Sadhu et al. Energy Informatics (2022) 5:35
https://doi.org/10.1186/s42162-022-00249-w

Energy Informatics

RESEARCH

Open Access

Optimal joint operation of coupled transportation and power distribution urban networks

Kaushik Sadhu, Kawsar Haghshenas*, Mohammadhadi Rouhani and Marco Aiello

*Correspondence: Kawsar.haghshenas@iaas.uni-stuttgart.de

Service Computing Department, IAAS, University of Stuttgart, Stuttgart, Germany

Abstract

The number of Electric Vehicles (EVs) and consequently their penetration level into urban society is increasing which has imperatively reinforced the need for a joint stochastic operational planning of Transportation Network (TN) and Power Distribution Network (PDN). This paper solves a stochastic multi-agent simulation-based model with the objective of minimizing the total cost of interdependent TN and PDN systems. Capturing the temporally dynamic inter-dependencies between the coupled networks, an equilibrium solution results in optimized system cost. In addition, the impact of large-scale EV integration into the PDN is assessed through the mutual coupling of both networks by solving the optimization problems, i.e., optimal EV routing using traffic assignment problem and optimal power flow using branch flow model. Previous works in the area of joint operation of TN and PDN networks fall short in considering the time-varying and dynamic nature of all effective parameters in the coupled TN and PDN system. In this paper, a Dynamic User Equilibrium (DUE) network model is proposed to capture the optimal traffic distribution in TN as well as optimal power flow in PDN. A modified IEEE 30 bus system is adapted to a low voltage power network to examine the EV charging impact on the power grid. Our case study demonstrates the enhanced operation of the joint networks incorporating heterogeneous EV characteristics such as battery State of Charge (SoC), charging requests as well as PDN network's marginal prices. The results of our simulations show how solving our defined coupled optimization problem reduces the total cost of the defined case study by 36% compared to the baseline scenario. The results also show a 45% improvement on the maximum EV penetration level with only minimal voltage deviation (less than 0.3%).

Keywords: Electric vehicle, Optimal transport-power flow, Semi-dynamic traffic assignment, Transportation network, Power distribution network, Optimization-based interdependency

Introduction

Electric Vehicles (EVs) are a promising solution to reduce greenhouse gas emissions and the reliance on fossil fuels (Electric Power Research Institute 2007). EVs use electricity instead of burning fossil fuels and rely on a grid power infrastructure for the charging of their batteries. The increasing penetration of EVs (IEA 2021) in the Transportation

Network (TN) comes with important loads affecting the Power Distribution Networks (PDN) (Clement et al. 2009). In other words, meaningful parts of the needs of the transportation network that were traditionally served by gas stations are now moving to the power network. The fact that such load is mobile, that is, a car can and will charge at different points of the power network, poses additional challenges to the infrastructure. This is especially true of urban networks where there is a high density of population and, consequently, large use of transportation and power infrastructures.

There are two main challenges that EVs impose on the power grid. First, due to the uncontrolled charging schedules of the EV users, the power load might increase during peak hours. This can be a source of grid stress and consequent failure due to factors such as voltage instability and power losses. Therefore, a rapidly growing EV market would need additional investment in grid infrastructure to decrease the risk of grid overload. Second, due to the power capacity constraints, the charging stations may not be able to fulfill all EV charging requests. In addition, the optimal installation of rapid chargers is expensive and the lack of incentives on smart charging behavior defer users to make the switch to EVs. Thus, appropriate EV routing along TN network and charging scheduling can mitigate the adverse impacts of EV charging on PDN network, as well as prevent potential traffic congestion in the TN network.

A way of looking at this current trend is to realize that the transportation and power urban infrastructures are becoming increasingly correlated, and therefore their operation should be optimized jointly. The challenge for such optimization is due to the nature of EVs. In fact, these are distributed mobile energy consumers whose energy demand behavior is highly influenced by multiple factors including the State of Charge (SoC) of the EV Battery, the type and capacity of the battery, the average travel distance, traffic, distance to the charging stations, and charging duration with charge preferences (Wu et al. 2018). While residential EV charging demand is fairly predictable in nature, as the average user's driving pattern can be identified with reasonable accuracy, the public EV re-charging behavior is stochastic and difficult to predict as they are influenced by erratic traffic flow.

These interactions between TN and PDN networks, exemplified in Fig. 1, pose a complex problem to the management of the power system (Wei et al. 2019; Marmaras et al. 2017).

The present work contains a proposal for an optimal transportation-power network model to study the impact of variable traffic flow and congestion scenarios on power distribution loads. The operation of coupled TN and PDN networks with the objective of minimizing costs is formulated as an optimization problem. Obviously, the interconnected system's load capability constraints are taken into account in the developed model. Integrating traffic flow information with the queuing theory, our methodology achieves equilibrium traffic flow to minimize the impact on the PDN. Ultimately, the aim is to minimize the social costs mutual to both TN and PDN networks.

Each EV in a TN is defined by multiple parameters including driver behavioral profiles, traffic elements, Origin-Destination (OD) points, trip travel time, energy consumption, EV battery capacity, and battery SoC. These parameters are identified based on stochastic travel behavior and traffic flow. The fundamental Wardrop principle (Wardrop 1952) is used to estimate the distribution of EV flows in the TN

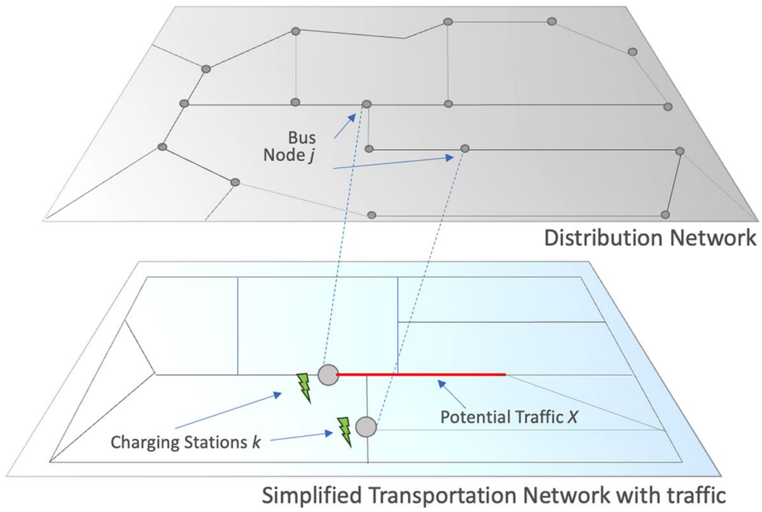

Fig. 1 Hierarchical coupling of TN and PDN networks

which leads to a stable equilibrium of traffic-flow pattern known as Dynamic User Equilibrium (DUE) in Dynamic Traffic Assignment (DTA) setup. The DUE model can be computationally very expensive as it enumerates all possible paths in the OD pairs (Janson 1991). The DTA model was developed to generate approximate solutions to DUE which can be applied to larger networks (Janson 1991). We utilize the Semi-Dynamic Traffic Assignment (SDTA) model which has lower computational complexity. The mobility and charging demand of EV users are assessed using traffic elements. Finally, by modeling both TN and PDN networks independently and then linking them with coupling constraints, optimized traffic-constrained transportation power flow solution is developed.

Several research works have proposed individual operational methodologies and optimization techniques to ensure secure operation under peak demands when EVs are connected to the power grid, e.g., (Diaz-Cachinero et al. 2021; Spitzer et al. 2019). However, to the best of our knowledge, a model considering the coupling of the interdependent TN and PDN networks which considers the time-varying, dynamic nature of all the parameters in their spatial temporal variations has not been studied.

A bottom-up approach is used to model the characteristics of individual EV driving and charging behavior creating a unique load profile for each scenario. However, the energy consumption of EVs at charging stations is accumulated over time periods to ascertain the electrical impact on the power grid. We resort to quantitative techniques with an agent-based simulation method coupled with MATLAB for power flow analysis. The mobility model is realized in the JAVA Agent Development Framework (JADF) and power flow model calculations are done with MATLAB using a standard radial distribution network. In addition, the ACN-Dataset is used for public EV charging to have realistic charging information (https://ev.caltech.edu/dataset). Our proposed methodology takes a unique interdisciplinary approach by finding the inter-relations between TN and PDN by combining a multi-agent system framework into the TN with traffic information. We evaluate the feasibility and achievable improvements of our proposed approach using the most used IEEE test systems. In our case study, the interactions between EV users are captured in a semi-realistic distributed environment.

