Towards Integrated Infrastructures for Smart City Services: A Story of Traffic and Energy Aware Pricing Policy for Charging Infrastructures

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Abstract: Developing smart-city solutions and services, which lead to optimal utilization of cities' limited resources and enhancement of their reliability and efficiency, requires collaboration of currently vertical and isolated city infrastructures. The interdependency among critical infrastructures makes such collaborative solutions even more essential. In this paper, two of such critical infrastructures, including the electric-vehicle (EV) charging infrastructure and the electric infrastructure, are considered and an integrated framework for modeling their interactions are developed. This model is a probabilistic model based on a networked Markov chain framework, which enables capturing of stochastic aspects of these two systems and how they affect each other. Using the developed model and a proposed algorithm, which works hand in hand with the model, charging prices are assigned for the EV charging stations with the goal of increasing the likelihood of having balanced charging and electric infrastructures. The role of the cyber infrastructure in such collaborative solutions are discussed through the charging and power infrastructure pricing scheme. The presented results show the importance of integrated modeling and the pricing solution, which considers the state of both systems. We hope that this study and modeling approach can be extended to other smart city solutions and other interdependent infrastructures.

1 INTRODUCTION

Cities are key elements in developing resilient and sustainable societies and nations. The global urban population is expected to grow by 72% by 2050 according to recent studies (Heilig, 2012). Such urbanization trend suggests the need for smarter solutions for managing future cities. We believe one of the key enablers of smarter solutions for cities is collaboration and cooperation among various smart-city infrastructures in order to optimize city services and solutions. The importance of this cooperation is due to the increasing interdependency among critical infrastructures and the fact that the operation state of one infrastructure can affect the operation of other infrastructures. In this paper, we will focus on energy and transportation critical infrastructures and discuss how their cooperation can lead to a more reliable operation of the energy system and improve certain aspects of transportation systems through one source of their interdependency: the electric vehicles (EVs) charging infrastructure. On the other hand, the cyber infrastructure will play a key role in enabling such collaboration and cooperation among infrastructures, while also explicitly benefit from the reliable energy system as the source of electricity.

The increase in the number of hybrid electric transportation systems, including plugin hybrid EVs and hybrid electric trains have introduced new interdependencies between the energy and transportation infrastructures (He et al., 2013), (Liu, 2012), (Rahman et al., 2014), (Hatton et al., 2009), (Lee et al., 2015), (Recker and Kang, 2010), (Bass and Zimmerman, 2013). For instance, vehicle-to-grid (V2G) technology allow EVs to discharge their energy to the power grid using bi-directional power electronic dc/ac interfaces, which can help in stabilizing the power grid during disturbance and power shortage (Pillai and Bak-Jensen, 2010), (Liu et al., 2011). Another source of interdependency between energy and transportation infrastructures comes from the EV charging infrastructure. The EV charging infrastructures are emerging in cities (Sioshansi, 2012) similar to the traditional gas stations. On one hand, in the charging infrastructure, traffic patterns and population distribution can affect the energy demand in the electric grid at various times and locations. On the other hand, the demand on the energy grid can affect the char-

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ging price and consequently affect the traffic pattern in the transportation system. Such interdependencies are important as, for instance, during the peak-energy-consumption hours, inappropriate energy pricing signals at charging stations that motivate EV users to use specific charging stations, along with other factors, can lead to energy demand profiles that result in instability of the electric grid and in worse cases power outages (Wagner et al., 2013). As such, it is essential to design and operate these charging infrastructures while considering the interdependency between electric and transportation systems and the state of these systems. In particular, designing pricing incentives can provide a controlling mechanism for interdependency and reliable operation of these systems. The incentives will be communicated to the users through the cyber infrastructure.

Since various aspects of the energy and transportation systems are dynamic and stochastic, in this paper we adopt an abstract probabilistic approach to model the demand and traffic distribution in EV charging infrastructures. The goal of the model is to identify incentives, when and where they are needed, to design dynamic energy pricing signals based on the state of both of the systems, such that the incentives help in appropriate distribution of load in both systems and orchestrating their operation. The proposed approach is based on the influence theory (Asavathiratham, 2000), which is a mathematically tractable probabilistic framework based on a network of Markov chains. This framework allows modeling of interactions among components of both the charging and the electric infrastructures based on a data-driven dynamic probabilistic approach. Based on this probabilistic model, we identify incentives in terms of charging price using a topological sort on the active influence graph of the charging infrastructure. The identified incentives based on this model lead to higher probabilities of stable and balanced systems.

2 BACKGROUND

In this paper, we review the related work in two main categories. First, as the focus of this paper is on charging infrastructures, we review efforts on different aspects of design, operation and optimization of charging infrastructures. Second, we briefly review work on modeling, simulation, operation and design of integrated and interdependent infrastructure frameworks for smart cities.

