Spatial and temporal modelling of coupled power and transportation systems: A comprehensive review

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Abstract
The large-scale application of electric vehicles can lead to new challenges in the operation of the two complex and coupled networks of electricity and transportation systems, thus creating a new concept—a power—traffic network. The purpose is to provide a comprehensive survey of this emerging field. First, both the transportation system and power grid models are briefly introduced in terms of time and space scales. Then, the power traffic network model and applications at long-term, mid-term, and short-term time scales are summarized, and provided a unified view of these achievements. Based on this analysis, recommendations for future research are presented.

1 | INTRODUCTION

In recent years, due to excessive fossil fuel consumption, global greenhouse gas (GHG) emissions have steadily increased, drawing the attention of the international community to problems resulting from climate change. According to data from the National Aeronautics and Space Administration (NASA), the global surface temperature in 2019 increased by 0.99°C relative to the average temperatures in 1951–1980 [1]. The negative impact of climate change on economic and social development has become increasingly significant. In November 2016, the Paris Agreement, in which the signatories reached a consensus to limit GHG emissions, came into force [2]. Owing to the tremendous demand for reducing emissions, electric energy, as a clean and efficient secondary energy source, has become an important alternative to change the energy consumption structure [3].

In particular, the report in [4] indicates that the transportation sector is the primary source of anthropogenic GHG emissions in the United States, accounting for 28% of the total. To reduce the dependence of the transportation sector on fossil fuels, transportation electrification has been regarded as a key measure; consequently, this approach has attracted considerable interest from researchers and governments [5–7]. Electric vehicles (EVs) afford many advantages, including efficiency and environmental friendliness. In view of these, the use of EVs has been vigorously promoted worldwide, such as in the US [8], EU [9], and China [3, 7]. The number of EVs, such as electric buses, has rapidly increased in recent years [6], especially in the public transportation sector [10]. According to a report by the International Energy Agency [11], the global EV stock in the passenger light-duty vehicle sector reached 7.2 million in 2019. As a result, 53 Mt of CO₂-equivalent emissions from the same number of traditional fuel vehicles was avoided. The global EV stock is predicted to reach 245 million by 2030. The increasing global spread of EVs and their considerable charging demand are expected to introduce significant interdependence across power and transportation systems.

In this study, the concept of EVs refers only to battery electric vehicles (BEVs) and plug-in hybrid electric vehicles. The former are completely powered by batteries, whereas the latter are driven by both batteries and traditional fuel engines. As a result of the battery capacity limit, the current driving range of battery-based EV models is ≈100–250 km, and several models can reach 300–500 km [12]. These EV models rely on external power from the grid to charge their batteries. Therefore, charging facilities are critical components of EVs and are a medium between power and transportation systems. In
general, EV charging stations can be classified into two types: slow and fast charging. The former are usually installed at home or in the workplace, where the charging demand is regular and predictable [13]. The latter are typically built along the road and their charging demand is difficult to forecast owing to the impact of road congestion, route choice, electricity price etc. [14, 15]. Thus, traffic congestion, fast-charging station (FCS) siting, and sizing are critical in the field of EV technology development [16, 17]. In addition, from the perspective of the power system, the integration of EVs into the grid presents both challenges and opportunities. Depending on the operation and management level of the grid and EVs, large-scale EV integration may not only degrade the stability and reliability of the power system [18] but also contribute to “peak shaving” and “valley filling” of the load curve [19, 20].

Traffic congestion patterns not only influence the driving patterns and travel routes of EVs but also impact the spatial and temporal distributions of charging demands as well as the operation of the power system [15, 21]. Lower electricity prices can also be used as a stimulus for EV users to choose a particular charging station to reduce the traffic burden [22]. In the foreseeable future, the coupling between the power system and the traffic network is expected to be increasingly tight owing to the wide use of EVs [23], resulting in an even more complex coupled network—a power—traffic network (PTN).

In the PTN, EVs play a critical role in coupling the power grid and traffic network owing to their spatiotemporal behaviour. Unlike other fixed devices in the power grid, the main purpose of EVs is to satisfy the travel demands of users; hence, their spatiotemporal behaviour exhibits strong periodicity. For these reasons, space–time characteristics should be considered in the modelling and operation of PTNs.

A number of EV-related reviews, which can quickly update researchers on progress in the field, have been published. These reviews can be broadly categorized as (i) EV technology-related [6, 24–27], (ii) EV operation-related [28, 29] and (iii) power and traffic network coupling-related reviews.