In summary, the main contributions of our research work are as follows:

- The formulation of an optimization problem to minimize the total system cost of interdependent TN and PDN networks in a dynamic setting by analysing EV driving behavior profiles and energy prices.
- An integrated agent-based traffic assignment model for TN impact analysis and its cascading effect on power systems. Through our unique Agent Based Modeling (ABM), EV driving behavioral data samples are collected and energy requirements at charging stations are identified as loads connected to the power network bus nodes. The collected load profiles of EV charging load for a 24-h period are used to analyze the impact on PDN. This approach is a unique simulation-based optimization of coupled networks.
- The dynamics of large-scale EV penetration in an overlaid distribution and transportation network system are part of the model. As traffic behavior changes, variable load distributions in terms of the EV charging process are used.
- The development of an approach to achieve optimal route selection to nearby charging stations which eliminates the need for long waiting periods at public charging spots thereby reducing the load curve. A controlled smart-charging technique is also applied to reduce voltage problems that may arise in the distribution network due to multiple EVs recharging at the same time.

The rest of the paper is organized as follows. Section Related work contains a discussion of related work. Section Problem formulation presents the formulation of the optimization problem of TN and PDN models and introduces the approach for solving the problem. A case study based on a small region of the urban TN and its interdependent impacts on the PDN is illustrated in Case study and simulation results section. Finally, a summary of the contribution and a discussion of future work in the area of EV mobility in interconnected TN and PDN networks are drawn in Conclusions section.

Related work

There are many previous papers on modeling coupled TN and PDN networks as well as EV integration into the power grid. Marmaras et al. used an integrated simulation-based approach to model road traffic and EV battery charging (Marmaras et al. 2017). The main focus of Marmaras et al. (2017) is on the EV agent's characteristics and behavioral modeling rather than the inter-relation between TN and PDN. In most of the previous works on TN modeling, the Bureau of Public Roads (BPR) function (United States. Bureau of Public Roads 1964) is used to calculate the cost function of travel time which is quadratic in nature, however, in this paper, the Davidson's function (Davidson 1966) with queuing analysis has been used due to its linear properties.

The current state of the art in optimal operation of the interdependent transportation-power network system is based on graph network approaches where nodes and edges represent the interlinking elements. In addition, simple static traffic models without dynamic user equilibrium conditions have been used for traffic flow modeling. Tang et al. have discussed spatial and temporal impacts of EVs on traffic systems using a probabilistic model of expected nodal EV charging demand based on parking events (Tang and Wang 2016). Graph theory along with Dijkstra's algorithm is employed in Tang and Wang (2016) to calculate energy consumption based on trip distance. However, the model is generic with macroscopic characteristics taken into account without any coordinated charging events between EV users. Wei et al. presented a a dedicated traffic user equilibrium model to describe the steady-state distribution of traffic flows comprised of gasoline vehicles and electric vehicles (Wei et al. 2017). In that study, the impact of individual driving behaviors on the power grid has not been modeled.

Geng et al. have developed an integrated system of "vehicle-traffic-distribution" and solved the spatial-temporal distribution of EV charging load using OD matrix.

Geng et al. proposed a hybrid optimisation method using stochastic user equilibrium and information gap decision theory to study the impact of the uncertainties on the coordinated Electrified Transportation Network (ETN)-PDN operation (Geng et al. 2021). ETN enables the integration of EVs into an efficient PDN infrastructure with an emphasis on usage of renewable energies. A similar approach has been presented in Xiang et al. (2018) which utilizes cellular automata in an integrated traffic-power simulation framework to evaluate the feasibility of EV charging stations deployments without actually quantifying the impact on coupled TN and PDN.

The research on the interconnection between TN and PDN is still in its evolving phase. Only a few interdisciplinary studies have been made on the stochastic spatial-temporal electrical energy and mobility behavior of electric vehicles considering the dynamic activity of both networks. The studies made by Xie et al. (2021); Wei et al. (2016) and Jiang et al. (2018), aim at minimizing the total cost of both TN and PDN networks, but without considering the time-varying dynamics of the transportation traffic network. The static traffic Assignment model has been used which gives a coarse overview of traffic flows. In addition, the constraints associated with EVs' charging load at charging stations are not explicitly modeled.

All the above-mentioned works have considered the spatial-temporal behavior of electricity and vehicle traffic demands with static charging loads and/or static transportation traffic. To the best of our knowledge, the present treatment is the first work that considers the time-varying and dynamic nature of all the effective parameters in spatial-temporal variations to the coupled TN and PDN networks.

Problem formulation

The formulation of the models of both TN and PDN networks, the optimization problem, and the coupled transportation and distribution networks subject to their specific constraints are presented next. The interactions between EVs' charging impact on the PDN are central to the formulation. The idea is to make conjunction between the two generally independent networks and formulate an optimal operation that aims at minimizing total costs.

It is also possible to model the whole system using the weighted sum approach to merge multiple objectives into a singular objective function. However it results in multiple Pareto-Optimal solutions and the solver might encounter difficulties in convergence which results in sub-optimal solution (Watanabe and Sakakibara 2005). In addition, using multi-objective solvers to find global optimal solution is much higher time consuming. Therefore, in this work, the TN and PDN networks are modeled individually and then coupled by coupling constraints.

Table 1 lists the key notations used throughout this paper, in order of their presence in the text.

Modelling the transportation network

The topological structure of the transportation traffic network is a connected Graph $G(V, E)$ where each node $v \in V$ is an endpoint (either origin or destination) or an intersection of multiple road sections. These endpoints can be origin or destination nodes and their links have associated costs that represent the travel time for EV users.

Each EV inside the transportation network leaves from its origin s and travels to its destination d. Let $\vartheta_{e,t}$ stand for the traffic flow on link $e \in E$ generated by the traffic demand of OD pairs (s, d) connected by subset of nodes in V during time period t. The latency function $\tau_e(t)$ calculates the time to travel on link e during time period t, as a function of aggregated traffic flow.

Each EV user aims to minimize its travel time on the traffic roadways. Therefore, the optimization problem of TN as the minimization of the travel time and the associated energy cost during a charging event for aggregated EVs at a charging station, subject to a set of system constraints is formulated. In this paper, this optimization problem C_{TN} is defined as follows:

$$Min. \quad C_{TN} := \sum_{t \in T} \sum_{e \in E} [(w * \tau_e(t) + X_{e,t}^{cg}) * \vartheta_{e,t}] + G_{ch}^{\{ev\}} \tag{1}$$

subject to:

$$\tau_e(t) * \vartheta_{e,t} = \tau_e^0 * [1 + \alpha * (\frac{\vartheta_{e,t}}{cap_e - \vartheta_{e,t}})] \tag{1.a}$$

$$C_j^{ch} * \pi_j(t) = \sum_{e \in E} (\tau_e(t) * w) + P_{ch}^{ev} * \pi_j(t) \tag{1.b}$$

$$C_{p,t}^{sd} = \sum_{e \in p} \left(w * \tau_e(t) + X_{e,t}^{cg} \right) * \psi_p \tag{1.c}$$

$$T_{p,t}^{sd} = \sum_{e \in E} \tau_e(t) * \vartheta_{e,t} * \psi_{e,p} \tag{1.d}$$

$$\sum_{p \in P_{sd}} f_{p,t}^{sd} = \eta_{sd}(t) + X_{e,t}^{cg} * (x_{t-1}^{sd} - x_t^{sd}), \forall s, d \tag{1.e}$$

