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Resilience-oriented optimal post-disruption reconfiguration for coupled traffic-power systems

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Abstract

The increasing penetration of grid-enabled electric vehicles (EVs) renders road networks (RNs) and power networks (PNs) increasingly interdependent for normal operation. For this reason, recently few studies have started to investigate the vulnerability of a highly coupled traffic-power system in the presence of disruptive events. Actually, however, only very few of these studies have considered the impact of EVs on the interdependent traffic-power system during restoration from a disruptive event. In an attempt to fill this gap, in this study, we investigate the restoration planning of both independent RNs and PNs, and interdependent traffic-power systems. A mixed integer program model is formulated to provide optimal reconfiguration and operational solutions for post-disruption traffic-power systems recovery. The objective of the model is to minimize the total cost incurred by system performance loss, which is quantified by the cumulative unmet traffic demand for RNs and load shedding cost for PNs. Several reconfiguration strategies are considered, including links reversing in RNs and line switching in PNs, to optimize system resilience. In the proposed model, the integrated problem of system optimal dynamic traffic assignment and optimal power flow is solved to derive the optimal traffic-power flow. RNs and PNs are coupled through the coordinately allocated spatio-temporal charging demand of EVs. A partial highway network in North Carolina (NC), USA, and a modified IEEE-14 bus system are used to illustrate the application of the model. The numerical results obtained show the added value of coordinately planning restoration for traffic-power systems and the effects of different levels of EV penetration.

Keywords: Interdependent systems, Traffic-power systems, Electric vehicles, Resilience, Fast-charging stations, Optimal traffic-power flow

Acronyms

EVs	Electric vehicles
GVs	Gasoline vehicles
RNs	Road networks
PNs	Power networks
FCSs	Fast-charging stations

Nomenclature

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38 **Indices**

- 39 a index of links
40 t index of periods
41 s index of destinations
42 e index of energy levels for EVs
43 c index of EV classes

44 **The transportation network sets**

- 45 \mathcal{A} set of arcs
46 \mathcal{N} set of nodes
47 \mathcal{N}_{SR} set of origin and destination nodes
48 $A(i)(B(i))$ set of links whose tail(head) node is i
49 \mathcal{A}_R set of source arcs
50 \mathcal{A}_S set of sink arcs
51 \mathcal{A}_G set of general arcs
52 \mathcal{A}_C set of charging arcs
53 \mathcal{T} set of periods
54 \mathcal{E}_c set of energy levels for the EVs belonging to class c
55 \mathcal{C} set of EV classes

56 **Parameters**

- 57 ϕ time value
58 p_a^{ev} charging power of charging link a
59 $NC_a(t)$ number of chargers at charging link a during period t
60 δ period length
61 L_a physical length of link a
62 $k_{jam}/q_{max}/v_f$ jam density/ maximum flow/ free-flow speed
63 w backward shock-wave speed, $w = q_{max} \cdot v_f / (q_{max} - k_{jam} \cdot v_f)$
64 α_a^t average charging speed for charging link a during period t , $\alpha_a^t = p_a^{ev} / (\eta \cdot v_f)$
65 $f_a^I(t)$ inflow capacity of link a during period t

66	$f_a^O(t)$	outflow capacity of link a during period t
67	$DG_a^{s,c}(t)$	cumulative gasoline vehicle travel demand between the entry of origin link a and destination s , at the end of period t
68		
69	$DE_{a,c}^{s,e}(t)$	cumulative electric power travel demand of c class EV between the entry of origin link a and destination s with energy level e at the end of period t
70		
71	ν_a	free-flow travel time on link a , $\nu_a = L_a/(\delta \cdot v_f)$
72	β_a	travel time required by the backward shock wave from the exit to the entry of link a , $\beta_a = L_a/(\delta \cdot w)$
73		
74	N_h	number of links that can be reversed during restoration
75	Variables	
76	$U_a(t)$	cumulative number of vehicles that enter link a by the end of period t
77	$V_a(t)$	cumulative number of vehicles that leave link a by the end of period t
78	$UG_a^s(t)$	cumulative number of GVs that enter link a to destination s by the end of period t
79	$VG_a^s(t)$	cumulative number of GVs that leave link a to destination s by the end of period t
80	$UE_{a,c}^{s,e}(t)$	cumulative number of EVs of class c with energy level e that enter link a to destination s by the end of period t
81		
82	$VE_{a,c}^{s,e}(t)$	cumulative number of EVs of class c with energy level e that leave link a to destination s by the end of period t
83		
84	$x_{a,c}^{s,e}(t)$	occupancy of EVs of class c with energy level e at charging link a during period t
85	$\hat{x}_{a,c}^{s,e}(t)$	occupancy of EVs of class c with the updated energy level e at charging link a during period t
86		
87	h_a	binary variable that is equal to 1 if the direction of road a is reversed, and 0 otherwise
88	The power network sets	
89	\mathcal{P}_N	set of buses
90	\mathcal{P}_L	set of transmission lines
91	$\tilde{\mathcal{P}}_L$	set of damaged transmission lines
92	$\Gamma(j)$	successor set of bus j
93	Parameters	
94	p_j^{ramp}	ramp limits of generators at bus j
95	c_j^b	load shedding cost for the base load at bus j
96	c_j^{dc}	load shedding cost for the EV charging load at bus j

97	$\underline{p}_j^g/\overline{p}_j^g$	lower/upper limit of power generation at bus j
98	$p_{j,t}^b$	base power demand at bus j during period t
99	N_u	number of lines that can be switched off during restoration

100 Variables

101	$p_{j,t}^g$	power generation at bus j during period t
102	$p_{j,t}^{dc}$	charging load at bus j during period t
103	$P_{i,j,t}$	power flow from bus i to j during period t
104	$\theta_{i,t}$	phase angle at bus i during period t
105	$u_{i,j}$	binary variable that is equal to 1 if line (i, j) is switched in, being 0 otherwise
106	$LS_{j,t}^{dc}$	binary variable that is equal to 1 if the load of the attached FCSs is shedded at bus j during period t , being 0 otherwise
107		
108	$LS_{j,t}^b$	base load shedding at bus j during period t

109 EVs

110 Parameters

111	L_c^{max}	mileage of c class EV
112	E_c	maximum energy level of c class EV
113	η	average energy consumption efficiency for EVs

114 1. Introduction

115 Road networks (RNs) and power networks (PNs) are becoming increasingly interdependent
116 due to the increasing penetrations of grid-enabled electric vehicles (EVs). Such increased inter-
117 dependence makes the resulting system of systems more vulnerable also to the negative effects of
118 technology-nature and human-caused incidents and accidents. In particular, when a high-impact
119 low-probability (HILP) event occurs, e.g., an earthquake, an hurricane, a flood due to heavy rain,
120 the consequences can be devastating. For example, the 2003 North America blackout caused 50
121 million customers to suffer power outage [1]; during the landfall of Hurricane Sandy in 2012, 65%
122 of New Jersey's residents experienced disconnections from the power systems [2]; in July 2021,
123 the extremely heavy rainfall caused city-wide floods in Zhengzhou, Henan province, China [3] and
124 the flood severely damaged the critical infrastructures, including the transportation and the power
125 systems, for an estimated direct economic loss on the order of RMB 88.5 billion. These examples
126 highlight the pressing need of strengthening the resilience of RNs and PNs, also in view of the
127 increasing frequency and intensely of these events.

128 The concept of resilience has emerged in recent years, but it is not a completely new concept
129 and has strong relationships with the concepts of safety and risk. Resilience has various definitions
130 [4, 5, 6, 7], most sharing the general idea that is relates to the ability of a system to prepare
131 for, absorb, recover from and adapt to disturbances [8]. The risk concept concerns the threat of

132 an event to a system and its likelihood (probability) of occurrence and consequences, with less
133 emphasis on the system recovery ability. As for the concept safety, Aven [9] pointed out that it
134 has three perspectives:

- 135 • Safety I focuses on that things go wrong because of identifiable malfunctions or failures of
136 specific components of the system;
- 137 • Safety II is seen as the ability to succeed under varying conditions;
- 138 • Safety III is defined as freedom from unacceptable losses.

139 The concept of resilience somewhat combines Safety I and II, whereas Safety III emphasizes that
140 the system must be designed to be resilient and flexible to deal with surprising or unexpected
141 events [10]. Resilience management plays a critical role in risk management [11]. Improved system
142 resilience also means reduced risks [9].

143 From the definition of resilience, we can see that restoration ability is a key element. Effective
144 restoration strategies are crucial to enhance the system's resilience to disruptions. The restoration
145 problems can be generally divided into two stages: the long-term restoration problem and the
146 short-term restoration problem. For the long-term restoration, the restoration duration could be
147 days or weeks. For the PNs, it could be days, whereas it could be weeks for the RNs. During
148 long-term restoration, the main target is to repair the physically damaged system components
149 (e.g., transmission lines, road sections and generation stations) in order to recover the system
150 performance to the pre-disruption level. Scheduling repair crews, allocating resources and deter-
151 mining the restoration priority of components are generally the major concerns for the long-term
152 restoration problem. On the other hand, short-term restoration problem is also usually formed as
153 emergency response problem, which aims at minimizing the system service degradation, maintain-
154 ing the system service as much as possible, and trying to partially recover the disrupted service.
155 Such kind of emergency response is carried out based on the available resources within hours af-
156 ter the disruption. The long-term and short-term restoration problems are conventionally treated
157 separately, because there is no strong coupling relationship between them and they are different
158 in terms of required resources, time scales, expected achievements, etc.

159 Many studies [12, 13, 14] have investigated the post-disruption optimal restoration of RNs and
160 PNs.

161 Some studies [15, 16] treat the PN as an independent system. In these studies, restoration
162 strategies, such as topology control [17], generator rescheduling [18, 19] and control of distributed
163 energy storage systems, are often discussed. Among them, topology control is one of the most
164 efficient strategies to restore the service and to enhance the system resilience. Switching operations
165 has been intensively investigated [20, 21, 22] in PNs. In analogy to Braess's paradox in RNs Braess
166 [23], Zhang et al. [17], Glavitsch [24] showed that if one transmission line is removed from the an
167 electric power system, it can:

- 168 • enhance or reduce existing line currents,
- 169 • increase or decrease the losses in the neighboring lines,
- 170 • increase or decrease the magnitude of the nodal voltages.

171 Therefore, if the switching operations are optimized sophisticatedly and applied correctly, it is clear
172 that the control can be oriented towards overload reduction, control of voltage magnitudes and
173 reduction of losses and short-circuit currents. Typically, maximizing the network resilience and

174 minimizing the number of switching operations are the objectives of the proposed optimization
175 models. For example, Sekhavatmanesh and Cherkaoui [25] developed the concept of multiagent
176 automation in smart grids to restore a maximum of loads with minimum switching operations
177 after disruptions; Sabouhi et al. [26] presented an operational network reconfiguration strategy in
178 the event of high winds, to maximize network resilience and minimize the number of line switches
179 simultaneously. Sometimes, islanding or not islanding after disruptive events are treated differ-
180 ently. Agrawal et al. [27] developed a self-healing algorithm to restore the maximum priority loads
181 by reconfiguring network, without intentional islanding during blackouts. Guimaraes et al. [28]
182 proposed a three-stage algorithm for the dynamic reconfiguration of distribution networks with
183 islanding. The three stages of the algorithm included calculating the network reconfiguration so-
184 lutions in each hour, reducing the number of configurations, and generating the optimal sequence
185 of topologies. Li et al. [29] developed a concept of a fully decentralized multi-agent system to
186 build a restoration service framework for distribution networks. Based on this concept, a network
187 reconfiguration algorithm with intentional islanding was proposed for service restoration. Besides
188 reconfiguration, other corrective actions, such as generator re-dispatch, control of distributed en-
189 ergy storage systems (ESSs), and on-load tap changers, can also be considered as supplementary
190 strategies to enhance power system resilience. Liberati et al. [30] proposed a control system, which
191 optimized grid operations through network reconfiguration, control of distributed energy storage
192 systems and on-load tap changers. Sekhavatmanesh and Cherkaoui [31] developed an analytical
193 and global optimization model to find the most efficient restoration plan with the goal of mini-
194 mizing the number of de-energized nodes and minimizing the number of corrective actions as well.
195 The considered corrective actions included network reconfiguration, the tap setting modification
196 of voltage regulation devices, the nodal load-rejection, and the active/reactive power dispatch of
197 distribution generators. Zhang et al. [32] introduced two-stage stochastic models to deal with
198 the uncertainty in generation and demand during the recovery process. Switching transmission
199 lines and generator re-dispatch strategies were used to maximize load shed recovery in the bulk
200 transmission network. Nazemi and Dehghanian [33] introduced a framework for modeling seismic
201 and vulnerability of electric power systems. The generation re-dispatch strategy and corrective
202 network topology control were considered to maximize the load outage recovery after earthquakes.
203 Gholizadeh et al. [34] proposed a model to obtain the optimal allocation of sectionalizing switches
204 and fuses while the economical loss of both DG units and electricity customers were taken into
205 consideration. The results showed that the DG units and their economical loss could significantly
206 influence the placement of switch and fuse placement when tie switches did not exist in the network.