2.1 Charging Infrastructures

In recent years, a large body of work is focused on optimal placement of EV charging stations (Hess et al., 2012), (He et al., 2013), (Wagner et al., 2013), (Sweda and Klabjan, 2014), (Chen and Hua, 2014), (Guo and Zhao, 2015), (Li et al., 2015), (Vazifeh et al., 2015), (Xiong et al., 2015). In particular, optimization formulations with various criteria have been used for addressing this problem (Hess et al., 2012), (Wagner et al., 2013), (Li et al., 2015), (Guo and Zhao, 2015). Examples of such criteria include, minimizing the trip time of EVs to access charging stations (Hess et al., 2012), maximizing the coverage of charging stations (Wagner et al., 2013), minimizing trip and queuing time (Li et al., 2015), and maximizing sustainability from the environment, economics and society perspective (Guo and Zhao, 2015). In the work presented in (Chen and Hua, 2014), (Vazifeh et al., 2015), the set cover algorithm is used to optimize the location of charging stations from a set of possible locations. In addition, agent-based (Sweda and Klabjan, 2014) and game-theoretic approaches (He et al., 2013), (Xiong et al., 2015) have also been adopted in characterizing optimal deployment of charging infrastructures. Reference (Islam et al., 2015) presents a more detailed review of various approaches used for the optimal deployment of EV charging stations.

Another research aspect of charging infrastructures is their pricing mechanisms. Studies of traditional fueling infrastructures (Walsh et al., 2004), (Weis et al., 2010) show that the price of fuel impact the behavior of drivers, which suggests that the charging price for EVs can also impact the users' choice and behavior. Specifically, authors in (Xiong et al., 2016), discuss that the optimal placement of charging stations will be insufficient to handle rapid changes in traffic patterns and urbanization, hence an efficient pricing model that also minimize the social cost of traffic congestion and congestion at EV charging stations is needed. As another example, the impact of energy price and the interplay between the price and other factors, such as cost and emissions, on the charging decisions have been studied in (Sioshansi, 2012). Besides the studies on the impact of price on charging decisions and traffic patterns, some efforts are focused on designing and optimizing pricing and analyzing their impact on the users' behavior and the system operation. Examples of such efforts include the work presented in (Lee et al., 2015), which uses a game theoretical approach to study the price competition among EV charging stations with renewable power generators and also discusses the benefits of having renewable resources at charging stations. Similarly, game-theoretic approaches that model a game between the electric grid and their users, specifically for EV charging, in order to design pricing schemes, have been studied, for example in (Tushar et al., 2012). The model in (Tushar et al., 2012) provides strategies to EV chargers to choose the amount of energy to buy based on a pricing scheme to operate the charging infrastructures at their optimal levels.

The work presented in this paper is closest to the studies on pricing mechanism design and also the interplay between the electric and EV charging infrastructures. At the same time, it is different in the approach as it considers the stochastic dynamics of the interdependent EV charging infrastructures and the electric grid and their local interactions in designing the charging prices at stations.

2.2 Integrated and Interdependent Infrastructures for Smart Cities

The vision of smart cities has been described in different ways among practitioners and academia (Chourabi et al., 2012). Hall (Bowerman et al., 2000) visions the smart city as a city that monitors and integrates conditions of all of its critical infrastructures to optimize its resources and services to its citizens. Similar smart city visions has been described in (Harrison et al., 2010), (Commission et al., 2014). In the last decade a large body of work has emerged in modeling and understanding interdependent infrastructures. The general concepts of interdependencies among critical infrastructures, challenges in modeling interdependent systems and their control and recovery mechanisms have been intensively discussed in (Amin, 2002), (Little, 2002), (Rinaldi, 2004), (Min et al., 2007). These works mainly discuss the intrinsic difficulties in modeling interdependent systems and suggest new methodologies for their modeling and simulation as a single coupled system. The majority of the integrated infrastructure modeling has been focused on analyzing the reliability of coupled systems and the negative aspects of the interdependencies among critical infrastructures (Shao et al., 2011), (Shin et al., 2014), (Das et al., 2014). The work presented in the current paper is an effort to present an abstract and unified framework to model interactions among infrastructures, which can be used to design various smart-city solutions based on the state of interacting systems, for instance, the pricing mechanism based on the state of the EV charging infrastructure and the electric grid.

3 SYSTEM MODEL

In this section, we describe our system model for the interdependent EV charging and energy infrastructures; however, the model is adequately general to be applied to any interdependent infrastructure with interacting components. The schematics of the system under study is depicted in Figure 1. As the figure shows, our study considers three layers in the system: (1) the power/electric grid layer, (2) the EV charging infrastructure layer, and (3) the cyber layer, which enables the collaborative solution for the pricing between layer 1 and 2. Our modeling is mainly focused on the electric and the EV charging infrastructures. While the cyber layer is not a part of the theoretical model, we will discuss its key role in Section 3.1. The interactions among the layers of this system can be summarized as following. The EV charging infrastructure receives energy from the power grid and thus the load on charging stations may affect the load on power substations. The pricing scheme, which depends on the state of both power and EV charging infrastructures, will be communicated through the cyber layer to the users. Finally, the communicated price will affect the load distribution over the charging infrastructure and subsequently the load on power substations.