Key technologies, such as energy storage and generation systems as well as energy management strategies for pure EVs were reviewed in [24]. A comprehensive review of the current and future trends of hybrid EV and EV propulsion systems was provided in [25]. A review of the current situation of the EV market, standards, charging infrastructure and impact of EV charging on the grid was presented in [6]. Moreover, [26] focused on the wireless charging technology of EVs to improve the power grid and traffic network combination. A comprehensive EV adoption review and an analysis from a unique and valuable perspective were presented in [27].

Optimization models for EV operation management, including EV charging infrastructure planning, EV charging operations, public policy and business models were reviewed in [28]. Two types of planning models, namely, the flow-based and network equilibrium models were classified in this study. A comprehensive review of EV interaction with the power grid was presented in [29], which focused on scheduling methods and mathematical foundations.

Moreover, [21] proposed the concept of “vehicle–grid integration” with respect to coupled PTNs. PTN co-operation could aid in addressing the increasing need for grid resilience and carbon emission mitigation. However, the key challenges in PTN co-optimization are battery degradation and warranty issues. In [15], the traffic network and power grid interdependence were investigated. In this review, the corresponding power grid model, power flow model and user equilibrium-based traffic network model were introduced. Powered two-wheeler traffic (PTW) and intelligent transportation systems focused on macroscopic traffic problems were reviewed in [30].

The remainder of this paper is organized as follows. Section 2 expands on the network models of the power grid and traffic network. Section 3 introduces the coupled PTN model. The problems and future directions are discussed in Section 4. Finally, the conclusions are presented in Section 5.

## 2 | NETWORK MODELS

The main purpose of the power grid and transportation network is to transfer specific items from one location to another; hence, both power and transportation networks can be modelled using graph theory. A graph (denoted as $G = (V, E)$) consists of a non-empty set of vertices or nodes ($V$) and a set of edges ($E$). However, the vertices and edges represent different items in the power grid and transportation network at different spatial scales, as summarized in Table 1.

A large spatial scale ranges from hundreds to thousands of kilometres. A power transmission grid is used to transfer energy from energy resource centres to load centres using high-voltage alternating current (AC) or direct current (DC) transmission lines. A transportation network with the same spatial scale comprises a railway, highway or state road for moving people or goods from one city to another. A small spatial scale ranges from tens to hundreds of kilometres, and is usually located inside a city. On a small spatial scale, the vertices and edges of the power grid are typically transformers and distribution lines, respectively. In transportation networks, the vertices and edges are generally communities and city roads, respectively.

Although the spatial connection can be modelled through graph theory, a considerable difference exists between the media travel speeds in the power grid and traffic network. It is well known that electricity travels at approximately the speed of

| Table 1 | Graph model for transportation network and power grid |
|---------|---------------------------------------------------|
| **Spatial scale** | **Vertices** | **Edges** |
| **Transportation network** | Large | City/town | Railway/highway/state road |
|             | Small | Community | City road |
| **Power grid** | Large | Substation | Transmission line |
|             | Small | Transformer | Distribution line |

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Mathematical foundations.
light, whereas vehicles in a traffic network can travel no more than hundreds of kilometres per hour, even under the best conditions. When traffic congestion occurs, the entire system deteriorates. This means that a dynamic traffic network should be considered when modelling the PTN [31, 32]. Although the power flow (PF) model, optimal power flow (OPF) [33] or its convex relaxation [34] are well utilized in single-period power grid modelling, the multi-period optimal power flow [35] or security constraint unit commitment (SCUC) [36, 37] is a more appropriate choice for longer time spans.

### 2.1 Power grid models

The power grid can be modelled as a connected undirected graph $G_p = (N_p, E)$, where each node in $N_p$ represents a bus and each edge in $E$ represents a transmission or distribution line. The power flow distribution over a power grid can usually be obtained through power flow calculation [15]. However, in PTN research, OPF and SCUC are two common technologies for power grid modelling.

In 1962, Carpenter first reported the OPF problem, which is fundamental in power system engineering. A common OPF model is usually formulated as a complex quadratically constrained quadratic program, which is generally non-convex and NP-hard [38]. The solution to the OPF problem is a static optimal power flow distribution in a certain time slice; thus, it is normally applied to short-term temporal problems.