207 Some studies [35] treat the RN as an independent system in restoration planning. For short-
208 term restoration, reconfiguring network topology, controlling traffic lights and traffic demands
209 management are frequently adopted. For example, Wang and Wang [36] developed an integrated
210 reconfiguration strategy that considered the reconfiguration along both the supply and demand
211 sides of the transportation system. The traffic demand was reconfigured using a heterogeneous
212 fleet of vehicles and the network topology was reconfigured through a heterogeneous contraflow
213 control. Later on, they further refined the framework [37] for resilience analysis in consideration
214 of measurement and improvement. Two strategies were used to maximize the system resilience.
215 The first one used integrated reconfiguration of both traffic supply and demand to reduce traffic
216 demand through combining different traffic modes. The second one employed a contraflow strat-
217 egy to increase traffic capacity. Chiou [38] proposed a period-dependent traffic responsive signal
218 control model to enhance resilience of urban RNs. Koutsoukos et al. [39] developed a modeling
219 and simulation integration platform for experimentation and evaluation of resilient transportation
220 systems. Resilient traffic signal control in the presence of denial-of-service attacks was studied

221 in the case studies. Regarding the long-term recovery period, scheduling repair crew, allocating
222 resources and determining restoration priority of components [40] in the RNs are the common
223 strategies. Wu et al. [41] proposed a methodology to assess the resilience of transportation net-
224 works and a restoration priority measure was developed to support post-earthquake restoration of
225 damaged bridges. Zhao and Zhang [42] proposed a bi-objective bi-level optimization framework
226 to determine an optimal transportation network restoration plan. The lower-level problem consid-
227 ered elastic user equilibrium to model the imbalance between demand and supply. The upper-level
228 problem, formulated as bi-objective mathematical programming, determined the optimal resource
229 allocation for roadway restoration.

230 With the increasingly coupled RNs and PNs, considering the two networks as a whole has
231 become a need [43, 44]. Currently, only a few studies have investigated how to restore a coupled
232 traffic-power network after disruptions in an integrated way. Among these studies, considered
233 restoration strategies include optimally routing and scheduling mobile energy storage systems
234 (MESSs)/mobile energy sources [45, 46, 47, 48], coordinating with repair crews [46, 47, 48] and
235 switching lines [46, 47]. Most above-mentioned studies assume that only the PNs are damaged
236 by the disruption, whereas the RNs are not influenced and the time to transport the restoration
237 resources is the same as normal situation. However, the RNs may also be damaged during the
238 disruption, thus, the efficiency of the RNs may decrease. Only several works considered that the
239 disruption caused influences on both networks. Wang et al. [49] considered the PNs and urban RNs
240 coupled through traffic lights and mobile emergency resources (i.e., mobile emergency generators,
241 MESSs, electric buses and repair crews) for PNs. The availability of mobile emergency resources for
242 load restoration in PNs is related to their dispatch in the RNs, and the effect of PN-enabled traffic
243 lights on traffic flow is also modeled. They developed a service restoration method to maximize the
244 efficiency of both PNs restoration and RNs. Yao et al. [50] proposed a rolling integrated service
245 restoration strategy to minimize the total system cost by coordinating the scheduling of MESS
246 fleets, resource dispatching of microgrids and network reconfiguration of PNs. The integrated
247 strategy considered damage and repair to both the roads in RNs and the branches in PNs. Li
248 et al. [51] presented an optimization model for joint post-disaster PN restoration, considering
249 coordinated dispatching with electric buses of vehicle-to-grid (V2G) storage capability. Idle buses
250 placed at designated areas can feed power back to the grid via charging equipment in case of need.
251 The schedule of the remaining buses should meet the passenger transport demand. Belle et al.
252 [52] proposed a model to analyze the vulnerability of coupled railway and PNs where the power
253 network acted as an interface. They showed that failures in the power network could cause a
254 negative impact on the railway network.

255 Above-mentioned studies considered different interfaces between PNs and RNs. How to prop-
256 erly model the interfaces of the two networks is another key issue in investigating the optimal
257 service restoration of traffic-power networks. This paper considers that the RNs and PNs are
258 coupled through grid-enabled electric vehicles (EVs) and fast-charging stations (FCSs), which are
259 increasingly being deployed around the world [53]. Meanwhile, the risk of power outages in FCSs
260 due to natural disaster have raised serious concerns [54, 55]. This aspect has not been paid much
261 attention in the current literature.

262 In this paper, we focus on the emergency response problem for the coupled traffic-power net-
263 works through grid-enabled EVs and FCSs. The target of this problem is using the available
264 resources to quickly recover partial system service when the two networks are both damaged in a
265 disruptive event. The intensively investigated long-term restoration problem is out of the scope
266 of the present paper. For the emergency response strategies, the links reversing is considered,
267 because it can be easily taken as an operational response in most cases and also provide flexibility

268 to quickly restore part of the disrupted transport services. Other strategies are not considered
269 since, for example, traffic light controlling is not applicable to the electrified highway networks;
270 Traffic demand management is usually used for evacuation planning and, thus, is not appropriate
271 in our problems. Switching transmission lines are considered as emergency response strategy for
272 the PNs, since it almost is the most urgent first response. In RNs, vehicles may need to detour
273 and the RNs' performance, evaluated in terms of the satisfied traffic demand on a certain period
274 of time, therefore, may decrease. Due to the detoured vehicles, both the number of EVs and the
275 amount of charging demand for individual EV may increase in FCSs. Such charging demand may
276 become a burden for post-disruption PNs and the PNs may need to shed partial EV charging
277 load to protect the PNs from a total blackout. Consequently, the unavailability of the service in
278 FCSs can further influence the charging demand patterns and decrease the performance of the
279 RNs. However, in the current literature, there is a lack of models that are able to describe the
280 above-mentioned interactions within the two networks.

281 To fill the research gaps described before, this paper proposes a mixed integer program model
282 to minimize the performance loss of the coupled traffic-power systems upon the occurrence of
283 disruptive events. In our paper, the system performance loss is measured by the unsatisfied
284 travel demand and electricity demand. The unsatisfied/satisfied demand is a commonly used
285 performance indicator to be optimized for both the power and transportation systems in the
286 resilience-related literature. For example, Ref. [56] maximized the weighted sum of restored
287 loads, Ref. [57] minimized the total amount of lost power during the restoration process and
288 Ref. [13] used the energy not supplied as the indicator to estimate the system resilience. For
289 the transportation systems, minimizing the functionality losses of RNs [14], minimizing unmet
290 demand [42], maximizing network throughput [58] can be frequently found in the literature. For the
291 interdependent systems, they are assumed to be integrally operated by one decision-making agent,
292 therefore, minimizing the total system performance loss (i.e., total unsatisfied demand) [59, 60] is
293 proposed naturally. In this work, we firstly formulate the emergency response problem based on
294 network topology reconfiguration for the independent electrified RNs and PNs, respectively. Then,
295 the emergency response problem for the coupled traffic-power system is proposed from a centralized
296 decision-making perspective. Specifically, an integrated traffic-power systems model is developed
297 to describe the dynamic interaction between RNs and PNs, through EVs and spatiotemporal
298 distributed charging demand.

299 The main contributions of this paper are summarized as follows:

- 300 1. Most of the existing work studies PNs and RNs separately, or assumes that one single system
301 is damaged by a disruption. This work treats the PNs and RNs as a whole and assumes both
302 of them are partially damaged, where the degraded services influence each other.
- 303 2. To the best of our knowledge, this is the first work that investigates the emergency response
304 problem for the traffic-power systems coupled through grid-enabled EVs and FCSs.
- 305 3. A new integrated model is presented to explicitly model the interaction between PNs and
306 RNs, where the system optimal dynamic traffic assignment problem and the DC optimal
307 power flow problem are embedded, and the physical constraints from both networks are
308 considered.
- 309 4. The strategies of link directions reversing in RNs and line switching in PNs are mathemati-
310 cally formulated and originally modeled to mitigate the system performance loss in an inter-
311 dependent traffic-power system environment, and in independent RN and PN environments,
312 respectively.

313 The remainder of the paper is structured as follows. Section 2 formulates the reconfiguration
 314 problems in independent RN and PN, as well as in the interdependent traffic-power system. Section
 315 3 illustrates a case study to show the application of the proposed models and compares the solutions
 316 under different response resource levels, EV penetration levels and decision-making environments.
 317 Finally, Section 4 provides concluding remarks and future research directions.

318 2. Infrastructures models and reconfiguration problem formulation

319 In this section, models for the reconfiguration of independent RNs, independent PNs and
 320 interdependent traffic-power systems are formulated.

321 2.1. Reconfiguring electrified road networks

322 In this subsection, we present an electrified traffic system model considering the critical char-
 323 acteristics of EVs and FCSs. The model is based on the link transmission model (LTM) approach.
 324 The emergency response problem for the electrified RNs with reconfiguration techniques after disruption
 325 problem is, then, formulated based on the electrified traffic model presented. The main
 326 flowchart of the proposed methodology is shown in Figure 1.

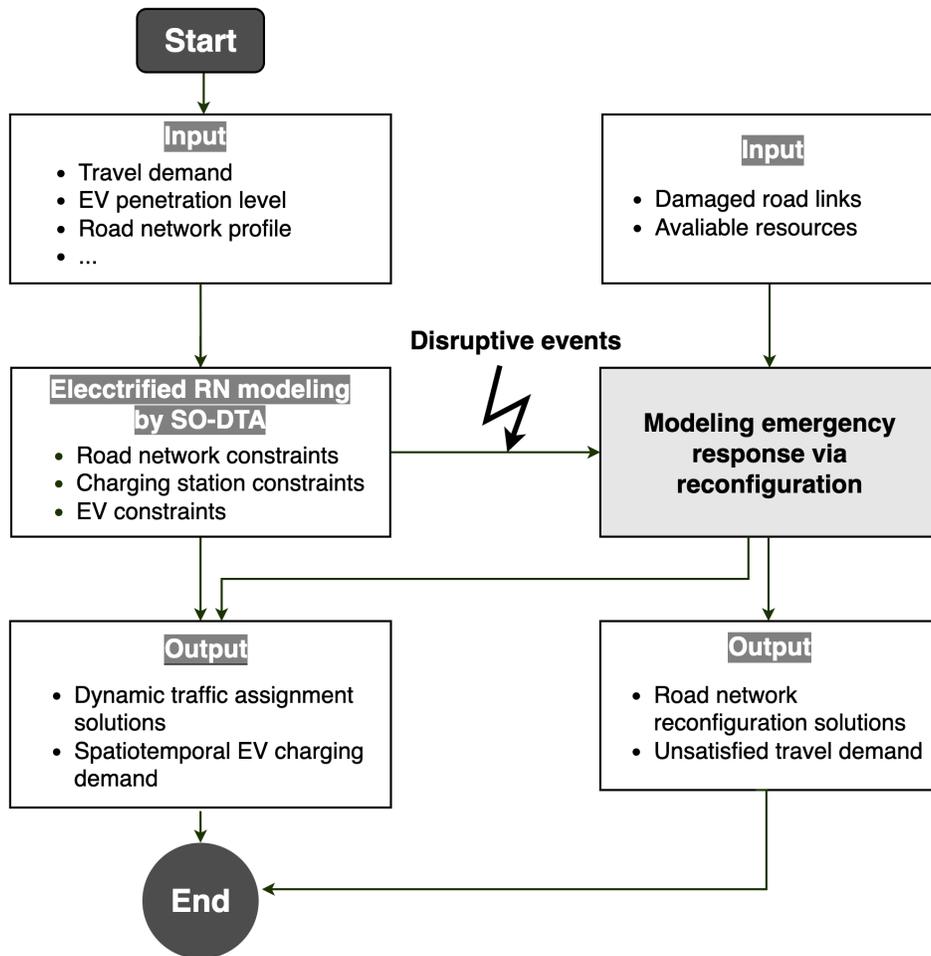


Figure 1: The main flowchart of modeling electrified road networks and its emergency response problem.