First, let us present the system model for the charging infrastructure. We denote the set of charging stations in a region in the smart city by $\mathcal{C} = \{C_1, C_2, ..., C_k\}$. For simplicity, we assume that the charging stations are distributed over a grid region such that each cell in the grid holds one charging station as shown in Figure1a). The charging stations are connected over a directed graph $G = (\mathcal{C}, E)$, where E represents the set of directed links specifying the possibility of travel between charging stations for the users. For instance, $e_{ij} \in E$ implies that users in the cell containing the station C_i can travel to station C_j for charging. These links help specifying the constraints on the travel for charging, for instance, based on the distance that the users are willing to travel and the distance that a EV with the need for charging can travel before it runs out of energy. We will explain later that when the right incentives are applied then there is a likelihood for each user to travel to other stations with direct links. In this paper, we focus on a graph, in which charging stations in adjacent cells are connected. Other graphs with different topologies can also be considered and will not change the model.

Next, we describe the power infrastructure layer. In this paper and as the first step toward this modeling, we simplify the intra-system model for the power infrastructure by only considering the power grid substations denoted by $\mathcal{S} = \{S_1, S_2, ..., S_m\}$ and their

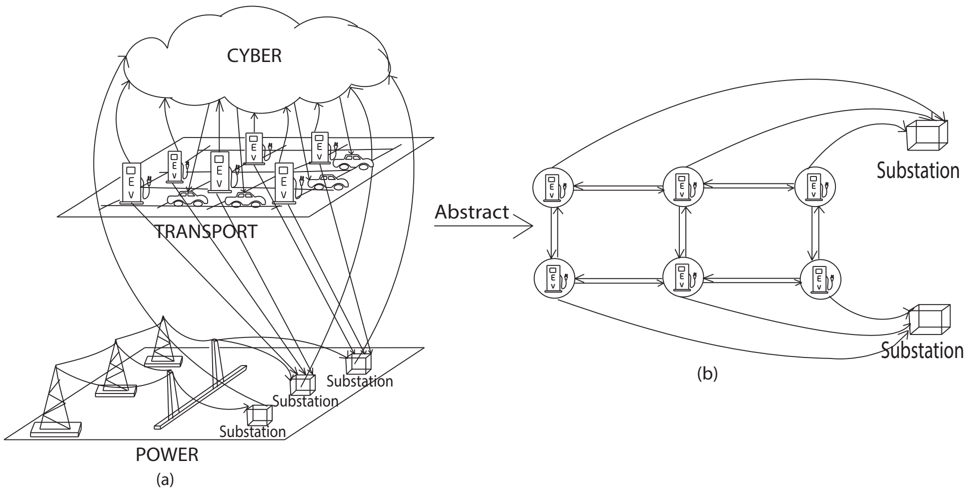

Figure 1: Interconnected networks of electric/power, charging infrastructure and cyber infrastructure.

internal dynamics (as will be explained in Section 3.1). In other words, we do not focus on the complete power grid model with generators and power lines; instead we only focus on substations as abstract and aggregated points of contact with the EV charging infrastructure. In future, we will expand the model to capture more detailed internal interactions in the power system. To model the inter-system interactions between the power and charging infrastructures we assume that multiple charging stations belong to the distribution network of one substation, as such we consider a set of inter-system links denoted by $\mathcal{L}$, where $L_{ij} \in \mathcal{L}$ specifies that charging station C_i affect the load of substation S_j. In this model, $C_i \in \mathcal{C}$ should have a link to one specific $S_j \in \mathcal{S}$ while each S_j can have multiple incoming links from different geographically co-located charging station. Also, note that there will be no links from S_j to any node in $\mathcal{C}$. Such interactions and the effects of power substations on charging stations will be indirectly through the incentives communicated by the cyber layer. Based on the above discussion, the total integrated system can be denoted by a graph as $G_u = (\mathcal{C} \cup \mathcal{S}, E \cup \mathcal{L})$. However, the model for the system is not simply a graph. Next, we will explain how each component in this graph stochastically and dynamically evolves and interacts with other components. We will specifically present a model to capture such dynamics. We have chosen a probabilistic approach for the modeling as various aspects of this system is stochastic. For instance, the state of a charging station (e.g., being busy or not) varies probabilistically at different times of the day and week and due to EV users mobility pattern and behavior. The state of the load in a substation also varies due to stochastic nature of the demand. The interactions among components are also stochastic and as components influence each other depending on their state. For instance, if charging stations, which have a link to substation S_j, become busy and overloaded with lots of demand then this increased demand will increase the likelihood of S_j to become overloaded and hinder the stability of the power grid. In such cases, we would like to distribute the load in the system using pricing incentives to increase the willingness of EV users to travel to other charging stations. These stochastic interactions and dynamics will be modeled in an Influence Theoretic framework as explained next.

3.1 Influence Model for Integrated Infrastructures

Here, we briefly review the Influence Model (IM) as first introduced in (Asavathiratham, 2000), (Asavathiratham et al., 2001) and present an IM-based framework for modeling the integrated charging and power infrastructures.