The SCUC problem refers to a time sequential generation schedule arrangement that satisfies the power system security constraints. The main body of SCUC is a unit commitment (UC) problem that determines the hourly operating status and output of units to satisfy the minimum system fuel and operational costs. The UC satisfies the system constraints (e.g., power balance and system reserve requirements) and unit operating constraints (e.g., unit ramping limits, minimum ON and OFF time limits, and generation capacity limits). In addition, the SCUC must satisfy the network security constraints in the normal state [37, 39]. Compared with the multi-period OPF model, the SCUC is more appropriate for the simulation of the daily operation of larger power systems because it can handle not only generator startup/shutdown and ramping, but also certain security constraints, such as transmission line capacity or component failure.

Unlike the OPF, DC power flow is usually adopted in the SCUC to reduce the complexity of the model at the cost of neglecting the reactive power and bus voltage magnitude. In recent years, convex relaxations of power flow constraints, such as second-order cone programming (SOCP) for radial networks and semidefinite programs for general networks, have been adopted in the OPF [34, 37]. However, for mesh networks, SOCP relaxation is not effective because the phase angle cycle condition is rarely satisfied. Other convex relaxation methods are afforded by semidefinite [40] and chordal relaxations [41].

Linearization methods, such as the branch injection model (BIM) and branch flow model, are important methods, but DC power flow is the most widely known technique. By neglecting the active power losses and assuming that the magnitudes of the bus voltages are equal, the BIM can be simplified into linear DC power flow equations. It is suitable for transmission networks but unsatisfactory for distribution networks because of the high $R/X$ ratio of distribution lines [42]. Some linearization methods for distribution networks are presented in [15, 43].

### 2.2 Traffic network models

The distribution of vehicular traffic flow in a traffic network is considerably greater than that in a power grid. Unlike power flow, traffic flow is composed of many individual vehicles, which means that the interaction of traffic participants and infrastructure results in complex traffic flow. In PTN research, the traffic assignment problem (TAP) model is prevalent for traffic network modelling [5, 15]. TAP is one of four steps in the transportation planning problem: (1) trip generation, (2) trip distribution, (3) model split and (4) traffic assignment [44]. Although this four-step process originates from the traffic planning problem, many researchers use TAP to study traffic behaviour [45, 46].

The TAP can be classified into two categories: static traffic assignment (STA) and dynamic traffic assignment (DTA). The STA usually assumes that the traffic burden is fixed; hence, it can quickly determine the traffic loading distribution on a traffic network. In a static model, the inflow to a link is always equal to the outflow. DTA is used to illustrate the variation in the congestion level with time using a time-varying traffic flow. In dynamic models, the link volume–delay function is considerably more complicated because, in reality, the equality of link inflow and outflow cannot be guaranteed [45, 47].

#### 2.2.1 Static traffic assignment

In STA, the traffic network can be modelled as a connected directed graph, $G_T = (N_T, A)$ [22], where $N_T$ denotes the set of nodes (e.g. origin and destination points and intersections of physical roads), and $A$ denotes the set of links. Each link $a \in A$ represents a road in the traffic network. The traffic requirement is modelled by origin–destination (O–D) demand pairs; each pair $(r, s)$ is connected by a set of paths $K^r_s$ through the network. Let $f^r_k$ denote the traffic flow in path $k \in K^r_s$.

The traffic demand $q^r$ between $(r, s)$ and the total traffic flow $x_{as}$ on the link $a \in A$ are given by

\[
q^r = \sum_{k \in K^r_s} f^r_k, \forall (r, s) \quad (1)
\]

\[
x_{as} = \sum_{(r, c)} \sum_{k \in K^r_c} f^c_k \delta^c_{as}, \forall k \in K^c_r, (r, s) \quad (2)
\]

where $\delta^c_{as} = 1$ indicates that link $a$ belongs to path $k \in K^c_r$; otherwise, $\delta^c_{as} = 0$.

\[
f^r_k \geq 0, \forall (k, r, s) \quad (3)
\]
where Equation (3) is the nonnegative conditions of $f_{rs}^{\alpha}$.

$$t_a = t_a(x_a) \quad (4)$$

Equation (4) describes the relationship between link flow $x_a$ and link travel time, which is known as the link performance function or link travel time function. Usually, $t_a(x_a)$ is a monotonic function of link traffic flow [48].