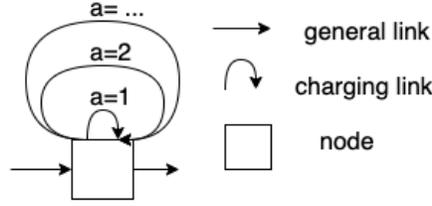


Figure 2: Link representation of different types of charges within a charging station.

327 *2.1.1. Modeling electrified road networks*

328 In this model, we assume that the electricity consumed by an EV is linearly related to the
 329 distance traveled. The electricity amount charged by an EV is linearly related to the charging
 330 time. All EV batteries have the same energy consumption efficiency, similar to Ref. [61].

331 A RN with multiple sources (origins) and sinks (destinations) is here denoted as $G(\mathcal{N}, \mathcal{A})$,
 332 where \mathcal{N} and \mathcal{A} are the sets of nodes and links, respectively. Links in the RN are classified into
 333 four types: source \mathcal{A}_R , sink \mathcal{A}_S , general \mathcal{A}_G and charging \mathcal{A}_C links. **Dummy charging links \mathcal{A}_C**
 334 **are originally defined to describe the FCS in the physical RN. A FCS is modeled by one or several**
 335 **charging links, represented by arcs having the same origin and destination, as shown in Figure 2.**
 336 **Chargers with different charging speeds are represented by different charging links.**

337 Nodes are classified into two types: source-sink \mathcal{N}_{SR} and general \mathcal{N}_G nodes. Within the RN,
 338 each source-sink node connects only one source and one sink link. All charging, source and sink
 339 links are dummy with lengths 0 so that no unnecessary travel time is counted on these dummy
 340 links. All source and sink links are with infinite outflow, inflow and storage capacities so that they
 341 will never become the bottlenecks of the traffic flow in the modeled RN. For the system optimal
 342 dynamic traffic assignment (SO-DTA) problem, the outflow capacity of all sink links are assumed
 343 to be 0, similar to Refs. [62, 63, 64]. It means that all vehicles are collected upon their arrival.
 344 The time horizon H is discretized into a finite set of periods $\mathcal{T} = \{t = 1, 2, \dots, T\}$. T is calculated
 345 according to $T = H/\delta$, where δ is the period length. The period length should be equal to or
 346 smaller than the smallest link travel time so that vehicles take at least one time unit to traverse a
 347 link [65].

348 A triangular fundamental diagram is defined in LTM, as an approximation of the macroscopic
 349 properties of roads [65]. The diagram is defined by three parameters: a jam density (k_{jam}), a
 350 maximum flow (q_{max}) and a fixed-free flow speed (v_f). The backward shock-wave speed w can be
 351 obtained by $w = q_{max} \cdot v_f / (q_{max} - k_{jam} \cdot v_f)$.

352 Given a certain class of EV denoted as c , its battery capacity is B_c kWh and the energy
 353 consumption efficiency is η kWh/mile, then, the mileage of this class EV is $L_c^{max} = B_c/\eta$ miles.
 354 We discretize its mileage into integer energy levels (ELs). When this EV has full battery, it has
 355 the maximum EL $E_c = L_c^{max}/(\delta \cdot v_f)$. Once this EV traveled $\delta \cdot v_f$ miles, its ELs decrease one
 356 unit EL, i.e., 1 unit EL = $\delta \cdot v_f$ miles. We assume that there are C EV classes represented as
 357 $\mathcal{C} = \{\mathcal{E}_1, \mathcal{E}_2, \dots, \mathcal{E}_C\}$. Each element \mathcal{E}_c in set \mathcal{C} is a set, which contains the energy levels that EVs
 358 of class c could have, denoted as $\mathcal{E}_c = \{1, 2, \dots, E_c\}$.

359 In the LTM, the traffic flow dynamic evolution is obtained by calculating the cumulative number
 360 of vehicles at entry and exit of each link, in each period of time t .

361 Newell's simplified theory [66, 67] is used in LTM to calculate sending $S_a(t)$ and receiving $R_a(t)$

362 capacities of link a :

$$S_a(t) = \min\{U_a(t - \nu_a) - V_a(t - 1), f_a^O(t)\} \quad (1a)$$

$$R_a(t) = \min\{V_a(t - \beta_a) + L_a \cdot k_{jam} - U_a(t - 1), f_a^I(t)\} \quad (1b)$$

364 where $U_a(t)/V_a(t)$ denotes the cumulative number of vehicles that enter/leave link a by the end of
 365 period t . $f_a^I(t)$ and $f_a^O(t)$ are the inflow capacity at the entering point and outflow capacity at the
 366 leaving point of link a during period t , respectively. They can be obtained by computing $\delta \cdot q_{max}$
 367 at the corresponding location and period. L_a is the length of link a . ν_a is the free-flow travel time
 368 on link a and β_a is the travel time required by the backward shock wave from the exit to the entry
 369 of link a . They can be obtained by $\nu_a = L_a/(\delta \cdot v_f)$ and $\beta_a = L_a/(\delta \cdot w)$, respectively.

370 The inflow and outflow of link a during interval t are constrained by its corresponding sending
 371 and receiving capacities:

$$U_a(t) - U_a(t - 1) \leq R_a(t), \forall a \in \mathcal{A} \setminus \{\mathcal{A}_C\}, \forall t \quad (2a)$$

$$V_a(t) - V_a(t - 1) \leq S_a(t), \forall a \in \mathcal{A} \setminus \{\mathcal{A}_C\}, \forall t \quad (2b)$$

373 Substituting Eqs. (1) and (1b) into the system of inequality (2), we obtain the following system
 374 of linear LTM-based flow constraints:

$$V_a(t) \leq U_a(t - \nu_a), \forall a \in \mathcal{A} \setminus \{\mathcal{A}_C\}, \forall t \quad (3)$$

$$V_a(t) - V_a(t - 1) \leq f_a^O(t), \forall a \in \mathcal{A} \setminus \{\mathcal{A}_C\}, \forall t \quad (4)$$

$$U_a(t) - U_a(t - 1) \leq f_a^I(t), \forall a \in \mathcal{A} \setminus \{\mathcal{A}_C\}, \forall t \quad (5)$$

$$U_a(t) - V_a(t - \beta_a) \leq L_a k_{jam}, \forall a \in \mathcal{A} \setminus \{\mathcal{A}_C\}, \forall t \quad (6)$$

378 In the proposed LTM-based model, both EVs and conventional vehicles are considered as follows
 379 :

$$U_a(t) = \sum_{s \in \mathcal{N}_S} UG_a^s(t) + \sum_{s \in \mathcal{N}_S} \sum_{c \in \mathcal{C}} \sum_{e \in \mathcal{E}_c} UE_{a,c}^{s,e}, \forall a \in \mathcal{A} \setminus \{\mathcal{A}_C\}, \forall t \quad (7a)$$

$$V_a(t) = \sum_{s \in \mathcal{N}_S} VG_a^s(t) + \sum_{s \in \mathcal{N}_S} \sum_{c \in \mathcal{C}} \sum_{e \in \mathcal{E}_c} VE_{a,c}^{s,e}, \forall a \in \mathcal{A} \setminus \{\mathcal{A}_C\}, \forall t \quad (7b)$$

381 where $UE_{a,c}^{s,e}(t)/VE_{a,c}^{s,e}(t)$ denotes the cumulative number of EVs that belong to type c with EL
 382 e , that enter/leave link a to destination s by the end of period t ; $UG_a^s(t)/VG_a^s(t)$ denotes the
 383 cumulative number of GVs that enter/leave link a to destination s by the end of interval t .

384 Substituting Eq. (7) into the inequalities in Eqs. (3) - (6), we can have the following constraints
 385 for the mixed traffic of EVs and GVs:

$$\begin{aligned} \sum_{s \in \mathcal{N}_S} [VG_a^s(t) - VG_a^s(t - 1)] + \sum_{s \in \mathcal{N}_S} \sum_{c \in \mathcal{C}} \sum_{e \in \mathcal{E}_c} [VE_{a,c}^{s,e}(t) - VE_{a,c}^{s,e}(t - 1)] \\ \leq f_a^O(t), \forall a \in \mathcal{A} \setminus \{\mathcal{A}_C\}, \forall t, s \end{aligned} \quad (8)$$

$$\begin{aligned} \sum_{s \in \mathcal{N}_S} [UG_a^s(t) - UG_a^s(t - 1)] + \sum_{s \in \mathcal{N}_S} \sum_{c \in \mathcal{C}} \sum_{e \in \mathcal{E}_c} [UE_a^s(t) - UE_a^s(t - 1)] \\ \leq f_a^I(t), \forall a \in \mathcal{A} \setminus \{\mathcal{A}_C\}, \forall t, s \end{aligned} \quad (9)$$

$$\sum_{s \in \mathcal{N}_S} \sum_{c \in \mathcal{C}} \sum_{e \in \mathcal{E}_c} [UE_{a,c}^{s,e}(t) - VE_{a,c}^{s,e}(t - \beta_a)] + \sum_{s \in \mathcal{N}_S} [UG_a^s(t) - VG_a^s(t - \beta_a)] \leq L_a k_{jam}, \forall a \in \mathcal{A} \setminus \{\mathcal{A}_C\}, \forall t, s \quad (10)$$

388 For GVs, the cumulative outflow disaggregated by destinations should also be constrained by
389 the boundary condition at the inflow. Hence, we have

$$\sum_{s \in \mathcal{N}_S} VG_a^s(t) \leq \sum_{s \in \mathcal{N}_S} UG_a^s(t - \nu_a), \forall a \in \mathcal{A} \setminus \{\mathcal{A}_C\}, \forall t \quad (11)$$

390 For EVs, the disaggregated cumulative outflow should also be constrained by the battery con-
391 dition at the inflow. Hence, we have

$$VE_{a,c}^{s,e}(t) \leq UE_{a,c}^{s,e+\rho_a}(t - \nu_a), \forall a \in \mathcal{A} \setminus \{\mathcal{A}_C\}, e \in \mathcal{E}_c \cap \{e \leq E_c - \rho_a\}, \forall s, c, t \quad (12a)$$

392

$$VE_{a,c}^{s,e}(t) = 0, \forall a \in \mathcal{A} \setminus \{\mathcal{A}_C\}, e \in \mathcal{E}_c \cap \{e > E_c - \rho_a\}, \forall s, c, t \quad (12b)$$

393 where, ρ_a is the ELs required to traverse link a and it is calculated by $\rho_a = L_a/(\delta \cdot v_f)$. Eq. (12a)
394 guarantees that outflow should be less than or equal to the inflow. It also guarantees that the
395 outflow ELs are updated from the inflow after the EVs traversed the corresponding links. Eq.
396 (12b) ensures that all EV ELs should be less than their maximum ELs.

397 The traffic demand is satisfied by letting the cumulative inflows of source links equal the
398 cumulative demands:

$$UG_a^s(t) = DG_a^s(t), \forall a \in \mathcal{A}_R, \forall s, t \quad (13a)$$

399

$$UE_{a,c}^{s,e}(t) = DE_{a,c}^{s,e}(t), \forall a \in \mathcal{A}_R, e \in \mathcal{E}_c, \forall s, c, t \quad (13b)$$

400 where $DG_a^s(t)/DE_{a,c}^{s,e}(t)$ represents the cumulative GVs/EVs travel demand between the entry of
401 origin link a and destination s at the end of period t .