Table 1 Notations summary

General parameters and variables			
C_{TN}	Objective function (travel time cost and associated cost of energy during a charging event - Cost of TN)	w	Parameter—Associated cost of travel time estimated in Euros
$\tau_e(t)$	Latency function to calculate the travel time on link *e* during time period *t*	$X^{cg}_{e,t}$	Traffic congestion cost on link *e* during time period *t*
$\vartheta_{e,t}$	Total aggregate of traffic flow on link *e* during time slot *t*	$G^{\{ev\}}_{ch}$	Aggregated charging costs of all EVs
T	The predefined time period for optimization	τ^0_e	Free flow traveling time on link *e*
α	Co-efficient for real traffic observation data	cap_e	Capacity of traffic flow on road link *e*
C^{ch}_j	Associated cost (Euros) of electricity at the charging station connected to bus node *j* of PDN	$\pi_j(t)$	Locational Marginal Price (LMP) of bus j in PDN during time period *t*
P^{ev}_{ch}	Average EV charging power (kW) for unit traffic flow	$C^{sd}_{p,t}$	Cost of travel on path *p* in the OD pair (*s*, *d*) during time period *t*
ψ_p	Decision parameter to state if path *p* is chosen or not	$T^{sd}_{p,t}$	Time to travel on path *p* in the OD pair (*s*, *d*) during time spot *t*
$\psi_{e,p}$	Decision variable which states if link *e* belongs to path *p* or not	$f^{sd}_{p,t}$	Traffic flow on path *p* in the OD pair (*s*, *d*) during time period *t*
$\eta_{sd}(t)$	The traffic demand on OD pair *(s,d)* during time period *t*	x^{sd}_t	Binary variable if vehicle makes a trip from source *s* to destination *d* during time period *t*
P^{ev}_{max}	Maximum charging power rate of electric vehicle *ev*	$SoC_{min}Q$	Minimum state of charge of the battery capacity Q
$SoC_{max}Q$	Maximum state of charge of battery capacity Q	Cap_{ch}	Number of charging stations
Cap^{ch}_k	Number of charging piles at charging station *ch*	$P^{ev}_{ch,k}$	Charging Power (kW) of the electric vehicle *ev* in pile *k* of charging station *ch*
l_{ch}	The load that the charging station can handle	N_{ch}	Power efficiency factor of charging station *ch*
π_{ch}	Charging price (Euros) at charging station *ch*	$\vartheta_{e,ch,k}$	Traffic flow captured by the charging station *ch* in pile *k* through link *e*
$A^{\{ev\}}_{ch}$	Amount of Energy (kWh) to be charged by all EVs at charging station *ch*	C_{PDN}	Objective function (energy cost of PDN for charging all EVs)
Φ_j	The cost (Euros) of generating power from bus node *j*	$p^{gen}_x(t)$	Average generated power (MW) by bus node *x* during time *t*
$\pi_{cs}(t)$	Contract energy cost charged per kWh during time period *t*	$\Gamma_c(t)$	The purchase energy cost from main power grid excluding contract price, during time slot *t*
λ_j	Set of all bus nodes which are at the end of the distribution line	$P_{ij}(t)$	Active power flow from bus node *i* to *j* during time period *t*
r_{ij}	Reactance of active power line connecting bus node *i* to *j*	$I_{ij}(t)$	Current from bus node *i* to bus node *j* during time period *t*
$P_{jk}(t)$	Average active Power flow (MW) from bus node *j* to pile *k* during time period *t*	$p^{dem}_x(t)$	Total active power demand (MW) at bus node *x* during time period *t*
$Q_{ij}(t)$	Average reactive power flow (MVar) from bus node *i* to *j* during time period *t*	$q^{gen}_x(t)$	Average reactive power (MVar) generated at bus *x* during time slot *t*
x_{ij}	Reactance of reactive power line connecting bus node *i* to *j*	$Q_{jk}(t)$	Average reactive power flow from bus node *j* to pile *k* during time period *t*
$q^{dem}_j(t)$	Average reactive power (MVar) demand at bus node *j* during time period *t*	$U_x(t)$	Average voltage drop at bus node *x* during time period *t*
$U^f_i(t)$	Lower bound of square voltage magnitude at bus node *i* during time slot *t*	$U^r_i(t)$	Upper bound of square voltage magnitude at bus node *i* during time slot *t*
p^f_i	Lower limit of active power generation at bus node *i*	p^r_i	Upper limit of active power generation at bus node *i*
q^f_i	Lower limit of reactive power generation bus node *i*	q^r_i	Upper limit of reactive power generation bus node *i*
$p^r_i(t)$	Regular power demand at bus node *i* during time period *t*	Ψ	Unit traffic flow charging demand rate

Table 1 (continued)

General parameters and variables			
N_b^{ch}	The binary variable is set to 1 if charger b is connected to charging station ch	P_{sd}	Paths from origin s to destination d
Indices			
t	Index for time period	e	Index for link
p	Index for path	s, d	Index for OD pair
i	Index for source bus node	j	Index for demand bus node
ch	Index for charging station	ev	Index for electric vehicle
k	Index for pile		

$$\vartheta_{e,t} = \sum_{p \in P_{sd}} f_{p,t}^{sd} \psi_{e,p}, \forall e \in E \tag{1.f}$$

$$0 \leq P_{ch}^{ev} \leq P_{max}^{ev} \tag{1.g}$$

$$P_{ch}^{ev} + SoC_{\min} Q \leq SoC_{\max} Q \tag{1.h}$$

$$\sum_{ch=1}^{Cap_{ch}} \sum_{k=1}^{Cap_k^{ch}} P_{ch,k}^{ev} \leq Cap_{ch} * l_{ch} * N_{ch} \tag{1.i}$$

where w, $X_{e,t}^{cg}$, and $G_{ch}^{\{ev\}}$ stand for the estimated cost of travel in Euros, traffic congestion cost index on link e, and aggregated charging cost of all EVs at charging station ch, respectively. Therefore, the first term of the objective function refers to the total travel cost associated with traffic flow for all EVs including travel and traffic congestion costs.

The parameter τ_e^0 refers to the travel time on link e in free flow. cap_e and α in Eq. (1.a) represent the capacity of link e and the co-efficient for real traffic observation parameter in Davidson function (Davidson 1966), respectively. In this work, the Davidson's function is used as it is linear and it is easy to fit to actual traffic data.

The variables $C_{ch}^{\{ev\}}$, P_{ch}^{ev}, and $\pi_j(t)$ in (1.b) show the charging cost of all EVs at the charging station ch, the charging power rate of unit traffic flow in the network, and the Locational Marginal Price (LMP) connected to bus j during time period t, respectively.

In (1.c), $C_{p,t}^{sd}$ denotes the travel cost on path p in OD pair (s, d) during time t and the decision variable ψ_p shows whether the path p is chosen or not. In addition, $C_{ch}^{\{ev\}} * \tau_e(t)$ denotes the aggregated link travel-time and charging cost at charging station ch. The parameter $T_{p,t}^{sd}$ is the travel time on path p between the OD pair (s, d) in the constraint expressed by Eq. (1.d).

The fifth constraint Equation (1.e) satisfies flow conservation for all residual traffic flow in the OD pair (s, d) from the current to previous time period's traffic demand wrt. congestion index and added to the current traffic demand $\eta_{sd}(t)$. The parameter $f_{p,t}^{sd}$ is the traffic flow on path p between the OD pair (s, d). The constraint expressed by Eq. (1.f) ensures that the traffic flow on link e during time period t is the sum of all possible taken routes or paths through each link during time period t.

As the number of EVs grows, the charging demand grows significantly which adds several more constraints (Eqs. 1.g–1.i). Equation (1.g) guarantees that the charging rate is less than the maximum charging rate of an EV. Equation (1.h) ensures that the charged quantity (kWh) is less than the maximum vehicle battery capacity. Equation (1.i) states that the sum of all EV charging instances $P^{ev}_{ch,k}$ must be less than or equal to the total charging capacity of the charging station. Cap_{ch}, l_{ch}, and N_{ch} stand for the number of charging stations, the load that can be handled, and the power efficiency factor of station *ch*, respectively.