Given every link travel time, the path travel time can be derived using Equation (5).

$$c_{rs}^{\alpha} = \sum_{a \in A} t_a(x_a) f_{rs}^{\alpha}, \quad \forall k \in K^{\alpha}, (r, s) \quad (5)$$

It is reasonable to assume that every driver will try to minimize their own travel time when travelling from the origin to destination. When no traveller can improve their travel time by unilaterally changing routes, this is the characterization of the Wardrop’s user equilibrium flow pattern (UE) condition: the travel times on all the routes actually used are equal, and are less than that of a single vehicle traversing any unused route [49].

The UE link-flow pattern can be obtained by solving the following optimization model, where the objective function is the sum of the integrals of the link performance functions:

$$\min_{x} \mathcal{Z}(x) = \sum_{a} \int_{0}^{x_a} t_a(\omega) d\omega \quad (6)$$

Subject to Equations (1)–(3).

If the objective function is to minimize the total travel time spent in the network, it makes Wardrop’s system-optimization flow pattern (SO): the optimal system solution is the one that provides the total minimum time for the entire network [49, 50].

The SO results can be achieved by solving the following optimization model:

$$\min_{x} \mathcal{Z}(x) = \sum_{a} x_a t_a(x_a) \quad (7)$$

Subject to Equations (1)–(3).

UE and SO flow patterns share practically the same constraints but different objective functions because they are based on the user and system perspectives, respectively. Detailed models can be found in [51, 52]. Both are optimization models that can be solved by either a numerical optimization method [53] or a metaheuristic algorithm [54]. In certain cases, the UE can also be extended to stochastic user equilibrium by importing the user decision uncertainty [52, 55].

Wardrop’s UE principle can also be expressed by the following complementarity and slackness constraints:

$$\begin{cases} f_{rs}^{\alpha}(c_{rs}^{\alpha} - u_{rs}^{\alpha}) = 0 \\ f_{rs}^{\alpha} \geq 0, \quad \forall k \in K^{\alpha}, (r, s) \\ (c_{rs}^{\alpha} - u_{rs}^{\alpha}) \geq 0 \end{cases} \quad (8)$$

where $u_{rs}^{\alpha}$ is the minimum travel time between pair $(r, s)$. The above condition limits at most one of the traffic flows, $f_{rs}^{\alpha}$, and $c_{rs}^{\alpha} - u_{rs}^{\alpha}$ can be strictly positive. Moreover, no driver in the UE can reduce its travel time by unilaterally changing paths. Equation (8) is the classic variational inequality (VI) form of UE [56], which can also be used in DTA [57].

2.2.2 Dynamic traffic assignment

DTA can be applied to different sizes and resolutions, as well as different contexts for the time frame analysis, as shown in Figure 1. The size of the traffic network varies from facility to region; however, the minimum network should at least include alternative routes. In the time dimension, DTA can be applied not only in real time or near term to fine-tune the route choice but also in long-range planning. In terms of the model type, DTA can be categorized into macroscopic, mesoscopic and microscopic models [58, 59]. The microscopic level model mainly focuses on individual driver behaviour modelling [57, 60, 61]. Mesoscopic traffic flow describes vehicle behaviour in aggregate terms, such as inprobability distributions [62–64]. The macroscopic traffic flow model describes traffic flow as if it was a continuum flow, while individual vehicles are no longer modelled [65]. In recent years, artificial intelligence-based methods have been adopted to predict short-term and long-term traffic flow variations [66, 67].

In DTA, the traffic flow on link $a \in A$ at the beginning of time $t$ is given by:

$$x_a[t] = x_a[t-1] + v_a[t-1] - w_a[t-1], \forall a \in A, t \in T \quad (9)$$

where $v_a[t]$ and $w_a[t]$ represent the inflow and exit flow of link $a \in A$ at time $t$, respectively.

Considering continuous time instead of discrete time intervals, ordinary differential equations can be used to describe the

![FIGURE 1 DTA modelling considerations [46]](image-url)
traffic dynamics. The state equation of link $a$ is expressed as

$$\frac{d\xi_a^r(t)}{dt} = v_a^r(t) - w_a^r(t), \forall a \in \mathbf{A}_r, (r, s), t \in \mathbf{T} \tag{10}$$

with the flow conversation equation at midway nodes $j$ as

$$\sum_{a \in \mathbf{A}(j)} v_a^r(t) = \sum_{a \in \mathbf{B}(j)} w_a^r(t), \forall a \in \mathbf{A}_r, (r, s), t \in \mathbf{T} \tag{11}$$

where $x_a^r(t)$, $v_a^r(t)$ and $w_a^r(t)$ denote the traffic flow, inflow and exit flow of link $a \in \mathbf{A}$ at time $t$ via path $k \in \mathbf{K}^r$, respectively; $\mathbf{A}(j)$ and $\mathbf{B}(j)$ denote the set of links with traffic flows entering and exiting from node $j$.