402 The inflow and outflow of a general node should be restricted by the following flow conservation
403 constraints:

$$\sum_{a \in B(i)} VG_a^s(t) = \sum_{b \in A(i)} UG_b^s(t), \forall i \in \mathcal{N} \setminus \{\mathcal{N}_{SR}\}, \forall s, t \quad (14a)$$

404

$$\sum_{a \in B(i)} VE_{a,c}^{s,e}(t) = \sum_{b \in A(i)} UE_{a,c}^{s,e}(t), \forall i \in \mathcal{N} \setminus \{\mathcal{N}_{SR}\}, \forall e \in \mathcal{E}_c, \forall s, c, t \quad (14b)$$

405 where $A(i)/B(i)$ represents the set of links whose tail/head node is i .

406 For EVs, the current occupancy on charging link a should be limited by the maximum number
407 of chargers on this link:

$$\sum_{s \in \mathcal{N}_S} \sum_{c \in \mathcal{C}} \sum_{e \in \mathcal{E}_c} [UE_{a,c}^{s,e}(t) - VE_{a,c}^{s,e}(t)] \leq NC_a(t), \forall a \in \mathcal{A}_C, \forall t \quad (15)$$

408 where $NC_a(t)$ is the physical number of type a chargers on charging link a during period t .

409 The following equations are used to update the current occupancy and their ELs on a charging

410 link:

$$\begin{aligned} \hat{x}_{a,s}^{s,e}(t) &= x_{a,s}^{s,e}(t-1) + [UE_{a,c}^{s,e}(t-1) - UE_{a,c}^{s,e}(t-2)] - \\ &[VE_{a,c}^{s,e}(t-1) - VE_{a,c}^{s,e}(t-2)], \forall a \in \mathcal{A}_C, \forall e \in \mathcal{E}_c, \forall s, c, t \end{aligned} \quad (16)$$

411 where $\hat{x}_{a,s}^{s,e}(t)$ and $x_{a,s}^{s,e}(t)$ are the numbers of EVs before and after their ELs have been updated on
412 charging link a .

413 Based on the obtained occupancies, the following equations are used to model their charging
414 process where ELs of EVs linearly increase with time on charging links:

$$x_{a,c}^{s,E_c}(t) = \sum_{l=0}^{\alpha_a^t} \hat{x}_{a,c}^{s,E_c-l}(t), \forall a \in \mathcal{A}_C, \forall s, c, t \quad (17a)$$

$$x_{a,c}^{s,e}(t) = \hat{x}_{a,c}^{s,e-\alpha_a^t}(t), \quad \forall a \in \mathcal{A}_C, \forall e \in \{\alpha_a^t \leq e < E_c\}, \forall s, c, t \quad (17b)$$

$$x_{a,c}^{s,e}(t) = 0, \forall a \in \mathcal{A}_C, \forall e \in \{e < \alpha_a^t\}, \forall s, c, t \quad (17c)$$

417 where α_a^t represents the average charging speed for charging link a during period t , which translates
418 to how many energy levels can be supplied using type a charger during a period δ . Assuming the
419 charging power of charging link a is p_a^{ev} , then, α_a^t can be calculated by $\frac{p_a^{ev} \cdot \delta}{\eta \cdot \delta \cdot v_f} = \frac{p_a^{ev}}{\eta \cdot v_f}$. Eqs. (17a)
420 and (17c) constraint the upper and lower boundaries of the updated ELs. Eq. (17b) describes the
421 process of linear increase in ELs.

422 Additionally, the outflow disaggregated by each EL on charging link a should be less than its
423 occupancy, as formulated in Eq. (18):

$$VE_{a,c}^{s,e}(t) - VE_{a,c}^{s,e}(t-1) \leq x_{a,c}^{s,e}(t), \forall a \in \mathcal{A}_C, \forall e \in \mathcal{E}_c, \forall s, c, t \quad (18)$$

424 The occupancies on charging links are nonnegative, which is formulated as follows:

$$x_{a,c}^{s,e}(t) \geq 0, \quad \hat{x}_{a,c}^{s,e}(t) \geq 0, \forall a \in \mathcal{A}_C, \forall e \in \mathcal{E}_c, \forall s, c, t, \quad (19)$$

425 The cumulative flows should be nonnegative and nondecreasing:

$$VG_a^s(t) - VG_a^s(t-1) \geq 0, \forall a \in \mathcal{A}, \forall s, t \quad (20a)$$

$$VE_{a,c}^{s,e}(t) - VE_{a,c}^{s,e}(t-1) \geq 0, \forall a \in \mathcal{A}, \forall e \in \mathcal{E}_c, \forall s, c, t \quad (20b)$$

$$UG_a^s(t) - UG_a^s(t-1) \geq 0, \forall a \in \mathcal{A}, \forall s, t \quad (21a)$$

$$UE_{a,c}^{s,e}(t) - UE_{a,c}^{s,e}(t-1) \geq 0, \forall a \in \mathcal{A}, \forall e \in \mathcal{E}_c, \forall s, c, t \quad (21b)$$

429 The following constraints force the initial cumulative flows to be 0:

$$UG_a^s(0) = VG_a^s(0) = 0, \forall a \in \mathcal{A}, \forall s \quad (22a)$$

$$UE_{a,c}^{s,e}(0) = VE_{a,c}^{s,e}(0) = 0, \forall a \in \mathcal{A}, \forall e \in \mathcal{E}_c, \forall s, c \quad (22b)$$

431 The objective of electrified RNs model is to minimize the total travel time of all vehicles. The
432 total travel time is calculated by the total presence time of all vehicles on all links during the whole

433 time horizon and the total charging time of all EVs. Under normal situation, the whole model for
 434 the electrified RN is formulated as follows:

$$\begin{aligned}
 & \min \sum_{s \in \mathcal{N}_S} \sum_{t \in \mathcal{T}} \sum_{a \in \mathcal{A} \setminus \{\mathcal{A}_C, \mathcal{A}_S\}} \delta[UG_a^s(t) - VG_a^s(t)] \\
 & + \sum_{s \in \mathcal{N}_S} \sum_{t \in \mathcal{T}} \sum_{a \in \mathcal{A} \setminus \mathcal{A}_S} \sum_{c \in \mathcal{C}} \sum_{e \in \mathcal{E}_c} \delta[UE_{a,c}^{s,e}(t) - VE_{a,c}^{s,e}(t)]
 \end{aligned} \tag{23}$$

435 subject to:

$$\text{Eqs. (7) - (22)} \tag{24}$$

436

437 2.1.2. Modeling reconfiguration strategy in electrified road networks

438 To mitigate the impacts after disruptions, we consider the strategy of contraflow to reconfigure
 439 the topology of the highway networks. Contraflow can be easily implemented by reversing the
 440 direction of lanes of highway networks. Fig. 3 shows how the contraflow assists increasing the
 441 throughput of the network after disruptions. Assuming that there are 20 vehicles per minute
 442 starting from node O to D and 10 vehicles per minute from node D to O. The number along
 443 each link represents the time required to traverse the link at a free-flow speed. Fig. 3(a) shows
 444 that there are 30 and 60 vehicles arriving at nodes O and D, respectively, after 6 minutes, when
 445 each link works normally. If the link from node O to D fails, the arrivals on node D decrease to
 446 40 vehicles, as shown in Fig. 3(b). However, if we reverse the direction of the link a_1 , the total
 447 number of arrivals can be increased from 70 to 80 vehicles after the disruption, as shown in Fig.
 448 3(c). This example shows that reconfiguring the highway network after disruption could effectively
 449 reduce the system performance loss. Another example can be found in Ref. [68], which shows how
 450 contraflow strategy increases the network outbound capacity and mitigates congestion.

451 To model the contraflow strategy, we constrain each link in the highway network to have only
 452 one unique opposite link corresponding to it. For example, there are two links a_1 and a_2 from nodes
 453 O to D in Fig. 3: their corresponding opposite links are \hat{a}_1 and \hat{a}_2 , respectively. Dually, links a_1
 454 and a_2 are the opposite links of links \hat{a}_1 and \hat{a}_2 . Mathematically, we use variable h_a to denote
 455 whether link a is changed to the opposite direction or not. \hat{a} represents the unique opposite link
 456 of link a . If the direction of the link is reversed, the outflow capacity, the inflow capacity and the
 457 maximum number of vehicles that can be present on that link of direction will be correspondingly
 458 reconfigured. Therefore, Eqs. (8) - (10) are reformulated as follows:

$$\begin{aligned}
 & \sum_{s \in \mathcal{N}_S} [VG_a^s(t) - VG_a^s(t-1)] + \sum_{s \in \mathcal{N}_S} \sum_{c \in \mathcal{C}} \sum_{e \in \mathcal{E}_c} [VE_{a,c}^{s,e}(t) - VE_{a,c}^{s,e}(t-1)] \\
 & \leq (1 - h_a) \cdot f_a^O(t) + h_{\hat{a}} \cdot f_{\hat{a}}^O(t), \forall a \in \mathcal{A} \setminus \{\mathcal{A}_C\}, \forall t
 \end{aligned} \tag{25}$$

459

$$\begin{aligned}
 & \sum_{s \in \mathcal{N}_S} [UG_a^s(t) - UG_a^s(t-1)] + \sum_{s \in \mathcal{N}_S} \sum_{c \in \mathcal{C}} \sum_{e \in \mathcal{E}_c} [UE_a^s(t) - UE_a^s(t-1)] \\
 & \leq (1 - h_a) \cdot f_a^I(t) + h_{\hat{a}} \cdot f_{\hat{a}}^I(t), \forall a \in \mathcal{A} \setminus \{\mathcal{A}_C\}, \forall t
 \end{aligned} \tag{26}$$

460

$$\begin{aligned}
 & \sum_{s \in \mathcal{N}_S} \sum_{c \in \mathcal{C}} \sum_{e \in \mathcal{E}_c} [UE_{a,c}^{s,e}(t) - VE_{a,c}^{s,e}(t - \beta_a)] + \sum_{s \in \mathcal{N}_S} [UG_a^s(t) - VG_a^s(t - \beta_a)] \\
 & \leq (1 - h_a) L_a k_{jam} + h_{\hat{a}} L_{\hat{a}} k_{jam}, \forall a \in \mathcal{A} \setminus \{\mathcal{A}_C\}, \forall t
 \end{aligned} \tag{27}$$

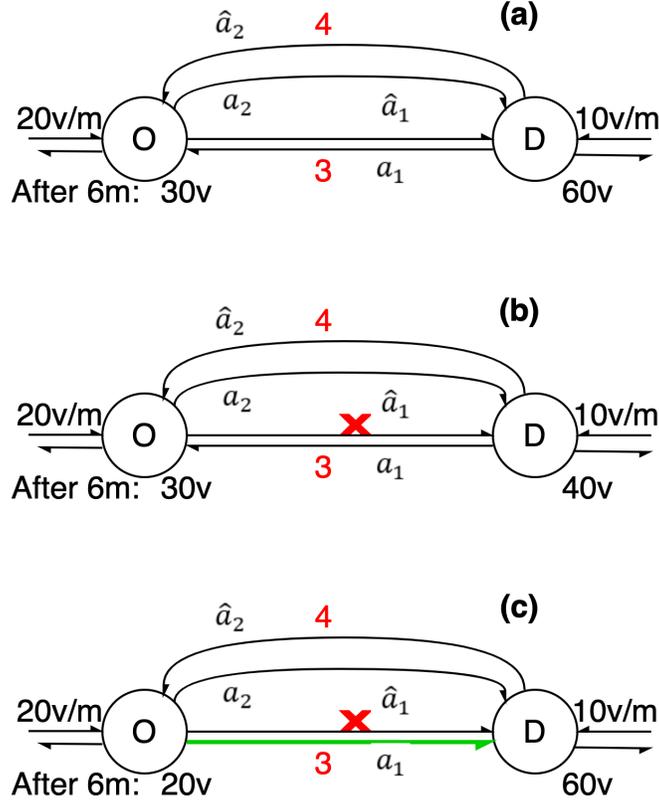


Figure 3: Contraflow illustration: (a) Normal condition (b) After disruption (c) After reconfiguration

Eq. (25) states that the outflow on link a are constrained by the status of links a and \hat{a} . If $h_a = 0$ and $h_{\hat{a}} = 0$, no link is reversed and the outflow capacity on the direction of original link a is unchanged, i.e., the outflow capacity of link a ; if $h_a = 1$ and $h_{\hat{a}} = 1$, both links are reversed and the outflow capacity is modified to the outflow capacity of link \hat{a} ; if $h_a = 1$ and $h_{\hat{a}} = 0$, the direction of link a is reversed and the outflow capacity becomes 0; if $h_a = 0$ and $h_{\hat{a}} = 1$, the direction of the opposite link \hat{a} is reversed and the outflow capacity increase to the sum of outflow capacities of links a and \hat{a} . Similarly, we can have Eqs. (26) and (27) to constrain the inflow and maximum occupancies on the direction of original link a after reconfiguration:

$$h_a, h_{\hat{a}} \in \{0, 1\}, \forall a, \hat{a} \in \mathcal{A} \setminus \{\mathcal{A}_C\} \quad (28)$$

$$\sum_{a \in \mathcal{A} \setminus \{\mathcal{A}_C\}} h_a \leq N_h \quad (29)$$

Eq. (28) guarantees that h_a and $h_{\hat{a}}$ are binary variables. Eq. (29) constrains the total number of links that can be reversed. This constraint reflects the limited resources that can be used in emergency response.