Finally, the aggregated charging cost $G^{\{ev\}}_{ch}$ for all EVs at each charging station *ch* is calculated based on the charging power of each EV and the electric charging cost at the charging station connected to a bus in the PDN. Given the charging price π_{ch} at charging station *ch* and EVs' charging energy $A^{\{ev\}}_{ch}$, the function $G^{\{ev\}}_{ch}$ estimates the charging cost. Summing up all the charging instances for each vehicle considering traffic flow on link *e* connected to the charging pile *k* at the charging station *ch* multiplied by the amount of energy it requires to be recharged, gives us the total aggregated charging cost. Formally,

$$G^{\{ev\}}_{ch} = \sum_{ch=1}^{Cap_{ch}} [\pi_{ch} * \sum_{e=1}^{Cap^{ch}_{k}} (\vartheta_{e,ch,k} * A^{\{ev\}}_{ch})] \tag{2}$$

The optimization variables in optimization problem presented in Eq. (1) are ψ_p, $\psi_{e,p}$, and $A^{\{ev\}}_{ch}$ that need to be optimized to achieve the objective of minimizing the travel time cost and associated cost of energy during a predefined period of time, under defined constraints.

Modelling the power distribution network

Power distribution networks usually take the shape of a radial or mesh graph (Pagani and Aiello 2011). These can be represented as an undirected graph $G(M, B)$, where M shows the set of buses and B denotes the set of branches or power distribution lines. In this definition, a slack bus is indexed as O and the bus-bus pair i, j is used to denote a link between bus i to bus j. If a generator is connected to a bus node $i \in M$, then its corresponding electric power demand or bus injection power is set to 1.

The voltage and power loss are contributing factors that determine the safe operation of a Direct Current Optimal Power Flow (DCOPF) model (Eldridge et al. 2017). However, DCOPF power flow equations are not suited for the distribution systems because of high voltage fluctuations and power losses that are higher than in transmission systems. DCOPF solutions also may not satisfy all non-linear power equations. To stabilize the voltage magnitudes, reactive power must be injected into the system. In addition, these defects can decrease the scalability of these solutions for bigger networks.

Concerning the above-mentioned issues, convex relaxations of AC power flow equations have been adopted via a Second Order Cone Programming (SOCP) (Baradar et al. 2013). In general, solving AC Optimal Power Flow (ACOPF) problems through convex relaxations provides a feasible way to obtain a globally optimal solution. If the solution is not achievable, a lower bound on the objective function is provided by solving the OPF. ACOPF problems are NP-hard (Lehmann et al. 2015;

Bienstock 2019), however, relaxations on ACOPF can lead to convex optimization problems which can be computed in practice.

An Optimal Power Flow (OPF) problem is defined as the power flow problem combined with the Economic Dispatch (ED) problem. As the standard power flow problem does not consider power generation costs, the ED problem is used to minimize the operating cost which mainly includes fuel costs of a power distribution network. During each time period t, branch flow equations are iterated to calculate power flows. As some constraints in the optimization problem are non-linear, the SOCP technique for OPF is utilized to relax and transform the problem into a convex optimization problem and finally be able to solve it. This ensures that the problem can be solved in polynomial time and makes it tractable.

Our approach to formulate the power flow equations and relaxations are similar to the ones presented in several related works, namely (Eldridge et al. 2017; Gan et al. 2014; Low 2014). It is assumed that there is a distribution network operator in the smart grid who manages the operations of the PDN.

The operational energy production cost of the PDN (C_{PDN}) is formulated as:

$$Min. \quad C_{PDN} := \sum_{j \in M} [\Phi_j * p_j^{gen}(t) + \pi_{cs}(t) * \sum_{c \in \lambda_j} \Gamma_c(t)] \tag{3}$$

subject to:

$$P_{ij}(t) + p_j^{gen}(t) - r_{ij} I_{ij}(t) = \sum_{k \in \lambda_j} P_{jk}(t) + p_j^{dem}(t) \tag{3.a}$$

$$Q_{ij}(t) + q_j^{gen}(t) - x_{ij} I_{ij}(t) = \sum_{k \in \lambda_j} Q_{jk}(t) + q_j^{dem}(t) \tag{3.b}$$

$$\begin{aligned} U_j(t) = U_i(t) &- 2 * (r_{ij} P_{ij}(t) + x_{ij} Q_{ij}(t)) \\ &+ ((r_{ij})^2 + (x_{ij})^2) I_{ij}(t) \end{aligned} \tag{3.c}$$

$$I_{ij}(t) \geq \frac{\left(P_{ij}(t)\right)^2 + \left(Q_{ij}(t)\right)^2}{U_i(t)}, P_{ij} \geq 0, Q_{ij} \geq 0 \tag{3.d}$$

$$I_{ij}(t) \leq I_l^r, \forall l, U_i^f(t) \leq U_i(t) \leq U_i^r(t), \forall i \tag{3.e}$$

$$p_i^f \leq p_i^{gen}(t) \leq p_i^r, q_i^f \leq q_i^{gen}(t) \leq q_i^r, \forall i \tag{3.f}$$

where the first term in the equation includes the costs (convex cost function) for loads connected to the demand bus node j and the second term represents the cost of energy purchased from the main power grid during time period t.

Average power generated and demanded at bus j during time period t are denoted by $p_j^{gen}(t)$ and $p_j^{dem}(t)$, respectively. The parameters λ_j, $\pi_{cs}(t)$ and $\Gamma_c(t)$ stand for the set of buses towards the end of the distribution line starting from bus j, the co-efficient of energy production cost during time period t and the price of energy from the main grid, respectively. Variable Φ_j denotes the cost of generating power from bus j. It is assumed that the energy consumption is charged by the operator using LMP which is usually a fixed contract price in a region.

The constraints of Eqs. (3.a) and (3.b) guarantee the nodal active power balance and reactive power balance of the network. Equation (3.c) ensures Ohm's law of voltage drop on branch $\{i, j\}$ and Eq. (3.d) denotes the SOCP relaxation applied to nodal active and reactive power. Finally, Eqs. (3.e) and (3.f) put upper/lower bounds on current and voltage limits as well as generator output, respectively. Other parameters used in Eqs. (3.a)–(3.f) are defined in Table 1.

The optimization variables in optimization problem presented in Eq. (3) are $p_j^{gen}(t)$, $P_{jk}(t)$, and $Q_{jk}(t)$ that need to be optimized to achieve the objective of minimizing the power generation cost during a predefined period of time, based on EVs' charging demand and under defined constraints.

Modelling the coupled TN and PDN

The final aspect for the formulation of the optimization problem is defining the relation between the traffic and the power networks. An example is depicted in Fig. 1. The connections between the charging stations and the power network are shown in dotted lines. To analyze the impact of EV penetration in the power grid, the spatial and temporal EV mobility is considered. As EVs move, their battery charge decreases with time which initiates the charging necessity. As the charging stations in TN draw load from the PDN, charging EVs' battery impacts the load of the TN on the buses of the power distribution network. Therefore, assuming that one bus is connected to one generator, the total power demand at bus i is calculated as the sum of regular power demand at the bus and aggregated EVs' charging at the charging station.

It is assumed that the energy consumption at link e of TN network is a linear function of the traffic flow (Wei et al. 2016). Thus, the link between TN and PDN is formulated by Eq. (3.g). In addition, to model the coupling optimization problem, three more constraints are defined for the optimization problem defined in Eq. (1).

$$p_i^{dem}(t) = p_i^r(t) + \Psi \sum_{e \in S(i)} \vartheta_{e,t}, \forall i \in M \tag{3.g}$$

$$Cap_k = \sum_{e=1}^{Cap_k} \vartheta_{e,j,k} * A_{ch}^{\{ev\}} \tag{3.h}$$

where $p_i^{dem}(t)$ and $p_i^r(t)$ stand for the total power demand and regular power demand at bus i during time period t, respectively.

The parameter Ψ shows the unit traffic flow charging demand rate, which can be determined from real-world traffic data. This parameter is estimated on the basis of the EV penetration level or current EV charging rate on the given network. The higher the level of EV penetration, the greater will be the charging rate parameter. Finally, Eq. (3.g) establishes that nodal electric power demand is equal to regular power demand and

EV charging demand. The parameter $\vartheta_{e,t}$ shows the traffic flow through link e, where e belongs to the set of links connected to bus $i \in M$ $(S(i))$.