The IM is a framework consisting of a weighted and directed graph of interconnected nodes, in which, the internal stochastic dynamics of each node is represented by a Markov Chain (MC) and the states of the nodes varies in time due to the internal transitions of MCs as well as the external transitional influences from other nodes. The weights on the directed links represent the strength of influences that nodes receive from one another. In the following, we put the IM model in perspective with respect to the integrated charging and power infrastructures. In our model, graph G_u with two types of links and nodes (as introduced in Section 3) will serve as the underlying graph for the IM. To represent the internal dynamics of nodes, we consider that the state of the charging stations can be abstracted to three levels: (1) underloaded, (2) normal, and (3) overloaded levels. As such, we define a MC with state space of size three for each $C_i \in \mathcal{C}$. These states help describing the load (in terms of energy demand) on a charging station at each time. In general, the state of a C_i may change due to departure or arrival of EV users. On the other hand, we model a substation S_j with an internal MC, which has two possible states: normal and stressed. These states specify if a power substation is overloaded and stressed or it is working under normal conditions. The transition probability matrix of the internal MC for a node, say node $i \in \mathcal{C} \cup \mathcal{S}$, is denoted by $\mathbf{A}_{ii}$, which is an $m \times m$ row stochastic matrix, where m is the size of the state space. We use a data driven approach to characterize the transition probabilities of these internal MCs based on datasets of system dynamics and simulations as will be explained later. The links in graph G_u specify the influence relation among the nodes. In particular, there are two types of influences in our model: (1) when a charging station influences another charging station, then it means there is a likelihood that it will send users (using proper incentives) to the influenced station, and (2) when a charging station influences a power substation, then it means that there is a likelihood that the charging station increases the energy load on the power substation to a level that could change the state of the power substations (e.g., from normal to stressed). The weights on the links also specify the strength of the influence. Specifically, the influences among the nodes of the network is captured by the *influence matrix* denoted by $\mathbf{D}$, where each element d_{ij} is a number between 0 and 1 representing the amount of influence that node i receives from node j. The larger the d_{ij} is the more influence the node i receives from node j; with the two extreme cases being $d_{ij} = 0$ meaning that node i does not receive any influence from node j and $d_{ij} = 1$ meaning that the next state of node i deterministically depends on the state of node j. Note that receiving influence from a node itself, i.e., d_{ii}, specifies how much the state evolution of a node depends on its internal MC. The total influence that a node receives should add up to unity i.e., $\sum_{j=1}^{n} d_{ij} = 1$, and therefore, matrix $\mathbf{D}$ is a row stochastic matrix too.

In IM, the status of a node, say node i, at time t is denoted by $s_i[t]$, a vector of length m, where m is the number of possible states for the node. At each time, all the elements of $s_i[t]$ are 0 except for the one which corresponds to the current state of the node (with value 1). In our model, $s_{i1}[t]$, $s_{i2}[t]$, and $s_{i3}[t]$ correspond to overloaded, normal and underloaded states, respectively, for charging stations. Similarly, $s_{i1}[t]$ and $s_{i2}[t]$ correspond to normal and stressed states for power substations, respectively. The statuses of all the nodes concatenated together as $\mathbf{S}[t] = (s_1[t]s_2[t]...s_n[t])$ described the state of the whole system in time t, where $n = |\mathcal{C} \cup \mathcal{S}|$ and $|.|$ denotes the cardinality of the set.

The influence matrix $\mathbf{D}$ specifies how much two nodes influence each other. In order to specify how the states of the nodes will change due to the influences, we also need state-transition matrices $\mathbf{A}_{ij}$, which capture the probabilities of transiting to various states due to the state of the influencing node. Matrix $\mathbf{A}_{ii}$ represents the special case of self-influence, which is described by the internal MC of the node. Note that the $\mathbf{A}_{ij}$ matrices are row stochastic. In the general IM (Asavathiratham, 2000), the collective influences among the nodes in the network is summarized in the total influence matrix $\mathbf{H}$ defined as:

$$\mathbf{H} = \mathbf{D}' \otimes \{\mathbf{A}_{ij}\} = \begin{pmatrix} d'_{11}A_{11} & \cdots & d'_{1n}A_{1n} \\ \vdots & \ddots & \vdots \\ d'_{n1}A_{n1} & \cdots & d'_{nn}A_{nn} \end{pmatrix}, \quad (1)$$

where $\mathbf{D}'$ is the transpose of the matrix $\mathbf{D}$ and $\otimes$ is the generalized Kronecker multiplication of matrices (Asavathiratham, 2000). Finally, based on the the total influence matrix $\mathbf{H}$ the evolution equation of the model is defined as

$$\mathbf{p}[t+1] = \mathbf{S}[t]\mathbf{H}, \quad (2)$$

where vector $\mathbf{p}[t+1]$ describes the probability of various states for all the nodes in the network in the next time step. Steady state analysis of IM has some similarities with that of MCs and has been discussed for various scenarios in (Asavathiratham, 2000), (Asavathiratham et al., 2001). For a more detailed discussion on the IM please refer to (Asavathiratham, 2000), (Asavathiratham et al., 2001).

