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Promises of Interdependent Power and Energy Systems for Future Smart Cities

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ABSTRACT

Smart cities aim at providing hardware and software platforms to enable novel functionalities. The main goal is to integrate modern technologies while upgrading the available resources at all systems within the future cities, including power systems, communication networks, societal networks, and transportation networks. Each subsystem in the smart cities has specific objectives and operational constraints. The ultimate goal of smart cities is to improve the quality of life while making sure all technologies are deployed in a sustainable manner. In this context, due to the ever-increasing electrification at various networks, power system modernization plays a pivotal role in city smartification. Interdependent power and energy networks can expedite the path towards intelligent infrastructures by supplying reliable and sustainable energy to the end-users. The main focus of this paper is on the promises of modern power systems for future smart cities. To this end, first the current practices for the transition from conventional fossil-fuel-based power systems towards smart grids are explained which are more reliable, secure, and environmental-friendly. Then, the potential advantages and contributions of modern power systems in smart cities are explored. As an example of emerging technologies in power systems that affect the future smart cities, demand response programs and their corresponding mathematical formulations are explained.

Keywords: Smart cities, Interdependent networks, Sustainability, Demand response, Optimization, Critical infrastructures

Introduction

The notion of sustainable smart cities has been emerged globally due to its pivotal role to meet the challenges of the urban areas [1]. It has been introduced to cope with the growing urbanization and the emerging challenges [2] (e.g., ensuring sustainable operation of critical infrastructures such as power grids, energy systems, transportation networks, and communication networks). Smart cities have been widely investigated by the researchers [3-6, 7]. Heng et al. [5] consider Singapore as an "intelligent city" by investing in modern telecommunication and information technologies.

In addition to the transition towards smart cities, there has been a transition from conventional power systems towards smart grids. There are several advantages and challenges introduced by smart grid technologies. They aim at improving the reliability, security, and increase efficiency of the generation-demand balance by optimally dispatching various resources at both generation and demand sides. Smart grids play a crucial role in smart cities. This is mainly due to the fast growing electrification at various infrastructures within the smart cities, such as transportation electrification. This will not only increase the dependency of smart city infrastructures on power systems, but also strengthens the interdependence among smart power grids and other critical infrastructures, including but not limited to transportation networks, gas networks, water networks, communication networks, and societal networks [6]. Amini et al. [8] provide a detailed investigation of smart cities infrastructure, the corresponding interdependences, and future directions for research and development. Among all these interdependencies, power systems and electrified transportation networks are highly coupled networks. Electric vehicles and charging stations are affecting the operation of transportation networks (by causing traffic congestion)

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and power systems (by increasing the load demand and potential power system congestions) respectively [9]. In order to model these interdependent nature, an optimal routing algorithm for electric vehicles in proposed in [10] which takes the electricity price, traffic conditions, and charging stations' location into account while finding the best route from an origin to destination. According to Amini and Karabasoglu [10], considering these interdependencies improve the operation of both networks by leveraging the flexibilities of electric vehicles, e.g., charging at different location and time to reduce their charging cost.

Motivated by these ever-increasing interdependencies, this paper first provides a big picture of smart cities and the position of smart grids as a subset of future cities. It also elaborates two major networks which are affected/affecting power systems in the context of smart cities.

The rest of this paper is provided as follows. Section II is devoted to an overview of smart cities infrastructures and the role of modern power systems in energizing the networks within smart cities. In Section III, the paper zooms into one of the specific applications in power systems, which increases the interdependence among power systems and other critical infrastructures in a smart city, including societal systems. Also, some of the notable formulations to integrate demand response programs in power systems as well as energy market studies are presented. Section IV concludes the paper.

An Overview of Smart Cities Infrastructures

Smart cities infrastructures provide a platform to sense, collect, and analyze data from various sources and enable optimal decision making [11]. Previous works study the architecture of smart cities. For instance, Wenge et al. [12] developed a novel architecture from data analysis point of view. Further, a pyramid framework is proposed in [13] based on human-system interaction. This framework includes multiple level as follows:

1. "Smart infrastructure", including power, gas, water, and communication systems;
2. Intelligent data storage;
3. Smart home/residential energy management systems;
4. Intelligent (user) interface
5. "Smart cities" as an umbrella to cover other layers [11,12].

Anthopoulos et al. [14] developed a 5-layer framework for smart cities. Further, Krylovskiy et al. [15] introduced an all-inclusive framework, called DIMMER system. DIMMER is capable of interacting with residential systems and utilities to integrate various measured data. There was also a smart city project based on DIMMER system to enhance the energy efficiency of urban infrastructures [15]. They consider three pivotal information structures for smart cities:
Geographic Information Systems (GIS);

1. Building Information Models (BIM);
2. System Information Models (SIM).

They further analyzed these concepts.BIM is the digital representation of physical building aspects [16]. GIS is mainly related to control and evaluation of geo-labeled data. Even though GIS provides spatial understanding of a wide geographical area, it may not be effective for building applications and indoor navigation [16]. In order to deal with this issue, Lie et al. presented a novel BIM system that provides detailed and accurate data about home appliances. An improved A* methodology is proposed in [17] to improve BIM performance by minimizing the lift path for offshore oil for the disassembly process.