The emergency response problem for electrified RNs with contraflow options is formulated as follows:

$$\min \sum_{s \in \mathcal{N}_S} \sum_{t \in \mathcal{T}} \sum_{a \in \mathcal{A}_S} [DG_a^s(t) - UG_a^s(t) + \sum_{c \in \mathcal{C}} \sum_{e \in \mathcal{E}_c} (DE_{a,c}^{s,e}(t) - UE_{a,c}^{s,e}(t))] \cdot \phi \quad (30)$$

475 subject to:

$$\text{Eqs. (11) – (29)} \quad (31)$$

476 where ϕ denotes the time value. The objective of the transportation operator is to minimize the
 477 system performance loss cost, measured by the unsatisfied traffic demand, after disruptions within
 478 a certain period. More specifically, it is calculated by the cumulative difference between the target
 479 demand (i.e., $DG_a^s(t)$ and $DE_{a,c}^{s,e}(t)$) and the number of vehicles arrived at their destinations (i.e.,
 480 $UG_a^s(t)$ and $UE_{a,c}^{s,e}(t)$, $a \in \mathcal{N}_S$). In Eq. (30), the first term is the cumulative unsatisfied GVs travel
 481 demand and the second term is the cumulative unsatisfied EVs travel demand.

482 2.2. Reconfiguring power networks

483 In this subsection, the classic DC optimal power flow (OPF) model [69] is used to model the
 484 transmission network operation. Based on this model, the emergency response problem for the
 485 PN using switch options is formulated. The main flowchart of modeling power networks and its
 emergency response problem is shown in Figure 4.

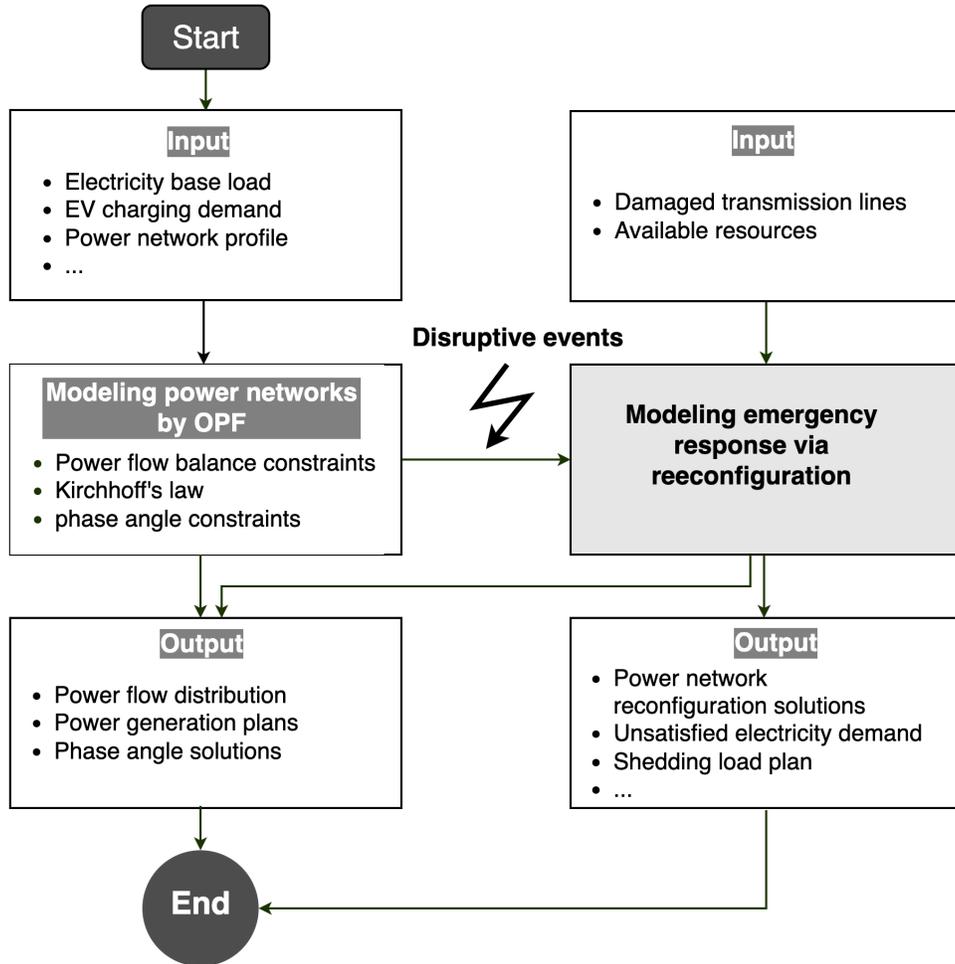


Figure 4: The main flowchart of modeling power networks and its emergency response.

486 We consider a PN $\mathcal{G}_P(\mathcal{P}_N, \mathcal{P}_L)$, where \mathcal{P}_N and \mathcal{P}_L represent the sets of buses and branches,
 487 respectively. $\tilde{\mathcal{P}}_L$ represents the set of damaged transmission lines after a disruption, $\tilde{\mathcal{P}}_L \subset \mathcal{P}_L$.
 488 $\Gamma^-(j)$ and $\Gamma^+(j)$ denote the sets of predecessors and successors of bus j , respectively.

490 After the disruption, the objective of the independent system operator is to minimize the cost
 491 of unsatisfied load demand, which is formulated as follows:

$$\min P_P = \sum_j \sum_t [c_j^b \cdot LS_{j,t}^b + c_j^{dc} \cdot LS_{j,t}^{dc} \cdot p_j^{dc}(t)] \cdot w_j \quad (32)$$

492 where c_j^b and c_j^{dc} are the costs of shedding base load and EV charging load, respectively; w_j , with,
 493 $\sum_j w_j = 1$, denotes the priority weight of load bus j , which can be heuristically determined, e.g.,
 494 by considering the nature and importance of the load at each bus; $LS_{j,t}^b$ is a continuous variable
 495 representing the amount of unsatisfied base demand at bus j in period t ; $LS_{j,t}^{dc}$ is a binary variable
 496 denoting where the charging demand $p_j^{dc}(t)$ at bus j in period t is shedded or not.

497 The power flows in the PN are subjected to the following constraints:

$$p_{j,t}^g + \sum_{i \in \Gamma^-(j)} P_{i,j,t} - \sum_{k \in \Gamma^+(j)} P_{j,k,t} = p_{j,t}^b - LS_{j,t}^b + (1 - LS_{j,t}^{dc}) \cdot p_j^{dc}(t), \forall j \in \mathcal{P}_N, \forall t \quad (33)$$

$$- \bar{P}_{i,j} \cdot u_{i,j} \leq P_{i,j,t} \leq \bar{P}_{i,j} \cdot u_{i,j}, \forall (i,j) \in \mathcal{P}_L \setminus \{\tilde{\mathcal{P}}_L\}, \forall t \quad (34)$$

$$P_{i,j,t} = 0, \forall (i,j) \in \{\tilde{\mathcal{P}}_L\}, \forall t \quad (35)$$

$$B_{i,j} \cdot (\theta_{i,t} - \theta_{j,t}) - P_{i,j,t} + (1 - u_{i,j}) \cdot M_{i,j} \geq 0, \forall (i,j) \in \mathcal{P}_L \setminus \{\tilde{\mathcal{P}}_L\}, \forall t \quad (36)$$

$$B_{i,j} \cdot (\theta_{i,t} - \theta_{j,t}) - P_{i,j,t} - (1 - u_{i,j}) \cdot M_{i,j} \leq 0, \forall (i,j) \in \mathcal{P}_L \setminus \{\tilde{\mathcal{P}}_L\}, \forall t \quad (37)$$

$$-p_j^{ramp} \leq p_{j,t}^g - p_{j,t-1}^g \leq p_j^{ramp}, \forall j \in \mathcal{P}_N, \forall t \in \mathcal{T} \quad (38)$$

$$0 \leq LS_{j,t}^b \leq p_{j,t}^b, \forall j \in \mathcal{P}_N, \forall t \quad (39)$$

$$0 \leq P_{j,t}^g \leq \bar{p}_j^g, \forall j \in \mathcal{P}_N, \forall t \quad (40)$$

$$\sum_{(i,j) \in \mathcal{P}_L} (1 - u_{i,j}) \leq N_u \quad (41)$$

$$u_{i,j} \in \{0, 1\}, \forall (i,j) \in \mathcal{P}_L \quad (42)$$

$$LS_{j,t}^{dc} \in \{0, 1\}, \forall j \in \mathcal{P}_N, \forall t \quad (43)$$

508 Constraint (33) relaxes the power flow balance constraint at each bus by allowing to shed unsatisfied
 509 demand. Constraint (34) guarantees that the power flows in the transmission lines do not exceed
 510 their capacities if they function. Constraint (35) forces the amount of power flow on the damaged
 511 lines to be 0. Constraints (36)-(37) denote Kirchhoff's power flow equations, where power flow
 512 are limited by lines' susceptance and the phase angle difference between the two end buses. It
 513 is necessary to include the big-M in the equations. In fact, if the constraint is directly written
 514 as $B_{i,j} \cdot (\theta_{i,t} - \theta_{j,t}) = P_{i,j,t} \cdot (1 - u_{i,j})$, when the line status is not switched and in service (i.e.,
 515 $u_{i,j} = 1$), this equation works normally, whereas when the line is switched off (i.e., $u_{i,j} = 0$), the
 516 phase angle between the two end buses of this line would be forced to be 0, which is not logical for
 517 the power flow in the network. Constraint (38) limits the generator ramp between two successive
 518 periods. Constraint (39) gives the lower and upper boundaries of the amount of base load that can
 519 be shedded at each bus. Constraint (40) ensures that the flow generated by generators is within
 520 their capacity. Constraint (41) limits the number of lines that can be switched. Constraints (42)
 521 - (43) state that $u_{i,j}$ and $LS_{j,t}^{dc}$ are binary decision variables.