The work in (Siavashi, 2016) extends the original IM to a constraint or rule-based influence framework such that the influences among the nodes can dynamically get activated and deactivated depending on the state of the system. Also, as explained in (Siavashi, 2016), influencing can change the state of the influencer as well (transiting from overload to normal due to sending load to another station). (Siavashi, 2016) specifically defined a constraint matrix $\mathbf{C}$, where the entry c_{ij} for $i, j \in \mathcal{C} \cup \mathcal{S}$ is a binary variable specifying whether node i gets influenced by node j or not. In particular, $c_{ij} = 1$ indicates that node i gets influenced by node j and $c_{ij} = 0$ indicates otherwise. Moreover, each node always influences itself based on its internal MC (i.e., $c_{ii} = 1$ for all $i \in \mathcal{C} \cup \mathcal{S}$). As explained in (Siavashi, 2016), one can define the value of c_{ij} according to boolean logic to capture the rules of interactions in the network. In other words,

c_{ij}s are functions of the state of the nodes. For instance, when a charging station in the EV charging infrastructure is in overloaded state and based on G_u it has a link to another station, which is underloaded, the influence over that link should get activated to motivate the EV users to travel from the overloaded state to underload state. These types of rules can be specified using boolean functions such as the following examples. Function $c_{ij} = s_{i3}s_{j1} + s_{i2}s_{j1}$, where $i, j \in \mathcal{C}$ specifies the rules that can be applied to the transport layer of the model to show influences from charging station j to charging station i. Specifically, a transport node i will receive influence from transport node j if node i is underloaded and node j is overloaded or if node i is normal and node j is overloaded. Also, the power substations receive influences from the charging stations because overloaded charging stations can cause a power substation to go to overloaded state. Example of boolean function describing this rule is $c_{k\ell} = s_{k1}\prod_{j\in C_{S_k}} s_{ji} + s_{k2}\prod_{j\in C_{S_k}} s_{ji}$, where $k \in \mathcal{S}$ and $\ell \in \mathcal{C}$ and $C_{S_k} \subseteq \mathcal{C}$ is the set of charging stations connected to the power substation k. Specifically, a power substation, say k will receive influence from charging station ℓ when all the charging stations connected to the power substation are overloaded. As a power station is generally built with a capacity to accommodate large demand, the power substation will go to a stressed state provided that all the influence links connected to it are activated. This is just one example of influence rule and other conditions to specify the rules are also possible.

Note that as the goal of the integrated study of these two systems is to increase the probability of having power substations in normal conditions and charging stations not overloaded, the interaction rules defined in $\mathbf{C}$ should support this goal. In order to achieve this goal the influences among the charging stations should be engineered such that it forces the whole system toward desirable states. The second type of influence, which is from the charging station to power substations cannot be engineered and we assume that when the charging stations, which are receiving energy from a substations, are overloaded they influence (increase the likelihood) the substation to transit to a stressed state.

In (Siavashi, 2016), the constraint matrix $\mathbf{C}$ and the influence matrix $\mathbf{D}$ are used to define the constraint-based influence matrix denoted by $\mathbf{E}$, as

$$\mathbf{E} = \mathbf{D} \circ \mathbf{C} + \mathbf{I} \circ (\mathbf{D} \times (\mathbf{1} - \mathbf{C}')), \tag{3}$$

where $\circ$ is the Hadamard product (aka entrywise product), $\mathbf{1}$ is the matrix with all elements equal to 1 and $\mathbf{C}'$ is the transpose of matrix $\mathbf{C}$. Using $\mathbf{E}$, the IM-based state evolutions can be summarized as

$$\mathbf{H} = \mathbf{E}' \otimes \{\mathbf{A}_{ij}\}, \tag{4}$$

and $\mathbf{p}[t+1] = \mathbf{S}[t]\mathbf{H}$.

As discussed in (Siavashi, 2016), this formulation may or may not allow the asymptotic analysis of the behavior of the system. However, no matter if the analytical solution of the model exists or not, this model can be used for Monte-Carlo simulation of the behavior of the system in order to study how influences and interactions affect the state of the whole system. Based on this formulation, as the state of the system varies in time, various sets of influences get activated. Note that in IM, when a node influences another node, it may result in state change for the influenced node based on the adjusted transition probabilities that are captured through $\mathbf{H}$ and the formulation of $\mathbf{p}[t+1]$. As such, an activated influence in our model increases the probability of transitioning to a normal state for an underloaded charging station due to receiving load from the influencer (based on our definition of influence). In real-world, proper incentives for the users are needed to make that influence occur (transfer of load from one charging station to another). As such, to achieve the goal of the system which is increasing the probability of normal states, we use the status of the influence links (active or inactive) to guide the charging price design. In the next section, we explain how this model will help in designing proper prices and together with the rules of interactions can lead to more balanced system for both EV charging and power infrastructures.

4 MECHANISM FOR DESIGNING CHARGING PRICE AT EV CHARGING STATIONS

The model described in the previous section needs an external factor in real-world scenarios to provoke an EV user to travel from one charging station to another for charging (i.e., activating the described influence between charging stations in real-world). This external factor can be in terms of incentives or hampers that an EV user may get if they move from one cell to another. A good incentive would be lower charging prices (whenever the influence should be active) in the station, which should receive some load. The lower prices can motivate the EV users to move from their currently occupied cell to the other station. However, not every EV user will respond to such incentives in the same way and thus not every user will travel from the first cell. Particularly, the probabilistic nature of the IM helps in capturing the random behavior of the users. Intuitively, the higher the influence strength the more we expect that the users travel to the other station, which can help in characterizing the price reduction that is needed. A key point to notice is that the cyber layer plays a key role in letting the desired influences to occur to let the system identify its next states based on IM. Specifically, the cyber layer should communicate the lower charging price only to the users in the cell that is influencing the station. Otherwise, if the reduced price is communicated in the system globally and all the EV users in the city know about the reduced price in a station, this will activate influences among neighbor stations (neighbors are defined as according to G_u) that should not be activated according to the IM model. Thus, in order to only activate the influences that the IM model identifies for leading the system to a more balanced system in each step, the cyber layer plays a key role in communicating the prices to the right EV users based on their location.