The VI forms of time dependent Wardrop condition for the DTA are:

$$\begin{cases}
    f^r_k(t)(v_k^r(t) - u_k^r(t)) = 0 \\
    f^r_k \geq 0, \forall k \in \mathbf{K}^r, (r, s) \\
    (c_k^r(t) - u_k^r(t)) \geq 0
\end{cases} \tag{12}$$

Queuing theory (QT) is typically employed to simulate the first-in–first-out rule in DTA [68]. In addition, DTA can be applied to model the route choice from the traveller’s standpoint, the routing policy from the standpoint of the system, etc. The DTA model can be further divided into two types: equilibrium-based and non-equilibrium-based [46].

The equilibrium-based DTA approach is also based on Wardrop’s principle [51]; however, the UE is extended to the dynamic (time-dependent) user equilibrium (DUE or TDUE) condition [47]. The goal of DUE models are to achieve a satisfactory level of convergence under the equilibrium condition by iteratively completing three sequential steps: network loading, path set updating and path assignment adjustment.

The non-equilibrium-based DTA approach is usually employed to analyse the reaction of vehicle drivers to unexpected events, such as traffic conditions or environmental conditions. It is also possible to modify vehicle routes in response to endogenous and/or exogenous stimuli in a non-equilibrium-based DTA model.

3 | COUPLED POWER AND TRAFFIC SYSTEMS

Figure 2 shows a typical PTN. As illustrated, the power grid and traffic network are coupled through EVs. There are two typical categories of coupled items in the PTN based on how the EVs are connected to the power grid: node–link and link–link connections. Both of them are based on the EVs’ activities. In the node–link connection, the EVs are connected to the power grid at specific nodes (charging stations), which are distributed among the links in the traffic network, and function as a part of the traffic flow. The link–link connection only works when wireless charging technology is employed. Wireless charging devices are deployed along traffic roads. When driving EVs travel along roads with wireless and undergo charging/discharging, this will cause power flow and traffic flow variation simultaneously along the distribution lines in the power grid and roads in the traffic network, resulting in a link–link connection between the two networks through driving EVs [69, 70].

PTN applications are divided into three categories: long-term, mid-term and short-term time scales.

3.1 | Long-term time scale

Research on long-term time-scale PTNs mainly focuses on planning problems, mostly FCS planning, that is sizing and location of charging stations, electric power lines, transportation roads and energy storage systems [80]. In this section, multi-energy system planning [86] is also discussed.

Table 2 summarizes the long-term time-scale PTN models. There are three types of models in the traffic network segment: (1) simplified model, including historical/forecasting charging demands, Google map API, and GPS trajectory data; (2) flow refueling location model (FRLM), which highly simplifies the traffic network and considers the driving range of the EV as constraints and (3) the STA/DTA model.

In [71], mixed-integer second-order cone programming (MISOCP) was developed to solve multiple types of charging facility planning problems and minimize the annual social cost. A multi-objective optimization model, including EV transportation energy loss (EVTEL) cost, station build-up (SBU) cost, and substation energy loss (SSEL) cost, was presented in [72]. The traffic network model was simplified as travel demand in
### TABLE 2 Comparison of various PTN models in long-term time scale