522 2.3. Reconfiguring the coupled traffic-power networks

523 In this subsection, we assume that there is a decision-making agent (e.g., an emergency response
 524 authority) that integrally operates and reconfigures the traffic-power networks in a centralized way
 525 to minimize the total performance loss of the two systems. **The main flowchart of the proposed
 526 approach is shown in Figure 5.**

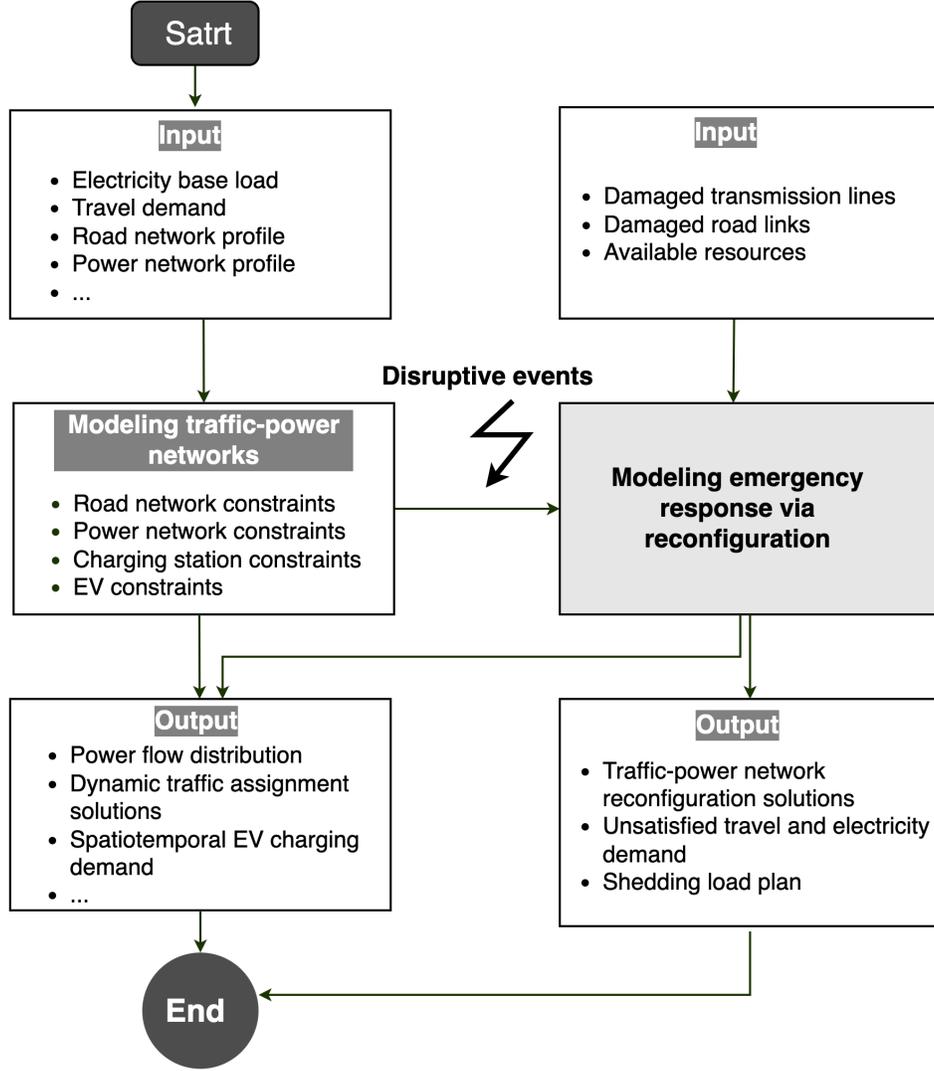


Figure 5: The main flowchart of modeling traffic-power networks and its emergency response problem.

527 In this situation, the EV charging load $p_j^{dc}(t)$ at each bus becomes a decision variable, which
 528 can be calculated by the following equation:

$$p_j^{dc}(t) = \sum_{a \in M(j)} \sum_{s \in \mathcal{N}_S} \sum_{c \in \mathcal{C}} \sum_{e \in \mathcal{E}_c} p_a^{ev} [U E_{a,c}^{s,e}(t) - V E_{a,c}^{s,e}(t)], \forall j \in \mathcal{P}_N, \forall t \quad (44)$$

529 where $M(j)$ is the mapping from bus set \mathcal{P}_N to charging links set \mathcal{A}_C , which specifies the connection
 530 between buses in the PN and charging links in the RN.

531 Since the traffic-power system is integrally operated, the charging locations and times of EVs
 532 can be flexibly arranged to contribute to minimizing the objective. Therefore, it is no longer

533 necessary to have variable $LS_{j,t}^{dc}$ to control whether the EV charging load is shedded or not. Eq.
 534 (33) is rewritten as follows:

$$p_{j,t}^g + \sum_{i \in \Gamma^-(j)} P_{i,j,t} - \sum_{k \in \Gamma^+(j)} P_{j,k,t} = p_{j,t}^b - LS_{j,t}^b + p_{j,t}^{dc}, \forall j \in \mathcal{P}_N, \forall t \quad (45)$$

535 The whole problem is formulated as follows:

$$\min \sum_{s \in \mathcal{N}_S} \sum_{t \in \mathcal{T}} \sum_{a \in \mathcal{A}_S} [DG_a^s(t) - UG_a^s(t) + \sum_{c \in \mathcal{C}} \sum_{e \in \mathcal{E}_c} (DE_{a,c}^{s,e}(t) - UE_{a,c}^{s,e}(t))] \cdot \phi + \sum_{t \in \mathcal{T}} c_j^b \cdot w_j \cdot LS_{j,t}^b \quad (46)$$

536 subject to:

$$\text{Eqs. (11) - (29), (34) - (42) and (44) - (45)} \quad (47)$$

537 In each time period, there are expected demand $E(t)$ and unsatisfied demand $\Delta E(t)$ in the
 538 system. The following equation is employed to measure the system performance $P(t)$ [1]:

$$P(t) = \frac{E(t) - \Delta E(t)}{E(t)} \quad (48)$$

539 where $0 \leq \Delta E \leq E$. This equation can be understood as the percentage of demand that can be
 540 satisfied in the system in period t .

541 In the studied traffic-power system, the expected demand includes the all vehicle types traffic
 542 demand over all OD pairs and base electricity demand over all buses, which is formulated as
 543 follows:

$$E(t) = \sum_{s \in \mathcal{N}_S} \sum_{a \in \mathcal{A}_S} [DG_a^s(t) + \sum_{c \in \mathcal{C}} \sum_{e \in \mathcal{E}_c} DE_{a,c}^{s,e}(t)] \cdot \phi + \sum_{j \in \mathcal{P}_N} c_j^b \cdot p_{j,t}^b \quad (49)$$

544 where time value ϕ and shedding load cost c_j^b are used, so that the system performance of PNs
 545 and RNs have the same physical dimension, and, additivity is allowed.

546 Substituting Eqs. (46), without summation over time, and (49) into Eq. (48), this letter is
 547 rewritten as follows:

$$P(t) = \frac{\sum_{s \in \mathcal{N}_S} \sum_{a \in \mathcal{A}_S} [UG_a^s(t) + \sum_{c \in \mathcal{C}} \sum_{e \in \mathcal{E}_c} UE_{a,c}^{s,e}(t)] \cdot \phi + \sum_{j \in \mathcal{P}_N} [p_{j,t}^b - LS_{j,t}^b] \cdot c_j^b}{\sum_{s \in \mathcal{N}_S} \sum_{a \in \mathcal{A}_S} [DG_a^s(t) + \sum_{c \in \mathcal{C}} \sum_{e \in \mathcal{E}_c} DE_{a,c}^{s,e}(t)] \cdot \phi + \sum_{j \in \mathcal{P}_N} c_j^b \cdot p_{j,t}^b} \quad (50)$$

548 The proposed emergency response problems for the independent RN (Eqs. 30-31), the inde-
 549 pendent PN (Eqs. 32-43) and the coupled traffic-power networks (Eqs. 46-47) are mixed integer
 550 linear proگرام problems. Such kind of problems can be efficiently solved by commercial solvers,
 551 such as Cplex and Gurobi.

552 3. Case study

553 The commonly used IEEE 14-bus system in the literature [70, 71] is adopted as the PN in this
 554 study. The original IEEE 14-bus test case is a portion of the American electric power system (in
 555 the Midwestern US) [72]. The weight of each bus is assumed to be equal. There are 14 buses and
 556 20 transmission lines, and the detailed data can be found in Ref. [73]. The road network is a
 557 partial of the highway network in North Carolina (NC), U.S., and it is shown in Figure 6. Figure
 558 6(a) shows the locations of EV charging stations within this area and the geographic data of the

Table 1: Connections between charging links and buses

Charging link	Bus	$NC_a(t)$
301	2	30
302	3	45
303	4	30
304	5	30
305	6	30
306	7	15
307	8	30
308	9	15

559 highway network are collected from Google map. This partial highway network is abstracted into
560 an approximated topology network as shown in Figure 6(b). The number along the link is the link
561 ID. There are 9 fast-charging stations in the studied highway network and their connections to the
562 served buses are listed in Table 1. The data used in this study is detailed in Appendix A.

563 The proposed model is illustrated by solving and analyzing the following hypothetical scenario:
564 it is reported that links 4, 17, 19 in the highway network and lines 2-3, 2-4, 7-8 in the PN are
565 destroyed, and they cannot provide services normally. This scenario is chosen since it causes the
566 most performance loss of the traffic-power system among the randomly generated scenarios, when
567 the number of damaged links in the RN and lines in the PN is 3. In practice, the disruption
568 scenarios are the input data of the proposed models. They can be detected by various manner
569 (e.g., drones and online monitoring systems) after disruptive events. After the system status is
570 collected, the proposed models can be utilized to assist the emergency response department solve
571 the problem: how to reconfigure and operate both the traffic and power systems, so that their
572 performance loss caused by the disruption can be minimized. In this example, the peak hours (i.e.,
573 17:00-18:59) are studied to consider the worst-case scenarios.

574 All of the numerical experiments have been run on a computer with an Intel Core i7-8700 3.2-
575 GHz CPU with 32 GB of RAM. All of the problems have been solved by the commercial software
576 IBM ILOG CPLEX (version 20.1.0.0).

577 3.1. The impact of the different response resource level

578 In this subsection, five different resource levels are investigated: $N_h = N_u = 0, 1, 2, 3, 4, 5$.
579 Figure 7 shows the system performance evolution over the considered time horizon under different
580 resource levels. Time step = 0 indicates the point in time of implementation of the reconfiguration.
581 The performance level denotes the percentage of the total demand that is satisfied. It can be seen
582 that the system performance levels are different under different resource levels. In practice, the
583 system performance increases with the resource levels, as expected. Note that when the PN
584 topology is reconfigured, the effect (i.e., the shedded load) is seen almost immediately. On the
585 contrary, the effect of reconfiguring an highway network is seen later, due to the time delay required
586 by the vehicles to complete their travel from origin to destination. If the response resource level
587 increases from 0 to 2, the system performance is largely increased from 76.58% to 86.26%. After
588 that, the marginal economic benefit of additional response resources reduces as the number of links
589 reversing and lines switching rises. This can also be seen in Figure 8. When the resource level is 2,
590 the nominal costs of both the RN and the PN reduce largely. This also shows the effectiveness of
591 reconfiguring network topology during the restoration period. Table 2 shows the reconfiguration
592 solutions of links in the RN and of lines in the PN. The third through the fifth columns represent

Table 2: Solutions under different resource levels

Resource levels	$h_a = 1$	$u_{i,j} = 0$	Vehicles	GVs	EVs	Charging demand (MW)
0			19091	17336	1755	182.8
1	117	4-7	22142	20322	1820	148.8
2	104,117	4-9,7-9	21573	19512	2061	165.68
3	5,104,117	4-7,4-9,6-13	21987	19656	2331	207.68
4	5,26,114,117	4-7,4-9,1-2,9-14	22005	19669	2336	222.88
5	5,25,26,114,117	4-7,4-9,1-2,6-12,13-14	21999.5	19656	2343.5	201.28

593 the number of GVs and EVs arrived at destination at the end of the studied horizon. The last
594 column represents the total charging demand during the studied horizon. The third column in
595 Table 2 shows that the optimal set of the switched lines for low resource level scenarios is not
596 necessarily a subset of the switched lines for high resource level scenarios. For instance, line 4-7
597 is switched off when resource level is 1, whereas lines 4-9 and 7-9 are switched off when resource
598 level increases to 2. However, this is not applied to the RN in this example. There could be two
599 reasons related to the traffic demand distribution: 1) the used gravity model generates high traffic
600 demand between two cities whose distance is short and population is large. This may cause high
601 traffic volume on some two-way road sections; 2) to model the directional differences of traffic
602 volumes, the direction of traffic demand between two cities is randomly selected. This could make
603 the bidirectional high traffic volumes become one-way high traffic volumes on some road sections.
604 Therefore, once the links with high traffic volumes are damaged (e.g., links 17 and 19), they may
605 always have priority of restoration so that the system loss can be minimized. Moreover, when there
606 are large volume differences between two opposite links, the link capacity can be greatly improved
607 by reversing the link with less volumes (e.g., links 5 and 26). In this sense, less nominal cost of
608 system performance loss and higher resource level do not mean that more vehicles can arrive at
609 the destinations. For example, Figure 8 shows that the nominal loss cost when resource level is 2,
610 is less than that when resource level is 1. However, Table 2 shows that there are also less arrivals
611 when the resource level is 2 than when the resource level is 1. It is because the vehicles arrive at
612 their destinations earlier when the resource level is 2 than when the resource level is 1. In other
613 words, there is a trade-off between the number of arrivals and their travel time for RNs.