Equation (3.h) ensures that the charging capacity Cap_k of the charging pile k is equal to the links' charging demand. In this constraint, the connection of the charging station pile k with bus node j is denoted by $\vartheta_{e,j,k}$ and the changing energy is presented by A^{ev}_{ch}.

Optimal transportation-power network flow model

In a coupled system of TN and PDN networks, when EVs recharge their batteries at charging stations, the required energy is provided by PDN. In this paper, the defined objective of the coupled system is to minimize total costs. To achieve this, it is assumed that there exists an independent system operator who manages both the TN and PDN networks. It aims to minimize the total costs of both interdependent systems.

In additions, the fundamental Wardrops Principle (Wardrop 1952) is adopted in generalized format to solve the traffic assignment problem. Taking into consideration both the networks, the optimization problem in Eq. (1) is updated to the following coupled formulation:

$$\begin{aligned} Min.\quad & OTPNF := [C_{PDN} + C_{TN}] := \\ & \sum_{j\in M}[\Phi_j * p_j^{gen}(t) + \pi_{cs}(t) * \sum_{c\in\lambda_j}\Gamma_c(t)] \\ & + \sum_{t\in T}\sum_{e\in E}[(w * \tau_e(t)] + X^{cg}_{e,t}) * \vartheta_{e,t}] + G^{\{ev\}}_{ch} \end{aligned} \tag{4}$$

subject to:
Transportation Network Constraints - (1.a - 1.i)
Power Distribution Network Constraints (3.a-3.f)
Coupling Constraints (3.g-3.h)

Case study and simulation results

The OTPNF (Eq. 4) is a mixed integer convex optimization problem that can be solved, e.g., through commercial solvers such as IPOPT, CONOPT, and COUENNE(convex over and under envelopes for nonlinear estimation) solver (Couenne 2006). Given the constraints of the models, one can assume the optimization problem to be convex. In fact, after relaxing the non-linear constraints and convexifying the objective function, the convex Mixed Integer Nonlinear Problem (MINLP) is solved using the Couenne solver (Couenne 2006) and AMPL (https://ampl.com/products/solvers/all-solvers-for-ampl/), which apart from handling convex MINLPs can also solve non-convex MINLPs. Global optimality is guaranteed for the Couenne solver, while it is not for other solvers. This is because Couenne implements linearization, bound reduction, and branching using branch-bound algorithm, therefore it can find the best solution or global optimum solution without interruption.

These tools are used for the evaluation of the cost reduction achieved by solving the proposed optimization problem compared to the baseline scenario. As a case study, the IEEE 30-bus power system test case with two connected charging stations CS1 and CS2 is used, as shown in Fig. 2. To validate the feasibility of our chosen method and analyse the effects of

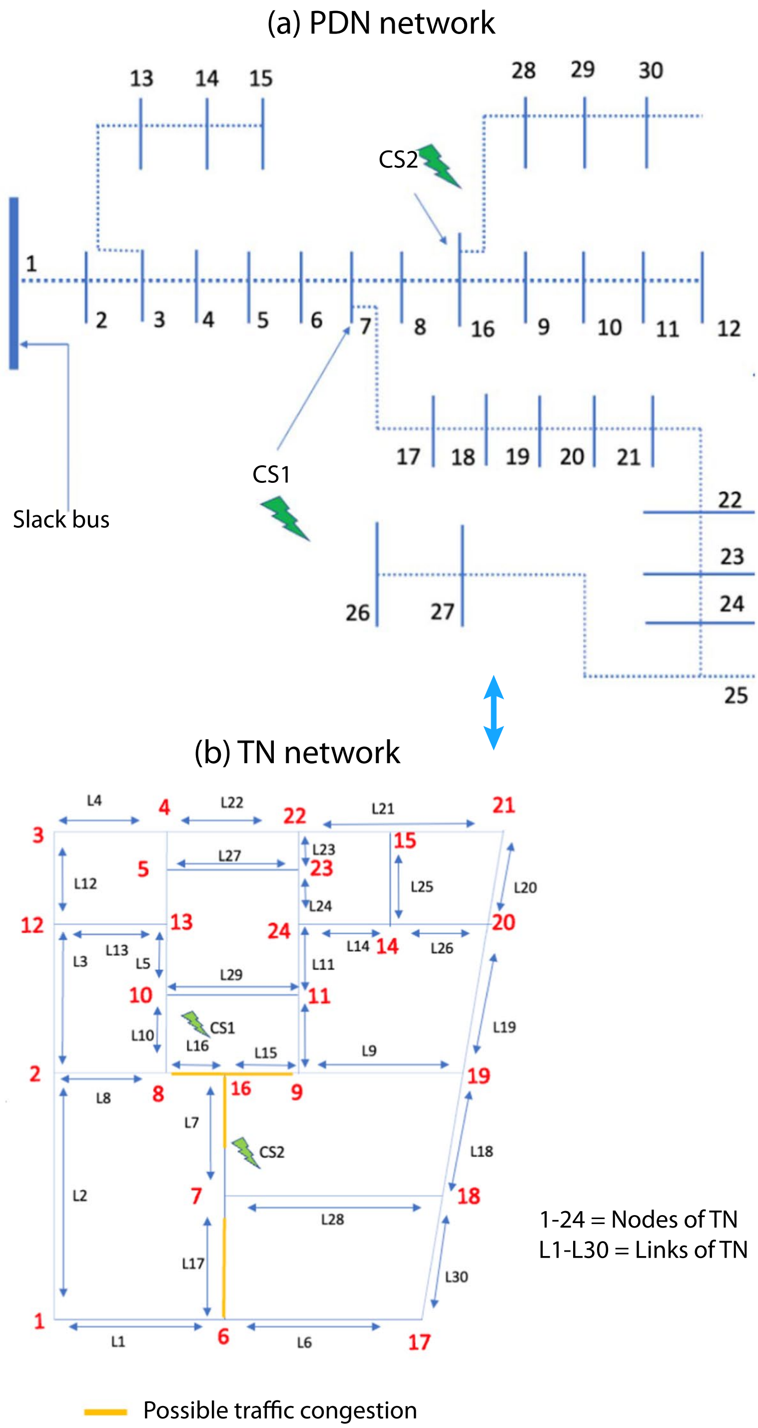

Fig. 2 **a** IEEE 30-node radial power network as a base layout for the PDN. **b** coupled with charging stations CS1 and CS2 in the transportation network with the travel links and nodes. The yellow lines in TN denote possible traffic congestion. The links of the TN are shown by L1–L30 and the nodes are denoted in red from 1 to 24

cascading line failures due to the EV charging load, the comparison with a standard power system is necessary. The IEEE standard test systems represent real systems and has been used in most of the similar works, in turn helping to compare the results (Xie et al. 2021;

Sun et al. 2019). The radial power system topology allows us to evaluate multiple EV flees power demand and discharge scenarios where links are serviced by an electrical bus. Links between nodes 7 and 16 serve as the main conjunction for the PDN. The charging station CS1 is placed at the conjunction of the main road connecting to bus node 7 in the distribution network and CS2 is placed at the branch node of Bus 16 which is located within the OD pair of the given transportation network.

Optimization results for the coupled TN and PDN

In this paper, the OTPNF optimization problem is solved using the Couenne Solver and AMPL code. For the ACOPF and DCOPF models, piece-wise linear generator costs are considered. The results of this evaluation are presented in Table 2 as the TN and PDN costs along with their formulation methods. The OTPNF formulation found a locally feasible optimal solution with an optimal cost of 5470.67 Euros/h. In addition, as the results in Table 2 show, the OTPNF model decreases the operating costs of both the TN and PDN networks when the stochastic dynamic user equilibrium traffic assignment formulation is used along with OPF. The optimal system cost due to our optimization formulation (OTPNF) resulted in 5470.67 Euros/h whereas the aggregated cost of the individual networks would have been 8604.67 Euros/h. Therefore, the cost savings is calculated as 36.42%, when compared to the aggregated cost of individual baseline scenarios (without the coupling constraints).