| Reference | Traffic model | Power grid model | Objective function | Final model | Algorithm |
|-----------|---------------|------------------|--------------------|-------------|-----------|
| [71]      | Simplified    | ACPF             | Annualize social cost of entire EV charging system | MISOCP      |           |
| [72]      | Google Map API | Energy balance   | Minimize EVTEL, SBU, and SSEL costs | MINLP       | Metheuristic binary lightning search algorithm (BLSA) |
| [73]      | Simplified    | ACPF             | Cost               | MINLP       | Evolutionary algorithm |
| [74]      | Simplified    | ACPF             | Cost               | MISOCP      |           |
| [75]      | Cell model    | None             | Minimize cost and maximize service quality | Bi-objective MILP | Genetic algorithm II |
| [17]      | CFRLM         | ACOPF            | Social welfare     | MILP        |           |
| [76]      | FRLM          | Cost             | MILP               | GA          |           |
| [77]      | FRLM          | Maximize number or share of network’s or nation’s completed/ served long-distance trips | MILP |           |
| [78]      | CFRLM+STA     | Aggregated costs in upper level, aggregated travel time of PEVs in lower level | Bi-level optimization model | MISOCP      |           |
| [79]      | UE-STA        | ACOPF            | Minimize coupled transportation and power system cost | MINLP       | Surrogate-based optimization (SBO) algorithm |
| [80]      | SO-STA        | ACPF             | Cost               | MIQCP       | Lagrangian relaxation method |
| [81]      | UE-STA        | Charging price   | Minimize cost functions incurred by drivers when following a generic origin-destination path | Auxiliary optimization problem (AOP) |           |
| [82]      | UE-STA        | Probabilistic ACPF | Minimize annual investment cost and energy losses | Chance constraint model | Point estimation method and Gram–Charlier expansion |
| [83]      | SO-STA        | ACPF             | Minimize total construction cost of charging stations, vehicle travel time, and expansion transportation network and power grid | MILP        |           |
| [84]      | UE-STA        | /                | Total system travel time or system net energy consumption in upper level, BEV-UE in lower level | Bi-level programming |           |
| [85]      | UE-STA        | ACPF             | Minimize overall annual cost of investment and energy losses and maximize annual captured traffic flow | Multi-objective NLP | Multi-objective evolutionary algorithm (MOEA/D) |
| [86]      | UE-STA        | ACPF             | Minimize investment and operational costs | MISOCP      |           |
| [87]      | DTA           |                  | Maximize user satisfaction within budget limit | MILP        |           |

[73], which proposed a multi-objective mixed-integer nonlinear problem to maximize the utilization of charging infrastructures and minimize the overall investment cost. The model considers the operational waiting cost of the shared EV charging service and power loss. In [74], a joint optimization of the transportation network and power grid was proposed for planning e-bus FCSs. Because e-buses travel routine paths, the traffic network can be simplified as a driving range limit, and the model is finally transferred to MISOCP. The cell model was used for traffic network modelling in [75], where generic algorithm II was adopted to solve the proposed model.

The FRLM is another popular model for charging station planning; it focuses on the EV driving range and charging station capacity limit instead of road traffic flow assignment. A capacitated-flow refuelling location model (CFRLM) for explicitly capturing plug-in electric vehicle (PEV) charging demands in the transportation network under driving range constraints was presented in [17]. A multi-period multipath refuelling location model was developed to expand public EV charging networks to dynamically satisfy the O–D trips with the growth of the EV market [76]. In [77], a mixed-integer linear programming (MILP)-based FRLM for long-trip EVs was presented. Branch-and-bound and GA were adopted to solve the proposed MILP model [76, 77]. In [78], a bi-level programming model was established. The CFRLM was adopted at the upper level to minimize the planning cost of FCSs, whereas the STA was utilized at a lower level to determine the spatial and temporal distributions of PEV flows.
TABLE 3  Comparison of PTN models in mid-term time scale

| Reference | Traffic model | Power grid model | Objective function | Final model | Algorithm |
|-----------|---------------|------------------|--------------------|-------------|-----------|
| [22]      | UE-semi-DTA   | SCUC             | Total operation cost| MILP        | Decomposition-based heuristic algorithm |
| [35]      | Semi-DTA      | ACOPF            |                     |             |           |
| [88]      | DUE-DTA       | ACOPF            | High-level objective function: minimize social cost and EV Charging and Discharging expenditures | Hierarchical coordinate operation | Hierarchical optimization approach |
|           |               |                  | Low-level objective function: minimize PDS cost |             |           |
| [89]      | VRPTW         | SCUC             | Operational cost    | MILP        | Lagrangian decomposition |
| [90]      | VRPTW         | SCUC             | Operational cost    | MILP        | Benders decomposition algorithm |
| [91]      | Stochastic    | VRPTW            | Expected operational cost | MILP        | Benders decomposition algorithm |

The STA remains the most popular model for long-term time-scale PTN applications. A time-dependent charging fee was presented in [79], in which the VI form of UE-STA was adopted to model the EV traffic burden, and AC optimal power flow (ACOPF) was used to model the power grid. In [80], the multi-period system-optimal STA and AC power flow (ACPF) of the power grid were adopted to build a coordinated planning model of a coupled PTN, which included electric power lines, transportation roads, energy storage systems and FCSs. The optimum location and sizing of the charging station model were proposed in [81] and tested in a real case study (an area located in the neighbourhood of Genova City). Based on QT, a stochastic framework was developed in [82]. Probabilistic power flow was performed using the combined point estimation and Gram–Charlier expansion (PEM–GSE) methods. In [79], an optimal expansion strategy for both traffic and power distribution networks, including the sites and sizes of new charging stations, was proposed.