614 3.2. Different EV penetration levels and decision environments

615 Without loss of generality, the maximum number of lines that can be switched in the PN and of
616 links that can be reversed in the RN are set to be 3 (i.e., $N_u = 3$ and $N_h = 3$). When the RN and
617 PN independently optimize their restoration plans, we assume that the RN operators share their
618 temporal and spatial charging demand with the PN operators at the beginning of the restoration
619 horizon and they no longer change their plans afterwards. This situation can be regarded as the
620 unmanaged charging demand scenarios from the PN operator perspective. In this case, the PN
621 operators have to satisfy all EV charging demands and only the base electricity load can be shedded
622 when they optimize their restoration plans.

623 Figure 9 shows the traffic-power systems performance evolution over the restoration horizon
624 under different EV penetration levels. Table 3 shows the benefit of line switching and link reversing
625 in terms of system performance loss, for different EV penetration levels and different decision-
626 making environments. As shown in Figure 9, the traffic-power system performance decreases as
627 the EV penetration increases. When EV penetration increases from 0% to 100%, the nominal
628 total costs of the traffic-power system increases from \$773300 to \$1133009, leading to a 46.7%
629 increase in costs. The extra charging time needed for EVs, compared to GV's refueling, and the

Table 3: Solutions under different EV penetration levels and decision environments

EV Penetration	Environments	$h_a = 1$	$u_{i,j} = 0$	Total cost (\$)	Cost for RNs (\$)	Cost for PNs (\$)	Vehicles	GVs	EVs	Charging demand (MW)
0%	Interdependent	5,104,117	4-7,4-9,6-13	773300	729300	44000	30540	30540	0	0
	Independent	-*	4-9,7-9,13-14	773300	729300	44000	22142	30540	0	0
25%	Interdependent	5,104,117	4-7,4-9,6-13	821260.15	775340.15	45920	26933.5	25346	1587.5	166.4
	Independent	-	4-7,4-9,9-14	824392.15	770192.15	54200	21987	19656	2331	255.2
50%	Interdependent	5,104,117	4-7,4-9,6-13	894274.2	845226.2	49048	21987	19656	2331	207.68
	Independent	-	4-7,4-9,13-14	897389.5	843069.5	54320	21999.5	19656	2343.5	294
75%	Interdependent	11,109,117	4-7,4-9,6-13	994669.5	945509.5	49160	13980	11325	2655	218.4
	Independent	-	4-7,4-9,13-14	998,262	943462	54800	14430	10437	3105	318
100%	Interdependent	22,102,117	4-7,4-9	1133009	1083849	49160	2822.5	0	2822.5	210
	Independent	117	4-7,4-9,13-14	1134561.5	1081801.5	52760	3272.5	0	3272.5	243.6

* The solution is the same for the interdependent environment

630 limited chargers are the main reasons of this result. When the EV penetration is equal to or
631 less than 50%, the reconfiguration solutions are stable for both the traffic-power systems and the
632 independently optimized RN. In this situation, links 5, 104 and 117 in the RN are reversed. Lines
633 4-7, 4-9 and 6-13 are always switched off, when the restoration plans of the PN are coordinately
634 optimized. When there are no EVs in the RN, both interdependent or independent plans of
635 restoration of the RN and the PN, have the same nominal total system performance cost. When
636 the proportion of EVs in RN increases, the nominal total costs of the interdependent plan for
637 the traffic-power system restoration are lower than those of the independent plans. This shows
638 the added value of coordinately operating the two networks. **The difference of the total charging
639 demand between the coordinately managed EV charging and the independently managed one is
640 reported in the last column of Table 3 and shown in Figure 10.** The charging demand in the
641 interdependent decision-making environment is always less than that in the independent one. This
642 leads to higher nominal loss costs in the RN and lower costs in the PN, but lower total costs for the
643 two networks, comparing to the independent decision making. This shows that the coordinated
644 scheduling of charging demands leads to a trade-off of performance loss between the two networks,
645 for the studied case.

646 4. Conclusion

647 In this paper, we have formulated mathematical models for the reconfiguration process of road
648 networks (RNs) and power networks (PNs) to minimize the system performance loss during the
649 restoration period after disruptive events. In both networks, system performance loss has been
650 measured by the unmet demand, i.e., cumulative unmet gasoline vehicles (GVs) and electric vehi-
651 cles (EVs) traffic demand for RNs and cumulative shedded electricity load for PNs. For RNs, the
652 proposed model was aimed to solve the system optimal dynamic traffic assignment problem con-
653 sidering the characteristics of EVs and fast-charging stations (FCSs). These characteristics include
654 driving range (battery capacity) and state of charge (SoC) of EVs, and physical constraints in FCSs,
655 such as number of chargers and charging power. Moreover, a mixed integer program model has
656 been proposed to minimize the integrated system performance loss during the restoration period.
657 Contraflow technique in the RN and line switches in the PN have been used as reconfiguration
658 strategies to enhance the system resilience after a disruptive event. The dynamic interactions
659 between the PN and RN have been considered in the proposed integrated traffic-power systems
660 model. The two networks have been coupled through EV charging demand, which is coordinately
661 managed in the proposed model. A partial highway network in North Carolina (NC), USA and
662 a modified IEEE 14-bus system have been used to illustrate the proposed methods. **The results
663 have shown that: 1) applying emergency response actions (i.e., network topology control) to the
664 coupled traffic-power networks, the system performance can be largely improved from 76.58% to**

665 86.26%; 2) it is better to integrally plan the emergency response for the PNs and RNs, since it
666 could reduce the system performance loss more than independently operating them; 3) the higher
667 EV penetration leads to the lower efficiency of the RN, which hints that the number of FCSs
668 should be well designed along the highway to guarantee a certain service level of the RNs under
669 extreme events. The negative impacts of increasing EV penetration on RNs and PNs require
670 further attention and investigation. The proposed models could be employed to provide effective
671 emergency reconfiguration solutions (e.g., links reversing in RNs and lines switching in PNs) for
672 traffic-power systems to enhance the system resilience. Operational solutions (i.e., system optimal
673 dynamic traffic assignment and optimal power flow distribution) could serve as a benchmark to
674 manage the traffic-power flow and EV charging demand.

675 For the computational efficiency, three points need to be clarified. Firstly, the computational
676 times of the proposed methods are influenced by many factors, such as the considered time horizon,
677 configuration of the FCSs, EV penetrations and their battery capacities. Especially, the numbers
678 of both the lines that can be switched in the power network and of the links that can be reversed
679 in the road network heavily influence the computational complexity. In practice, even if the whole
680 transmission network and the highway network are really large, the lines and links that can be
681 controlled are limited, because of regulatory policies, operational limitations, physical constraints
682 and so on. Secondly, if there is a really high requirement for the computational time, there are
683 two methods that can be considered to increase the computational efficiency of the proposed
684 approaches: 1) we may increase the time interval δ for updating the state of the traffic and power
685 flow; this can directly decrease the number of variables by reducing the set of periods, set of
686 links and set of energy levels of EVs, leading to less memory and computational time though at
687 the expense of less fine-grained results; 2) we can also adjust the optimality gap tolerance in the
688 mixed integer programming (MIP) solver, which can often significantly reduce the computational
689 time: in our cases, if we set the gap tolerance as 5%, most results can be obtained in minutes;
690 moreover, in practice, the exact optimal solution usually is not necessary and 5% of the optimality
691 gap tolerance is acceptable. Finally, the considered problem is a MIP problem, which is essentially
692 NP-hard. Decomposition algorithms such as Benders decomposition can be considered to improve
693 the computational efficiency of the proposed models in the future.

694 The main limitation of the proposed method is that many variables are designed to describe
695 the dynamic state of charge of EVs, which increases the complexity of the proposed model. In the
696 current work, these variables are used to constrain the driving ranges of EVs and calculate their
697 charging demand at FCSs. However, their SoCs at each time interval are not necessarily known
698 in the emergency response problem studied in the present paper. Therefore, in the future, a more
699 efficient modeling method is worthy exploring to improve the computational efficiency.

700 In this work we assume that the vehicles follow the system optimal principle to take their
701 paths. In normal situation, sophisticated economical mechanisms can be designed to make the
702 traffic flows follow the system optimum. However, under post-disruption situation, the originally
703 designed economical mechanism may not work any longer, since the network topology may have
704 been changed by the disruption. Moreover, the new economical mechanism may have not been well
705 designed or applied in times of disruption. However, in such emergency situations, authorities may
706 guide all vehicle drivers to follow the system optimal principle in order to mitigate the disruption.
707 Alternatively, replacing system optimality by user equilibrium in the dynamic traffic assignment
708 problem is a potential solution to model the situation where the drivers take the paths which meet
709 better their own benefits. But, it is challenging for the traffic-power systems model: satisfying user
710 equilibrium conditions requires a more complicated modeling of the charging behaviors of EVs,
711 which might result in extremely expensive computational cost.

712 This work can also be extended in the following two directions: 2) including mobile energy
713 storage systems (MESSs) into the emergency response strategies could be an effective way to
714 improve the resilience of RNs; however, how to integrate MESSs into the traffic-power system
715 model needs more research; 3) EVs are assumed to only replenish batteries in FCS, in the present
716 paper: the V2G technology at FCSs can be considered to more efficiently operate the coupled
717 traffic-power systems and strengthen their resilience.

718 Appendix A. Data discription

719 A partial highway network in NC, USA is shown in Figure 6. The used parameters of this
720 studied network are listed in Tables A.4 and A.5. The node ID, its corresponding town or city
721 name and its population within this area are listed in Table A.6. The cities or towns connected
722 source-sink nodes are those whose population is more than 11000. Considering their geographic
723 distances among these nodes and their population, the gravity model is used to generate the daily
724 traffic demand. The generic form of the gravity model [75] is usually written as $f_{od} = P_o^\alpha P_d^\beta / D_{od}^\gamma$,
725 where P_o and P_d are the population sizes of origin a and destination d , respectively, D_{od} is the
726 shortest distance between them, α , β and γ are fitting parameters. We set $\alpha = \beta = 0.92$ and
727 $\gamma = 1$, in this study. To consider the worst-case scenario, the traffic volumes at 17:00 and 18:00
728 are adopted, which is the peak of traffic and accounts for approximately 15.3% of the whole daily
729 traffic, in the basic time-of-day patterns [76]. The traffic volumes usually show the directional
730 differences and it is difficult to get the applicable statistics for time-of-day travel by direction for
731 each O-D pair [76]. For simplicity, only one direction is randomly selected for each O-D pair and
732 traffic volumes in the other direction are ignored. The obtained traffic demand is shown in Table
733 A.7.

734 According to Ref. [77], the electricity demand in U.S. has peak hours similar to traffic volumes,
735 and the demand does not change a lot during this period. For simplicity, it is assumed that the
736 base load at each bus is constant during this period and follows the standard test data [73].