The achieved improvement is due to the non-existence of nodal electric power demand according to links' charging demand for each EV connected to the charging pile, when modeled with individual not-coupled models. The additional coupling constraints ensures that the operational cost is within boundaries of the amount of energy to be charged by all EVs at the charging station which are connected to the bus nodes.

Evaluating the maximum EV penetration level based on our approach

With the given EV penetration level, the PDN network aims to handle as many charging requests as possible. Therefore, supporting the maximum number of EV charging demands without violating grid constraints and operational efficacy is a representative evaluation metric. The EV charging behavior is controlled by the EV owner or dispatcher unit from the grid. The optimization problem is modeled to find the largest EV adoption based on the maximum load from the charging stations and electricity drawn from the main grid.

$$Max.\{\mathcal{L}_v\} * \sum_{b \in j}^{Cap_j} N_b^{ch} \tag{5}$$

Table 2 Comparison of costs (Euro) associated with the TN and PDN

Formulation method	Solver	Individual TN cost	Individual PDN cost	Iterations	Optimal system cost
OPF	GUROBI	–	8812.22	N/A	8372.12
OTPNF	CONOPT/IPOPT	3384.28	5220.39	13	5470.67

subject to:
Power Distribution Network Constraints (3.a-3.f)
Coupling Constraints (3.g-3.h)

where $\mathcal{L}_v$ is the function determining the PDN flow load. The binary variable N_b^{ch} is set to 1 if charger b is connected to charging station ch otherwise is set to 0. The objective function maximizes the number of EV charging requests, respecting the distribution network constraints. The above problem is a mixed-integer non-linear model. By translating the problem into a running program for Couenne, an improvement of 45% for EV penetration level is achieved that can support charging demand without negative impact on the grid. Voltage magnitudes deviate between 0.1 and 0.3%. An amount absolutely acceptable by the infrastructure and would not cause power failure issues.

Evaluating the network congestion of the coupled networks

A sample network with 30 zones and 30 links having 552 OD pairs and 76 path links has been used in the simulations. In these simulations, the traffic flow is assumed to be 100 vehicles/h. The cascading effect of transportation traffic flow on the PDN network is shown in Fig. 3. This figure represents the voltage magnitude heatmap showing areas where nodes suffer from high EV charging demand.

The congestion index of TN is based on data from user equilibrium traffic flow by dividing the link capacity to the traffic flow. The traffic flow affects the power demand to the PDN and loading capacity. The congestion level of PDN is high at bus numbers 16 and 6 during the morning peak hours (7–9 am) and evening peak hours (5–7 pm). Bus 16 in our network provides a charging link where charging piles are present to support multiple incoming EVs. At this node, the voltage magnitude is low due to the high EV charging demand. In this simulation, the lower and upper bound of voltage magnitude are assumed to be 0.91 and 1.05, respectively. Figure 4 shows the PDN under EVs load, before and after optimization.

Evaluating user equilibrium traffic condition metrics

The results of the equilibrium travel time and traffic flow for our simulated case study are presented in Table 3. The user equilibrium travel time ($UE\_travelTime$) is measured in vehicle-minutes and user equilibrium traffic flow (UE_Flow) is measured in number of vehicles per hour. The congestion factor is calculated as the ratio of (UE_Flow) and the capacity of the road. A higher congestion intensity increases the travel time on the network, depending on the number of travelling vehicles. Congestion is minimized when agents are informed of alternative routes prior to reaching their destination. Ideally, lower congestion factor is preferred as it results in less aggregation of EVs at charging stations and ultimately leads to less stress on the PDN network.

Discussion

In Case study and simulation results section, the proposed system model for coupled TN and PDN networks was evaluated and compared with the baseline scenario. In addition, the maximum EV penetration level and the network congestion of the coupled networks were examined. The results presented in Table 2 indicate that our OTPNF model with

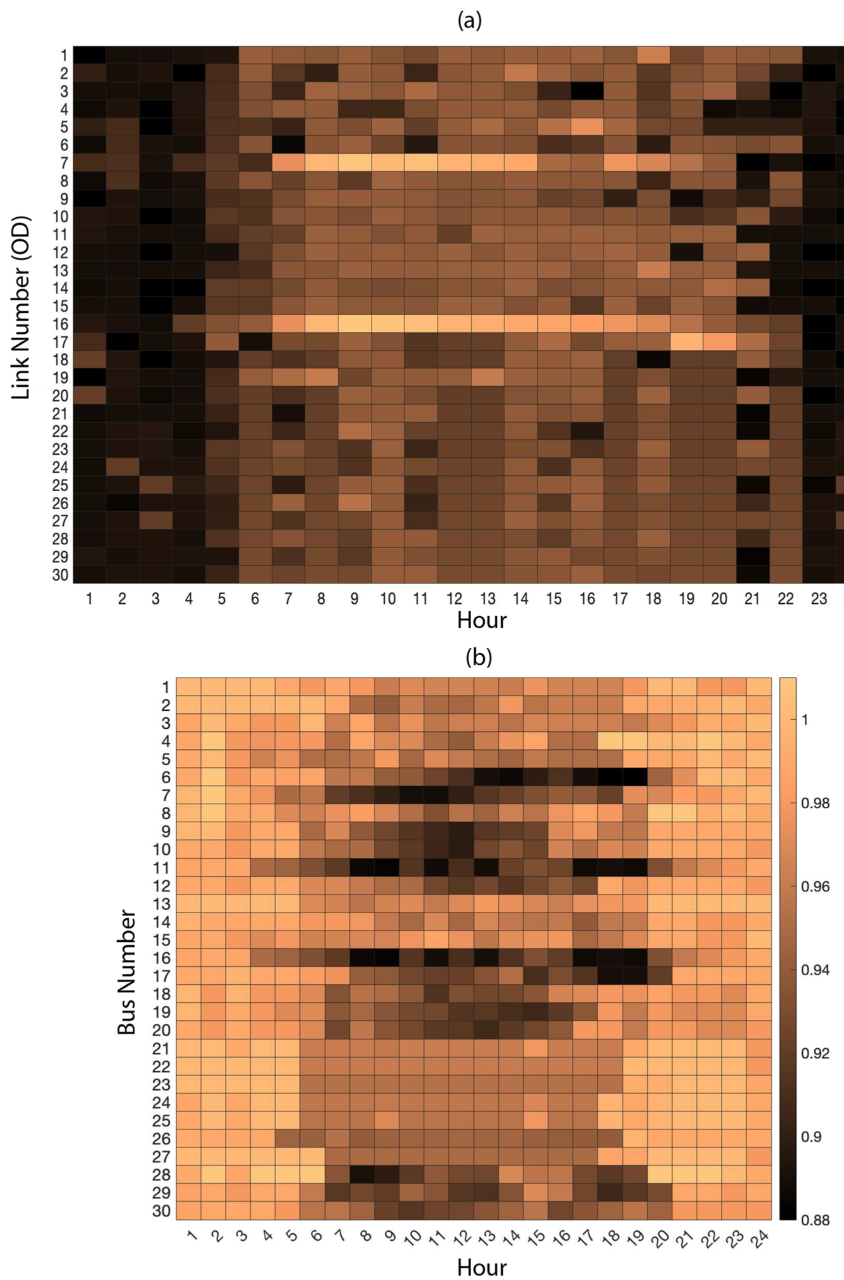

Fig. 3 **a** TN traffic flow (congestion levels) and **b** PDN bus voltage magnitude. The cascading impact of PDN bus magnitude values are shown in the heatmap (bottom) which indicates large scale traffic induced EV charging load from the TN traffic flow, indicating large scale traffic-induced EV charging load has impact on the Power grid

DUE network model is able to find an optimal solution with a significantly lower cost compared to the combined TN and PDN networks (36% saving in total cost). Therefore, this model framework can potentially be adopted to formulate traffic flow distributions with temporally-coupled network operations. In addition, the results on the maximum EV penetration level show a 45% improvement on the charging demand support without negative impact on the grid, imposing a voltage deviate less than 0.3% which is acceptable by the infrastructure and will not cause power failure.