Algorithm 1: Algorithm for Price Assignment to Charging Stations.

Input ▷ Graph of active influences, $G_t(\mathcal{C}, E_a(t))$. A maximum electricity price limit **A** and a reduction factor in price, α.
Output ▷ Charging price in each charging station in $\mathcal{C}$ such that the price of the influencer station is higher than the influenced station.
Calculate the topological sort **T** for G_t.
for i=1 to $|\mathcal{C}|$ **do**
  if $|I(\mathbf{T}(i))| = 0$ **then**
    Price($\mathbf{T}(i)$) = **A**
  else
    Price($\mathbf{T}(i)$)=$\sum_{j \in I(\mathbf{T}(i))}$ Price$(j)/|I(\mathbf{T}(i))|$
  end if
end for
Return Price.

In our model based on IM, whenever the set of activated influence links varies, we need to identify new set of prices for each station such that if station say i has an active influence link to station j, then the price at station i should be higher than that of station j. To identify the set of prices that satisfy this condition in the whole system, we propose the algorithm presented in Algorithm 1. This algorithm is similar to a constrained graph coloring problem. However, the problem of price assignment to the stations based on the above constraint is solvable with complexity $O(|\mathcal{C}| + |E|)$, which is because the graph of active influences denoted by $G_t(\mathcal{C}, E_a(t))$ and obtained from simulation of IM at step t is a directed and acyclic graph (note that $E_a(t) \subseteq E$, also note that $E_a(t)$ does not include self-influences as they do not affect the pricing). This property is due to the rule set with the goal of balancing the load in the system, which never result in a cycle in the graph of active influences. In other words, the rule set in the model is very important to ensure that the load is not circulating in the system and purposely directed to the proper charging stations. Algorithm 1 for price assignment uses a topological sort of the graph and then assigns the prices based on the identified order such that the prices ensure that the stations appearing later in the topological sort have lower prices (as they should receive influences or loads). In our algorithm, we consider a maximum price limit of A and each price reduction occurs by a constant α. The values of A and α are considered fixed in this paper for simplicity, but can be variable and adjusted based on other factors in the system. In this algorithm, function $I(.)$ receives a node and returns the set of nodes, which influences the input node.

5 EVALUATION AND RESULTS

In order to demonstrate the process of assigning prices to the charging stations dynamically as the system evolves in time while trying to lead both systems to more balanced states, we use an example network as shown in Figure 2 with 12 charging stations, which receive their energy from two power substations. In this example, we used a data driven approach to extract some of the parameters of the IM using available data sets of traffic information. Specifically, we used the taxi data in (Piorkowski et al., 2009), which contained GPS trajectories of 536 taxis in San Francisco, California from May 17, 2009-July 10, 2009 specifically to estimate $\mathbf{A}_{ii}$s. An example of $\mathbf{A}_{ii}$ based on the dataset is as following, where rows and columns are ordered from overload to normal and then underload:

$$\mathbf{A}_{ii} = \begin{pmatrix} 0.89473684 & 0.1052632 & 0.00000000 \\ 0.07262570 & 0.8770950 & 0.05027933 \\ 0.07142857 & 0.2142857 & 0.71428571 \end{pmatrix}. \tag{5}$$

In addition to $\mathbf{A}_{ii}$s, which characterize the internal dynamics of each station, we also need to consider $\mathbf{A}_{ij}$s to specify how the influences between two stations result in state transitions. An example of $\mathbf{A}_{ij}$ is shown in (6) in which each column specifies the probability of transition to overload, normal, and underload, respectively, depending on each row, which specifies the state of the influenced node. For simplicity and due to lack of detailed information in the datasets to characterize this matrix for all cells, we have simplified this matrix to have equal transition probabilities independent of the state of the influenced node (i.e., the same rows). Based on our model and the rules of influences, in order to lead the systems to balanced states a station only tries to send load to another station if the other station is not overloaded. As such the last row of the matrix in (6) does not play a role in the analysis.

$$\mathbf{A}_{ij} = \begin{pmatrix} 0.2 & 0.5 & 0.3 \\ 0.2 & 0.5 & 0.3 \\ 0.2 & 0.5 & 0.3 \end{pmatrix}. \qquad (6)$$

Similarly, an example of $\mathbf{A}_{ii}$ for power substations is as following where rows and columns are ordered from normal to stressed:

$$\mathbf{A}_{ii} = \begin{pmatrix} 0.8 & 0.2 \\ 0.5 & 0.5 \end{pmatrix}. \qquad (7)$$