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Table A.4: Parameters of the studied highway network

Link ID	Start	End	ν_a	β_a	ρ_a	Type	$L_a k_{jam}$	f_a^I/f_a^O	Lanes
1/101	2/1	1/2	5	10	5	G	13910	500	2
2/102	2/3	3/2	3	6	3	G	8346	500	2
3/103	3/8	8/3	4	8	4	G	5564	250	1
4/104	1/5	5/1	3	6	3	G	8346	500	2
5/105	2/5	5/2	3	6	3	G	8346	500	2
6/106	2/6	6/2	3	6	3	G	8346	500	2
7/107	3/4	4/3	1	2	1	G	1391	250	1
8/108	5/6	6/5	1	2	1	G	2782	500	2
9/109	4/6	6/4	3	6	3	G	4173	250	1
10/110	4/7	7/4	2	4	2	G	2782	250	1
11/111	4/8	8/4	3	6	3	G	4173	250	1
12/112	6/7	7/6	5	10	5	G	13910	500	2
13/113	6/7	7/6	5	10	5	G	6955	250	1
14/114	7/8	8/7	2	4	2	G	5564	500	2
15/115	7/8	8/7	2	4	2	G	2782	250	1
16/116	1/10	10/1	4	8	4	G	11128	500	2
17/117	10/14	14/10	3	6	3	G	8346	500	2
18/118	5/15	14/5	5	10	5	G	6955	250	1
19/119	11/14	14/11	2	4	2	G	5564	500	2
20/120	5/9	9/5	2	4	2	G	5564	500	2
21/121	6/9	9/6	2	4	2	G	5564	500	2
22/122	9/11	11/9	2	4	2	G	5564	500	2
23/123	11/9	9/11	2	4	2	G	5564	500	2
24/124	11/12	12/11	4	4	4	G	11128	500	2
25/125	6/12	12/6	4	4	4	G	11128	500	2
26/126	12/13	13/12	3	6	3	G	4173	250	1
27/127	7/13	13/7	2	4	2	G	2782	250	1
29/129	2/201	201/2	0	0	0	S/R	inf	inf	
30/130	10/202	202/10	0	0	0	S/R	inf	inf	
36/136	5/203	203/5	0	0	0	S/R	inf	inf	
31/131	11/204	204/11	0	0	0	S/R	inf	inf	
32/132	12/205	205/12	0	0	0	S/R	inf	inf	
33/133	14/206	206/14	0	0	0	S/R	inf	inf	
34/134	8/207	207/8	0	0	0	S/R	inf	inf	
35/135	3/208	208/3	0	0	0	S/R	inf	inf	

Table A.5: Parameters of the studied traffic-power system

Parameters	Values
v_f (m/h)	65
k_{jam} (veh/m)	214
δ (min)	6
q_{max} (veh/h/lane)	2500
p_a^{ev} (kW)	80
η (kMh/mile)	0.4
ϕ (\$/h)	13
C	1
E_c	10
α_a^t (ELs/ δ)	3
Initial EL of EV	3

Table A.6: Population of the towns and cities

Node ID	Name	Population	Node ID	Name	Population
1	Zebulon	4526	2	Rocky Mount	56650
3	Tarboro	11255	4	Pinetops	1351
5 & 6	Wilson	49436	7	Farmville	4695
8	Greenville	86142	9	Kenly	1344
10	Raleigh	418099	11	Selma & Smithfield	17901
12	Goldsboro	35609	13	Snow Hill	1611
14	Clayton	16529			

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Table A.7: O-D pairs and their traffic demand

Link ID	Node ID	Demand	Link ID	Node ID	Demand
130	203	6460	136	204	620
129	202	5700	129	208	620
130	206	5500	133	203	460
134	202	5380	131	205	460
130	205	3720	133	204	460
131	202	3560	131	201	400
136	201	2400	134	204	380
129	207	1720	129	206	320
136	207	1520	136	208	320
134	205	1120	133	205	280
130	208	960	134	206	260
132	203	940	132	208	160
132	201	760	135	204	100
135	207	680	135	206	60

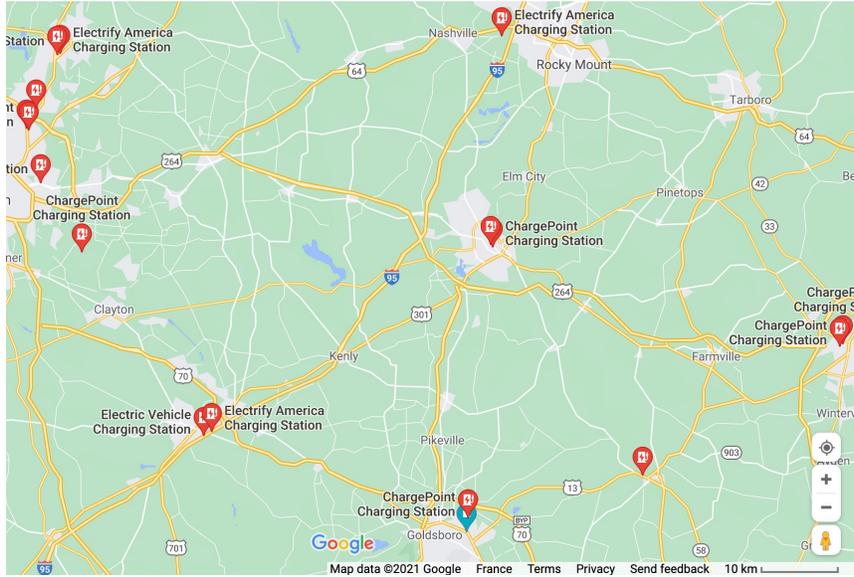
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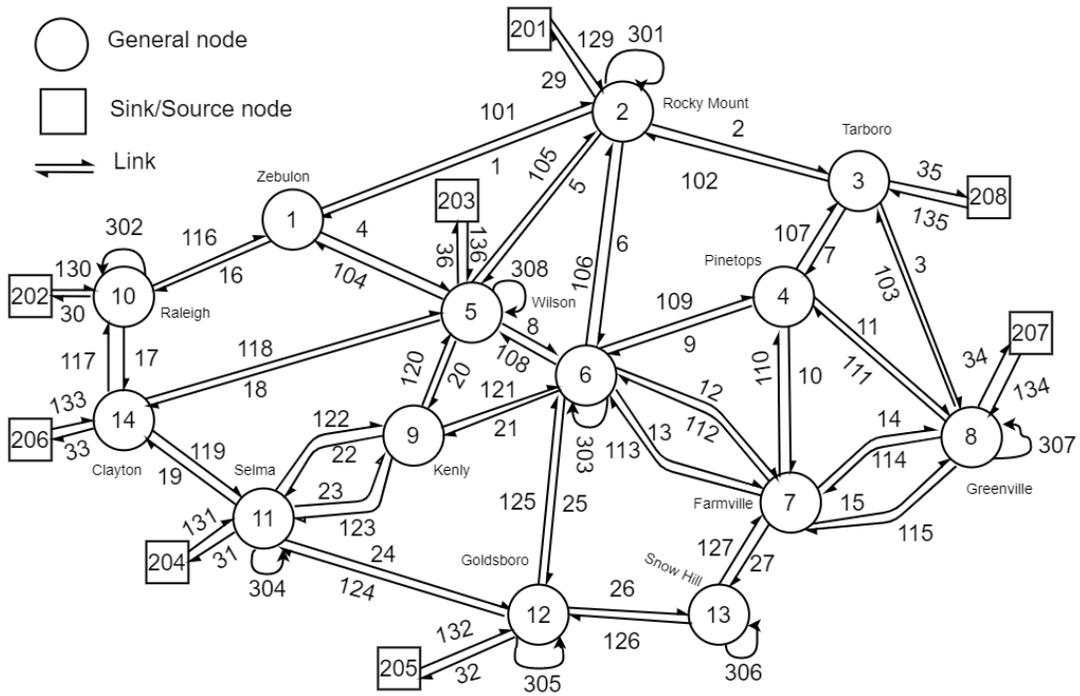
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(a) The partial highway network in NC



(b) The approximated topology network

Figure 6: The studied highway network [74]

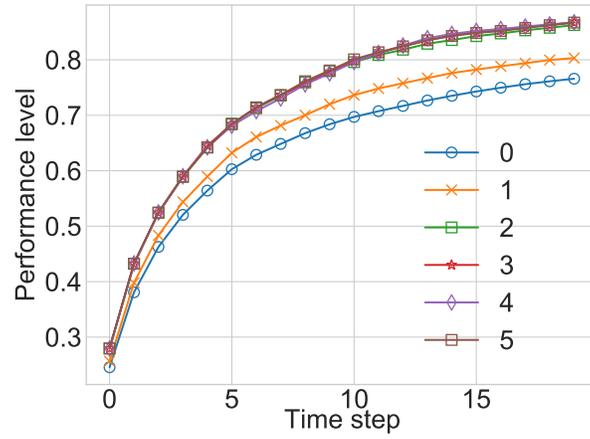


Figure 7: System performance evolution over restoration horizon under different resource level

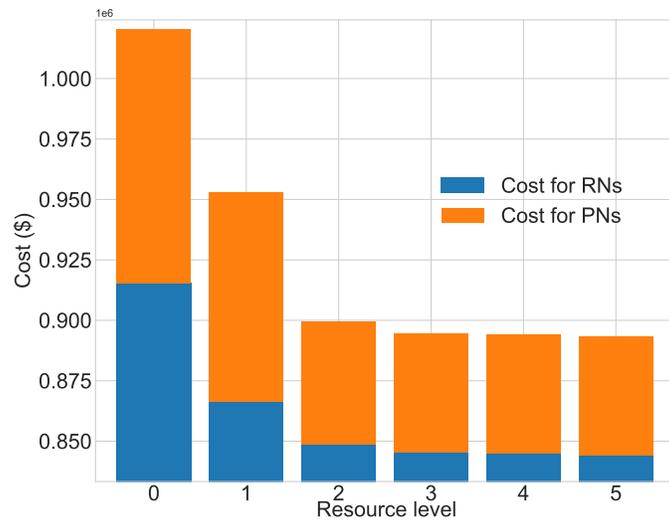


Figure 8: Nominal cost for the studied traffic-power systems under different resource level

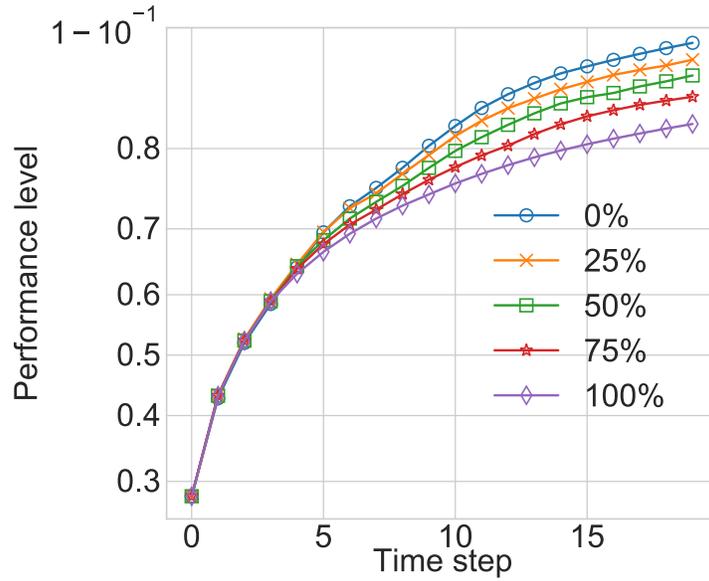


Figure 9: The traffic-power systems performance evolution over restoration horizon under different EV penetration levels

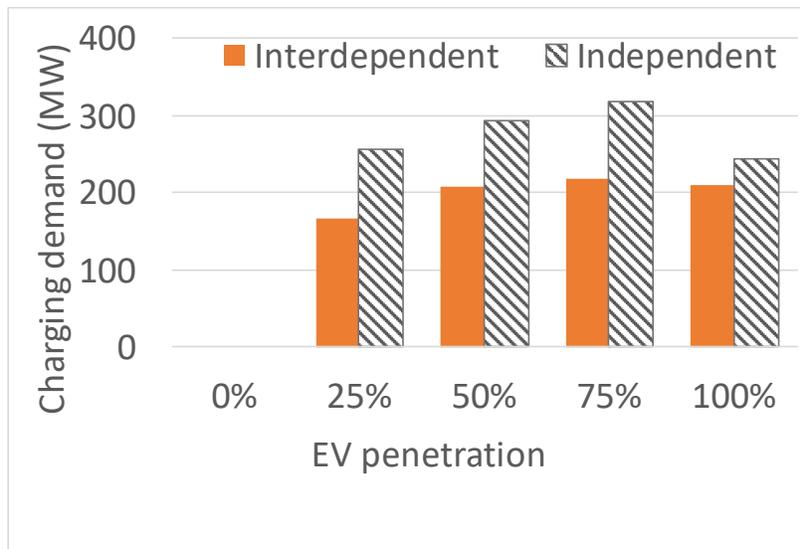


Figure 10: EV charging demand under different EV penetration levels and decision environments