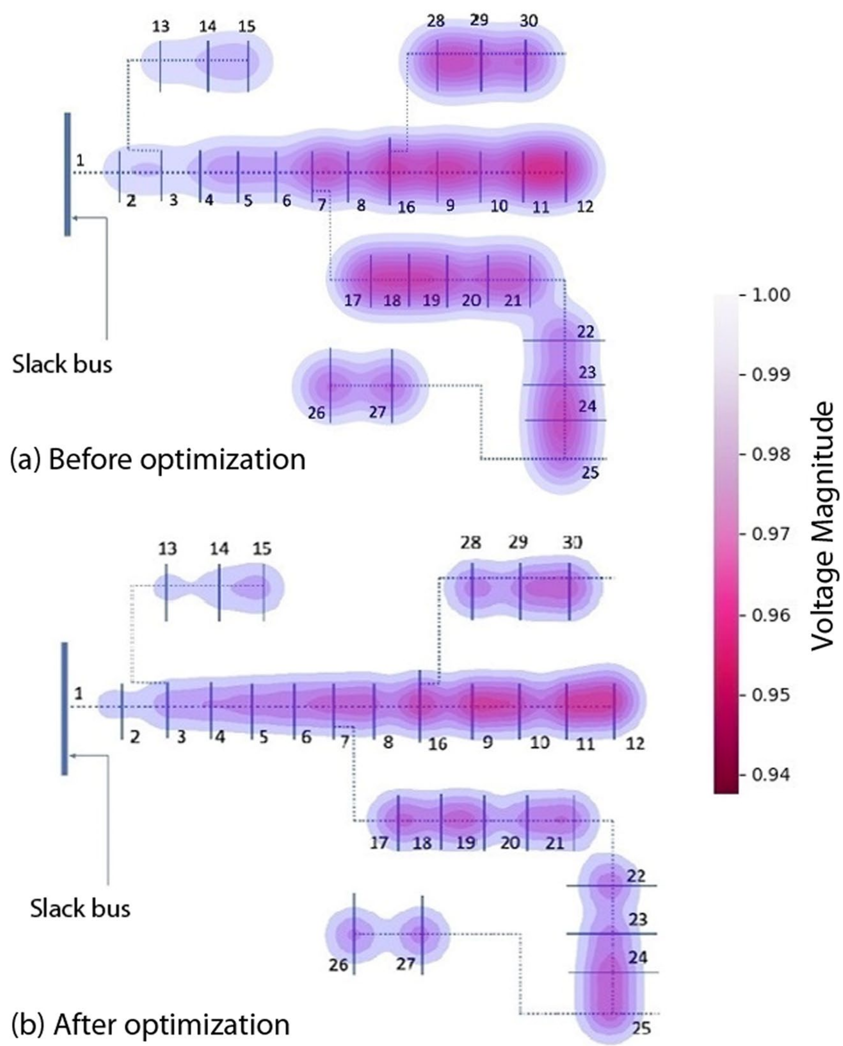

Fig. 4 Heatmap of voltage magnitude drop due to EV charging load and its cascading impact on subsequent nodes of the radial network. The voltage profile of affected nodes is alleviated after optimization which puts less strain on the power grid

Table 3 User Equilibrium traffic flow and congestion index for 24-Node transportation network

Arc	Capacity (vehicle-density)	UE_travelTime (vehicle-minutes)	UE_Flow (vehicle/hour)	Congestion Factor (UE_flow/capacity)
L1–L2	25900.20	6.0	4127.78	0.1593
L2–L3	23403.47	4.0	7742.51	0.3308
L4–L22	25900.20	6.4	4368.14	0.1686
L14–L26	4958.18	4.0	5857.34	0.9830
L23–L24	23403.47	4.3	7730.01	0.3303
L18–L30	17110.52	2.3	13679.45	0.7794
L8–L16	23403.47	7.8	10086.02	0.4309
L7–L17	11110.52	10.20	17463.84	1.572
L15–L16	8229.91	18.08	15096.87	1.834
L9–L19	23403.47	4.23	18448.87	0.7883
L20–L21	5000.0	3.63	4258.92	0.8517
L5–L10	15078.50	4.25	4908.82	0.3255

In another experiment, the network congestion of the coupled networks is evaluated. The results of this experiment are presented in Figs. 3, 4, and Table 3. Table 3 shows the results of the equilibrium traffic conditions for our simulated use case. Arc links L7–L17 and L15–L16 suffer the highest congestion due to spontaneous EV charging activities and demand response of the charging infrastructure. Subsequently the load on the PDN increases due to multiple incoming EVs with charging demand. There is a significant voltage drop in Bus Nodes 7 and 16 which has a cascading impact on the other bus nodes as depicted in Fig. 3. In addition, The results in Fig. 4 show how voltage magnitude drop and its cascading impact alleviated after optimizing the network using our proposed model and solution.

As illustrated in Related work section, there are many papers focused on modeling coupled TN and PDN networks, however, the research on this topic is still in its initial phase and just a few state-of-the-art studies have focused on EVs' stochastic electrical energy and mobility behavior. In this regard, Xie et al. (2021); Wei et al. (2016) and Jiang et al. (2018) are the closest studies to the present work. They aim at minimizing the total cost. However, none of these works consider the time-varying dynamics of all the effective parameters. In addition, the constraints regarding the EVs' charging load at charging stations are not explicitly modeled. Our paper considers the time-varying and dynamic nature of all the effective parameters in spatio-temporal variations to the coupled TN and PDN networks. Finally, although our research study proposed a novel optimal transportation-power network flow model which dynamically optimizes the network infrastructures jointly, it has a limitation regarding the impact of coordinated charging of EVs on a larger network which could be studied in the future.

Conclusions

With the increasing adoption of EVs, the coupling of the transportation and power networks is tightening. In the present work, such coupling has been modeled and evaluated using a case study. The key contributions of this paper include: (1) the formulation of the optimization problem of minimizing the system costs of both TN and PDN networks; (2) the development of an optimization strategy to minimize the total costs, in a temporally dynamic setting; and (3) capturing the stochastic nature of traffic flows, change in electricity prices, and EV charging demands while satisfying the concept of dynamic equilibrium in a computationally low footprint. Our proposed model considers the time-varying, dynamic nature of all the parameters in their spatio-temporal variations, an approach that has not been studied before.

To achieve this, the following steps were followed: First, by analyzing EV mobility behavior in a defined TN region, the spatial-temporal variations on all nodes of the TN are captured to determine the charging load on PDN. Second, the traffic flow on various links in the TN is calculated to identify hot spots within the distribution network bus nodes which could cause instability to the power grid. Finally, smart charging is applied to minimize the charging load at public charging stations by distributing the load across various charging piles. Our optimization framework decreases the total costs of both TN and PDN networks by focusing on the impact of EVs' load on the TN overlaid with the PDN. The results of the simulations highlight that large-scale EV penetration affects the optimal operation of PDN, which is solved using an optimal transportation-power network flow optimization model. In future work, we envision to improve the model by forecasting time varying traffic demands and electricity generation cost. In addition, evaluating the impact of renewable distributed generators integrated into the PDN together with the impact of random power output and power dispatch from EVs to the grid can also be considered. Finally, modeling the EVs not only as load but also as power storage for the balancing of the power system, can provide for new Smart Grid scenarios (Malya et al. 2021).

Abbreviations

EV	Electric vehicles
TN	Transportation network
PDN	Power distribution network
SoC	State of charge
OD	Origin-destination
DUE	Dynamic user equilibrium
DTA	Dynamic traffic assignment
SDTA	Semi-dynamic traffic assignment
JADF	JAVA Agent Development Framework
ABM	Agent based modeling
BPR	Bureau of Public Roads
LMP	Locational marginal price
DCOPF	Direct current optimal power flow
SOCP	Second order cone programming
ACOPF	AC optimal power flow
OPF	Optimal power flow
ED	Economic dispatch
MINLP	Mixed integer nonlinear problem

Author contributions

KS and MA conceived of the presented idea. KS developed the theory and performed the computations. KH and MR verified the analytical methods. KS prepared the initial manuscript and KH helped to improve the writing and the structure. All authors discussed the results and contributed to the final manuscript. All authors read and approved the final manuscript.