Since the detailed dynamics of the power grid is not considered in this paper, we only focus on how their state change when they are stressed by charging stations. But to consider the effects of internal dynamics of the power grid, we consider a small probability that a power substation changes state from normal to stressed due to different parameters in the system other than the charging stations (here this value is chosen to be 0.2). When the system is stressed (i.e., the second row on the matrix in (7)) then we assume there is an equal chance to get into normal state or stay stressed based on internal dynamics. However, as a part of influences in our IM-based model whenever the charging stations go back to normal or underloaded states then they can externally help the power substation to transit back to the normal state. Specifically, the set of rules for this study can be described as: (1) node i gets influenced by node j if and only if node i is underloaded and node j is overloaded or node i is in normal state and node j is overloaded for charging stations, and (2) for the influences between the power substations and the charging stations, the power substation gets influenced by a charging station if the power station is normal and the charging stations receiving power service from the substation are overloaded or if the power substation is stressed and the charging stations are normal or underloaded.

As mentioned earlier, based on the state of the components in the system, the influences among nodes may get activated and deactivated. In Figure 3, we show two samples of active influence graphs for the network shown in Figure 2. The activated links between charging stations suggest that the load should be transferred from one station to the station on the end of the directed link.

The set of activated influences in each iteration prompts a change of state in the charging stations and power substations as shown in Figures 4 and 5. Specifically, Figures 4a, 4b and 4c show the distribution

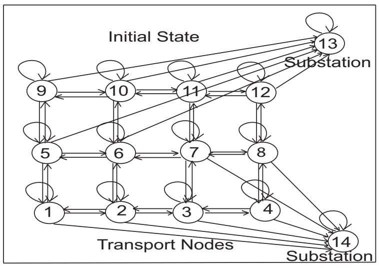

Figure 2: The integrated charging and power infrastructures model with 12 charging stations and two substations (i.e., graph G_u).

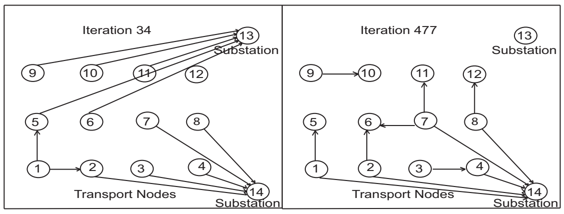

Figure 3: Two samples of active influence graph.

of the number of charging stations in underload, normal and overload states in each iteration respectively. Although the distributions are fluctuating but it can be observed from Figures 6 and 7 that the aggregated behavior of the system is independent of the initial state of the system as the likelihood of normally loaded charging stations and normal power substations is higher than other states. The results in Figures 8 and 9 are obtained over 1000 steps of the IM simulation. Figure 8 shows the state distribution of the charging stations and power substations with various initial states.

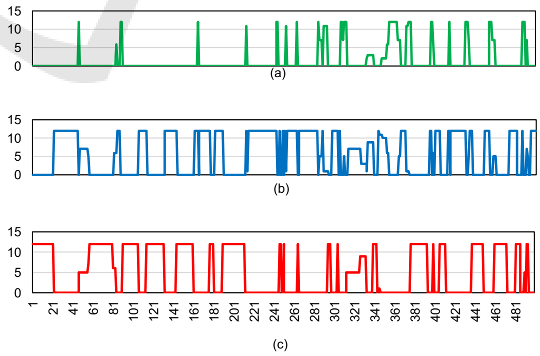

Figure 4: Number of charging stations in each iteration in: (a) underloaded, (b) normal, and (c) overloaded, states.

An important aspect of the influence model is the set of rules that specify how the nodes should interact and influence each other. To show how the rules of the interactions affect the behavior of the system, here, we have considered other influence rules similar to the rules of interactions defined in (Siavashi, 2016) as

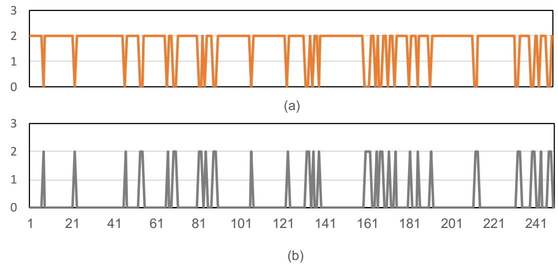

Figure 5: Number of power substations in each iteration in various states: (a) normal state, and (b) stressed state.

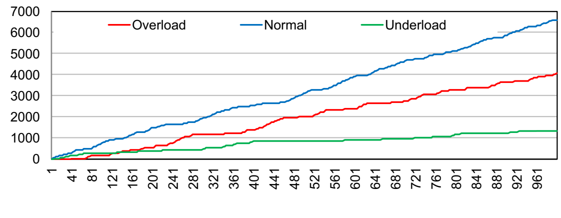

Figure 6: Aggregated states distribution for overloaded, normal and underloaded states for charging stations.

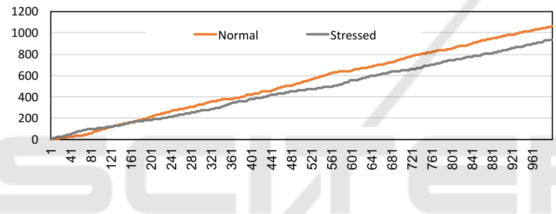

Figure 7: Aggregated state distribution for normal and stressed states for the power substations.

