, Z.Y.; Li, X.; Wong, K.P. A framework for electricity price spike analysis with advanced data mining methods. *IEEE Trans. Power Syst.* **2007**, *22*, 376–385. [CrossRef]
183. Chen, Y.; Wei, W.; Liu, F.; Sauma, E.; Mei, S. Energy trading and market equilibrium in integrated heat-power distribution systems. *IEEE Trans. Smart Grid* **2019**, *10*, 4080–4094. [CrossRef]
184. Morstyn, T.; Teytelboym, A.; McCulloch, M. Bilateral contract networks for peer-to-peer energy trading. *IEEE Trans. Smart Grid* **2018**, *10*, 2026–2035. [CrossRef]
185. Tushar, W.; Saha, T.K.; Yuen, C.; Smith, D.; Poor, H.V. Peer-to-Peer trading in electricity networks: An overview. *IEEE Trans. Smart Grid* **2020**, 1. [CrossRef]
186. Zhang, B.; Sun, Y.; Li, B.; Li, J.; Bingliang, Z.; Yutian, S.; Bingqiang, L.; Jianxiang, L. a modeling method for the power demand of electric vehicles based on monte carlo simulation. In Proceedings of the 2012 Asia-Pacific Power and Energy Engineering Conference, Shanghai, China, 7–29 March 2012; pp. 1–5.
187. Yang, X.-G.; Liu, T.; Gao, Y.; Ge, S.; Leng, Y.; Wang, D.; Wang, C.-Y. Asymmetric temperature modulation for extreme fast charging of lithium-ion batteries. *Joule* **2019**, *3*, 3002–3019. [CrossRef]

188. Macdonald, C. Radical Electric Car Battery Can be Fully recharged in FIVE Minutes. Daily Mail. 2017. Available online: http://www.dailymail.co.uk/sciencetech/article-4508314/Electric-car-battery-fully-charged-FIVE-minutes.html (accessed on 20 June 2019).
189. Lu, L.; Han, X.; Li, J.; Hua, J.; Ouyang, M. A review on the key issues for lithium-ion battery management in electric vehicles. *J. Power Sources* **2013**, *226*, 272–288. [CrossRef]

© 2020 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (http://creativecommons.org/licenses/by/4.0/).