Authors' information

Kaushik Sadhu studied his M.Sc. degree in Computer Science at the Institute of Architecture of ApplicationSystems (IAAS) of the University of Stuttgart.
Kawsar Haghshenas is a post-doctoral researcher in the Smart Energy Systems (SES) laboratory at the University of Stuttgart. She received her Ph.D. degree in Computer Science from University of Tehran in 2020, M.Sc. degree in Computer Engineering from Sharif University of Technology in 2014, and B.Sc. degree in Computer Engineering from K.N.Toosi University of Technology in 2012. She was visiting the Embedded Systems Laboratory (ESL) at EPFL University from 2017 to 2018. Her research interests include system level energy optimization, machine learning and workload scheduling in the area of datacenters and cloud computing.
Mohammad Hadi Rouhani is pursuing a master's degree in computing science at the University of Alberta, Canada. His research focuses on applications of machine learning and convex optimization in energy systems, queuing theory in electric vehicle charging behavior. He received his B.S. degree in Electrical Engineering (with honors) from Shiraz University, Shiraz, Iran.
Marco Aiello is professor of Computer Science and Head of the Service Computing Department at the University of Stuttgart, Germany. He is also an elected member of the European Academy of Sciences and Arts and honoraryprofessor of Distributed Systems at the University of Groningen, The Netherlands, where he was a faculty member from 2006 till 2018. He holds a PhD in Logic from the University of Amsterdam, the Habilitation in Applied Informatics from TU Wien, and a master degree in Engineering from La Sapienza University of Rome. His research interests are in Service Computing, Smart Grids, Smart Energy Systems, and Data Centers.

Funding

Open Access funding enabled and organized by Projekt DEAL. The presented research is funded by the Netherlands Organisation for Scientific Research (NWO) in the framework of the Indo-Dutch Science Industry Collaboration programme with project NextGenSmart DC (629.002.102).

Declarations

Competing interests

The authors declare that they have no competing interests.

Received: 20 September 2022 Accepted: 7 November 2022
Published online: 14 November 2022

References

Baradar M, Hesamzadeh MR, Ghandhari M (2013) Second-order cone programming for optimal power flow in vsc-type ac-dc grids. IEEE Trans Power Syst 28(4):4282–4291
Bienstock D (2019) Verma, a strong NP-hardness of AC power flows feasibility. Oper Res Lett 47(6):494–501
Caltech: ACN-Data. https://ev.caltech.edu/dataset
Clement K, Haesen E, Driesen J (2009) Coordinated charging of multiple plug-in hybrid electric vehicles in residential distribution grids. In: 2009 IEEE/PES Power Systems Conference and Exposition, pp. 1–7. IEEE
Couenne, an exact solver for nonconvex MINLPs. IBM and Carnegie Mellon University (2006)
Davidson K (1966) A flow travel time relationship for use in transportation planning. In: Australian Road Research Board (ARRB) Conference, 3rd, Sydney, vol. 3
Diaz-Cachinero P, Muñoz-Hernandez JI, Contreras J (2021) Integrated operational planning model, considering optimal delivery routing, incentives and electric vehicle aggregated demand management. Appl Energy 304:117698. https://doi.org/10.1016/j.apenergy.2021.117698
Eldridge B, O'Neill R, Castillo A (2017) An improved method for the dcopf with losses. IEEE Trans Power Syst 33(4):3779–3788
Electric Power Research Institute (2007) Environmental Assessment of Plug-In Hybrid Electric Vehicles. https://www.energy.gov/
Gan L, Li N, Topcu U, Low SH (2014) Exact convex relaxation of optimal power flow in radial networks. IEEE Trans Autom Control 60(1):72–87
Geng L, Lu Z, Guo X, Zhang J, Li X, He L (2021) Coordinated operation of coupled transportation and power distribution systems considering stochastic routing behaviour of electric vehicles and prediction error of travel demand. IET Gener Transm Distrib 15(14):2112–2126
IEA (2021) Trends and developments in electric vehicle markets. https://www.iea.org/reports/global-ev-outlook-2021/trends-and-developments-in-electric-vehicle-markets
Janson BN (1991) Dynamic traffic assignment for urban road networks. Transp Res Part B Methodol 25(2–3):143–161
Jiang H, Zhang Y, Chen Y, Zhao C, Tan J (2018) Power-traffic coordinated operation for bi-peak shaving and bi-ramp smoothing-a hierarchical data-driven approach. Appl Energy 229:756–766
Lehmann K, Grastien A, Van Hentenryck P (2015) AC-feasibility on tree networks is NP-hard. IEEE Trans Power Syst 31(1):798–801
Low SH (2014) Convex relaxation of optimal power flow-part i: formulations and equivalence. IEEE Trans Control Netw Syst 1(1):15–27
Malya PP, Fiorini L, Rouhani M, Aiello M (2021) Electric vehicles as distribution grid batteries: a reality check. Energy Inf 4(2):29
Marmaras C, Xydas E, Cipcigan L (2017) Simulation of electric vehicle driver behaviour in road transport and electric power networks. Transp Res Part C Emerg Technol 80:239–256
Pagani GA, Aiello M (2011) Towards decentralization: a topological investigation of the medium and low voltage grids. IEEE Trans Smart Grid 2(3):538–547. https://doi.org/10.1109/TSG.2011.2147810
Spitzer M, Schlund J, Apostolaki-Iosifidou E, Pruckner M (2019) Optimized integration of electric vehicles in low voltage distribution grids. Energies. https://doi.org/10.3390/en12214059
Sun Y, Chen Z, Li Z, Tian W, Shahidehpour M (2019) Ev charging schedule in coupled constrained networks of transportation and power system. IEEE Trans Smart Grid 10(5):4706–4716. https://doi.org/10.1109/TSG.2018.2864258
Tang D, Wang P (2016) Nodal impact assessment and alleviation of moving electric vehicle loads: from traffic flow to power flow. IEEE Trans Power Syst 31(6):4231–4242
United States. Bureau of Public Roads (1964) Traffic Assignment Manual for Application with a Large, High Speed Computer vol. 2. US Department of Commerce
Various: ALL SOLVERS FOR AMPL. https://ampl.com/products/solvers/all-solvers-for-ampl/
Wardrop JG (1952) Road paper: some theoretical aspects of road traffic research. Proc Inst Civ Eng 1(3):325–362
Watanabe S, Sakakibara K (2005) Multi-objective approaches in a single-objective optimization environment, pp. 1714–17212. https://doi.org/10.1109/CEC.2005.1554895
Wei W, Mei S, Wu L, Shahidehpour M, Fang Y (2016) Optimal traffic-power flow in urban electrified transportation networks. IEEE Trans Smart Grid 8(1):84–95
Wei W, Mei S, Wu L, Wang J, Fang Y (2016) Robust operation of distribution networks coupled with urban transportation infrastructures. IEEE Trans Power Syst 32(3):2118–2130
Wei W, Wu L, Wang J, Mei S (2017) Network equilibrium of coupled transportation and power distribution systems. IEEE Trans Smart Grid 9(6):6764–6779
Wei W, Danman W, Qiuwei W, Shafie-Khah M, Catalao JP (2019) Interdependence between transportation system and power distribution system: a comprehensive review on models and applications. J Modern Power Syst Clean Energy 7(3):433–448
Wu Q, Shahidehpour M, Li C, Huang S, Wei W (2018) Transactive real-time electric vehicle charging management for commercial buildings with pv on-site generation. IEEE Trans Smart Grid 10(5):4939–4950
Xiang Y, Liu Z, Liu J, Liu Y, Gu C (2018) Integrated traffic-power simulation framework for electric vehicle charging stations based on cellular automaton. J Modern Power Syst Clean Energy 6(4):816–820
Xie S, Xu Y, Zheng X (2021) On dynamic network equilibrium of a coupled power and transportation network. IEEE Trans Smart Grid 13(2):1398–1411

Publisher's Note