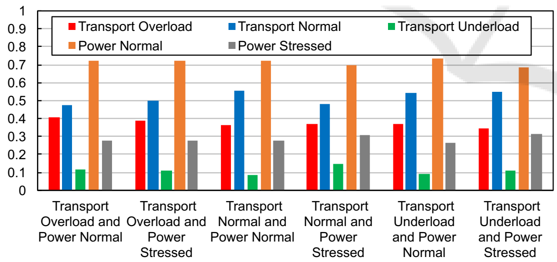

Figure 8: State distribution of charging stations and power substations with various initial states for the components.

follows:

- *Rule 1:* Node i gets influenced by node j if and only if (iff) node i is underloaded and node j is overloaded or node i is in normal state and node j is overloaded.
- *Rule 2:* Node i gets influenced by (receives workload from) node j iff node i is underloaded and node j is overloaded.
- *Rule 3:* Node i gets influenced by node j iff node i is underloaded and node j is overloaded or node i is underloaded and node j is in normal state.
- *Rule 4:* Node i gets influenced by node j iff either node i is underloaded and node j is overloaded, node i is underloaded and node j is in normal state or node i is in normal state and node j is overloaded.
- *Rule 5:* Node i gets influenced by node j iff either node i is underloaded and node j is overloaded, node i is underloaded and node j is in normal state, node i is in normal state and node j is overloaded or node i is in normal state and node j is in normal state too.

Note that these rules only focus on the interactions among the charging stations and the influences among charging stations and the power substations are assumed to be as before. Figure 9 shows the state distribution of nodes with all charging stations initially overloaded and all power substations initially normal for different rules applied to the model. It can be seen that rule 5 performs the worst among the all as the number of overloaded charging stations are higher compared to other cases.

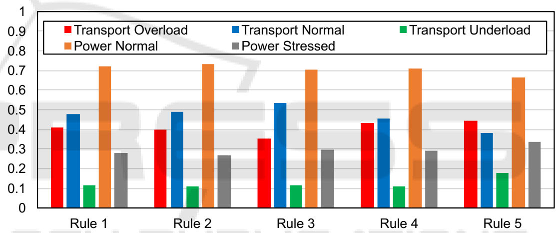

Figure 9: State distribution of charging stations and power substations with all charging stations initially overloaded and all power substations initially in normal states for different rules of interactions.

To design the incentives that enable influences and lead to the results shown in Figures 6, 7, 8 and 9, we need to design the prices for each charging station. To do so, we have used Algorithm 1 over the active influence graph obtained at each step of the simulation whenever there was a change in the active influence graphs. Note that Algorithm 1 receives graphs similar to the ones shown in Figure 3 where the self-edges are omitted. The price assignment based on this algorithm at each station is shown in Table 1 for sample steps of our simulation (with Rule 1). As it can be observed from the table, initially all the twelve stations have the same price of A but the prices vary over the network as the stochastic dynamics of the system change the states of the nodes.

In this section, we showed our preliminary study of collaborative pricing solution between the EV charging and electric infrastructures based on our IM-based model. Key takeaways from our results include:

Table 1: Charging prices in each EV charging station over various iterations.

	Charging Stations											
Iteration	1	2	3	4	5	6	7	8	9	10	11	12
1	A	A	A	A	A	A	A	A	A	A	A	A
18	A - α	A	A	A	A	A	A	A	A	A	A	A
245	A	A - α	A	A	A - α	A	A	A	A	A	A	A
246	A	A	A	A	A	A	A	A	A	A	A	A
247	A	A	A - α	A	A	A	A - α	A - α	A - α	A	A	A
261	A	A	A	A - α	A - α	A - α	A - α	A	A	A - α	A	A - α
446	A - α	A	A	A	A	A	A	A	A	A	A	A
650	A	A	A	A - α	A - α	A - α	A - α	A	A	A - α	A	A - α
892	A	A	A	A - α	A - α	A - α	A	A	A	A - α	A - α	A - α

(1) by designing proper rules of interactions among the integrated systems, the load distribution can be improved in both systems, and (2) the pricing assignment based on the obtained active influence graph enables the implementation of appropriate influences.

6 CONCLUSIONS

In this paper, we discussed the importance of collaborative solutions among critical infrastructures of smart cities. We specifically emphasized that the smart city solutions should consider the state of various systems interacting with each other rather than only an individual infrastructure. To demonstrate this point, in this paper, we focused on interdependent EV charging and the electric infrastructures and developed an integrated framework for modeling their interactions based on influence model, which is a networked Markov chain framework. We also proposed an algorithm, which assigns prices to charging stations based on the set of active links that can lead to more balanced systems. We discussed the role of the cyber infrastructure in enabling this pricing scheme, which considers the state of both of the systems. The work presented in this paper is an effort toward using integrated models for infrastructures to develop collaborative solutions for smart cities. In future, we will study, both analytically and using simulations, the role of various parameters of the model in the behavior of the system. We also hope that this study and modeling approach can be extended to other smart city solutions and interdependent infrastructures.

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