Dynamic wireless charging is another promising technology for PTNs. In [84], a sequential bi-level planning approach considering the objectives of both the public infrastructure planning agency and BEV users was proposed. A multi-objective collaborative planning strategy for integrated power distribution and EV charging systems was presented in [85]. In [86], PTN planning was expanded to a multi-energy system, and the MISOCP model was finally built to solve the proposed model.

3.2  Mid-term time scale

Table 3 summarizes the comparison of the PTN models in the mid-term time scale.

In [22], a UE-based semi-DTA model for capturing the daily varying pattern of traffic load in a city road was presented, and the SCUC was adopted to model the daily operation of a power system. The study showed that a flexible EV charge/travel schedule can simultaneously reduce power system generation and delivery costs as well as profit EV users. A multi-period optimal traffic and power flow model was presented in [35], where a semi-DTA model was used to model the traffic network, and a multi-period optimal power flow model was employed in the power grid. Convex relaxation technology was applied to make the proposed model solvable. A bi-level optimization model was formulated in [88], where EVs and charging stations acted as reserves to couple the power distribution system (PDS) and urban transportation system. The objective function of the upper level was to minimize the social cost, and the DUE was designed to determine the critical information for a lower level.

In power grid modelling, ACPF or ACOPF is the most popular model. This is because the dynamics of the power system are much faster than those of the traffic network. Thus, the steady-state distribution of the power flow is appropriate for power network modelling. Compared with ACPF, ACOPF is a better choice for its voltage and generation adjustment ability for generators. However, to better describe the time-varying nature of the power load, a time-series ACPF/ACOPF analysis is essential.
road traffic, the railway system is more controllable; hence, the vehicle routing problem with time window (VRPTW) was adopted to model the railway and battery fleets.

In mid-term time-scale PTN modelling, the DTA or vehicle routing problem (VRP) is commonly used in traffic network modelling. Based on the rational driver hypothesis, both of these two approaches can model the driver preference, which means that EV drivers will choose the route with the least cost. The VRPTW model is more appropriate for central dispatch transportation systems, such as public transportation and railway operation. On the other hand, DTA will have better performance in city road modelling because the link performance function of DTA is congestion-related. In power grid modelling, the SCUC and multi-period ACOPF/ACPF can both deal with the load time-varying pattern. However, SCUC is more suitable for transmission grid modelling because the ON/OFF constraints of generators are included in the SCUC. ACOPF/ACPF is a better option for distribution network modelling because the bus voltage and reactive power are also considered.

### 3.3 Short-term time scale

Table 4 lists the PTN models on a short-term time scale. Compared with the long-term and mid-term time scales, the short-term time-scale PTN model has undergone tremendous development in recent years. This is because of the growth in smart traffic and smart cities. VRP and STA/DTA are common models in short-term PTN, which mainly focus on charging station navigation, EV route choice, charging management and so on. Conversely, there are two different ways to deal with power grid modelling. One is to adopt the ACPF/OPF model to reflect the overall power grid operation conditions; the other uses the time-of-use electricity price to avoid complex power grid modelling.

The impact of road congestion on the selected routes of vehicles from a system-level perspective was analysed in [14], and the traffic flow pattern in the steady state was characterized by the UE. In [32], a network equilibrium model that captured the spatial and temporal variations of power and traffic flows for real-time analysis and management of both systems was developed. A distributed coordination pricing method that can obtain a suitable electricity charging price signal to better manage EVs was presented in [92]. In [69], the equilibrium of the traffic network was extended to the PTN.

In [93], a resource-constrained shortest path problem of a socially optimum operating point while keeping the operational data of each system private was formulated. An optimal routing and charging scheduling of an EV car-sharing service, considering multi-temporal and multi-task operations, was presented in [94], where the power grid was simplified as a time-of-use price signal. A social cost model was proposed in [95] to minimize the traffic flow and power system cost. In [96], a VI-form UE-STA model was used to describe the route choice behaviours of BEV drivers considering flow-dependent electricity consumption. Time-varying travel demand and flow dynamics were captured by the DTA model and the ACOPF was used to model the power grid. A novel navigation approach based on a multi-agent system was proposed to search for the FCS with the lowest
overall objective, consisting of both time consumption and financial cost in [97]. The EV fleet charging management model was presented in [98]; the charging station status and the EV and traffic conditions were required to ensure an acceptable quality of service. In [99], to reduce the travel costs of EV users and improve the load level of the distribution system, an EV route selection and charging navigation optimization model with real-time traffic information update was proposed.

4 | CHALLENGES AND FUTURE DIRECTIONS

Most existing studies focus on long-term analysis, especially on the location and size planning of FCSs; studies on mid-term and short-term time scales are relatively few. The authors believe that this is because the number of EVs was insufficient. When the EV penetration reaches a certain level, the significance of the co-optimization of PTN (i.e. mid-term and short-term time-scale PTN models) is expected to increase accordingly. This section presents some of the challenging issues and future trends in PTNs.

4.1 | Challenges of the PTN model

The availability of renewable energy, driver decision-making and traffic accidents, all of which are highly uncertain in nature and the representation of these and other types of uncertainties are critical factors in PTN modelling. However, studies that employ uncertainty modelling techniques, such as stochastic optimization [91] and robust optimization [14], in PTN modelling are limited. In [82], a probabilistic planning model was developed for the optimum allocation and sizing of FCSs, where QT was employed to handle the uncertainties of EVs. However, the EV owner's user preference is an important source of uncertainty in PTN. Quantitative modelling of user preferences is still an open question. Preliminary research in this field includes the quantification of the inconvenience caused by early departures [100] and the bounded rationality of EV users in travel choices [101]. One possible solution in this direction is to import more information from users directly via an application [102].

Battery degradation is a critical problem for EV users, especially EVs included in vehicle-to-grid power operation. Therefore, for PTN modelling, battery maintenance and aging mechanisms should be considered [38, 103, 104].

4.2 | Future trends

The power grid and transportation system are both critical facilities for smart cities [105]. In the foreseeable future, innovative travel methods, such as car-sharing and auto-piloted travel, are expected to become important features of smart traffic. A few EV car-sharing related studies have been conducted, such as charging station planning for shared EVs [106], optimal charging management [107, 108], space–time–battery network flow model for sharing EV route planning [109], EV unbalancing and VGI services [110]. In general, the realization of smart cities and smart traffic remains a subject requiring further research.

Resilience is another potential feature of PTNs. Urban transportation resilience was introduced in [111]. In [112], the enhancement of the resilience of interdependent traffic–electric power systems was investigated. In [10], a bi-level mixed-integer stochastic program was proposed to quantify the resilience of a coupled traffic–power network under a host of potential natural or anthropogenic hazard–impact scenarios.

5 | CONCLUSION

To become a carbon-neutral country by 2060, there will be many more EVs in China in the coming decades. The fast increasing utilization of EVs requires two basic facilities for modern smart cities: a power grid and a transportation network that are tightly coupled as a PTN. This paper presents an up-to-date review of PTN modelling research, especially traffic network modelling. The PTN models are categorized into three types: long-term (for planning), mid-term (for daily operation), and short-term (for one trip or real-time trips). Most studies have shown the benefits of co-operation between power grids and traffic networks. However, the concept of the PTN and its modelling technologies are still evolving. The rapid development of autonomous driving technology and intelligent transportation has led to a greater potential for middle-and short-term co-operation of PTN for advancing EV proliferation, even though many studies are still focused on the planning phase of PTN. The analysis and development trends indicate that uncertainty modelling, including driver preference modelling, is the key issue for PTN modelling. Finally, future trends of PTN research, including resilience and innovative travel methods, are presented. The authors believe that under pressure from objective environmental factors and subjective incentives from governments, PTN will play a key role in smart cities and draw more attention in the coming decade.

ACKNOWLEDGEMENTS

This work was supported by the National Natural Science Foundation of China (NSFC) under Grant 51777065.

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How to cite this article: Sun, Y., et al.: Spatial and temporal modelling of coupled power and transportation systems: A comprehensive review. Energy Convers. Econ, 2, 55–66 (2021). https://doi.org/10.1049/enc2.12034