Soto et al. [18] developed a smart city model, called ALMANAC, that takes into account legacy services, assets, sensing devices, and infrastructures. Location-based services play an important role in modernizing urban environments. They can be deployed in a wide range of applications from autonomous transportation networks towards location-based decision making of heterogeneous agents. They also enable optimal near-real-time decision making of smart cities agents considering spatiotemporal information collected by various sensors and devices, such as smart phones, smart meters, and phasor measurement units. Lohan et al. [19] investigated the role of location-based services in future cities. They identified the challenges and solutions in four major aspects: data collection, storing information, data analytics, and data visualization. Volk et al. [20] provided a survey on BIM, and outlines three major challenges based on a critical review of BIM:

1. Extensive modeling requirements from measured information from building into semantic BIM objects
2. Integrate and utilize this data in the BIM system
3. Modeling the stochastic data

Based on ISO 37120 standard, an ICT framework is developed in [21] to aggregate information from different types of sensors and to enable an energy-efficient IoT platform.

Smart cities infrastructures have been categorized from physical, communication and Information aspects in Fig. 1 [22]. They utilize sensor measurements, heterogeneous information exchange, and processors to collect information. Further, they use control devices and signals to manage difference infrastructures [22]. These components are elaborately explained as follows:

a) Measurement and Sensing Devices: There are various intelligent sensing devices at different networks within the smart cities. At the power system layer, smart meters and phasor measurement units are two examples of these sensors. In the transportation networks, road side

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units and intelligent traffic cameras are two notable examples. These sensors basically measure data from the physical layer and share it with processing layer for further data analytics and decision making [23]. These measurement devices have some limitations (e.g., sizes, energy consumption, and computation capabilities). Hence, they often analyze or compress the sensed data before sharing it with the network [22].

b) Heterogeneous communication networks: Heterogeneous communication networks bridge the gap between physical layer and information processing layer. They mainly provide the sensors with the required communication infrastructure to broadcast data to other layers [24]. This can be seamlessly enabled using cellular networks, local short-term communication platforms, peer-to-peer communication, and wireless sensor networks [22].

c) Processing unit: Processing unit is responsible for analyzing the collected information from various sensors, determine the optimal control signals to manage the operation of each network within the smart city, and send those signals to each agent through the communication platform accordingly.

d) Operation and Control Devices: These components are used for handling the operation of physical network based on the control signals from processing unit. They act as an interface between decision making units and physical world to improve quality of life in smart cities. For example, in power networks, providing reliable and cost-effective electricity is considered as an important factor for the end-users. Further, Supervisory Control and Data Acquisition (SCADA) [25] determine the optimal management strategy for controlling the operation of power systems, which ultimately translates into more reliable and secure power delivery and customer satisfaction.

Figure 2 represents some of the influential factors for modernizing urban infrastructures. Power systems and electrification are the core requirement for enabling these factors.

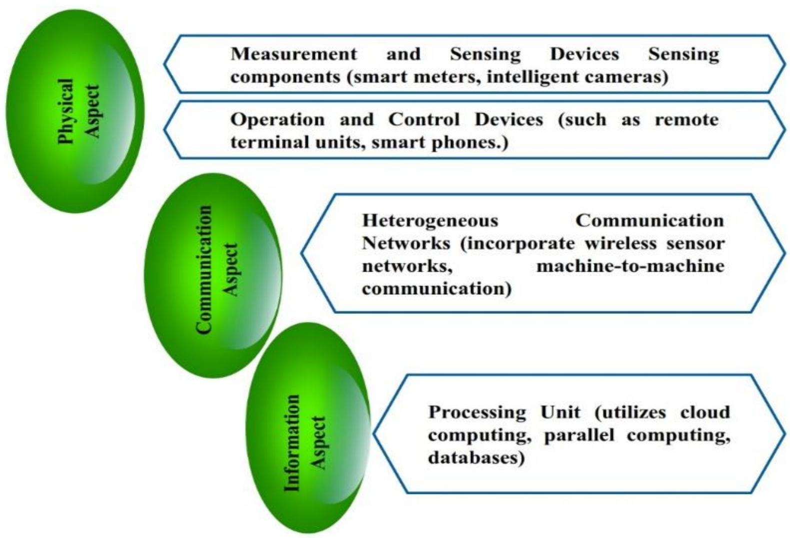

Figure 1. An overview of smart cities infrastructures: Physical, Communication and Information aspects [6, 23]

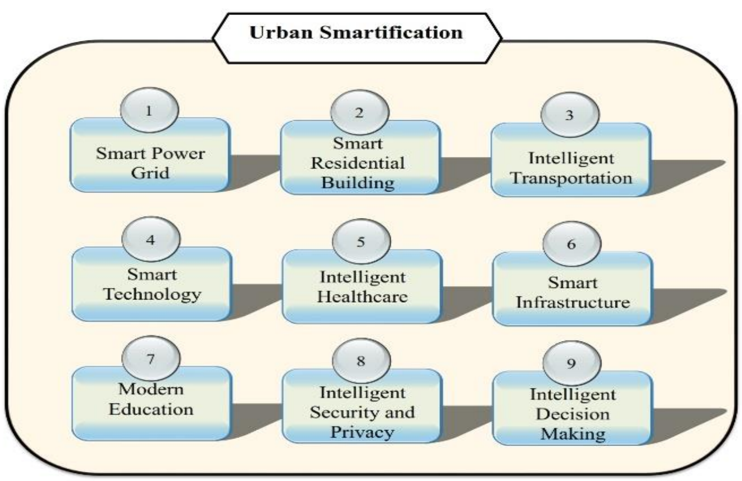

Figure 2. Influential factors for modernizing urban infrastructures [6]

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Demand Response: An Example of Interdependence among Power Systems and Other Smart City Infrastructures

The utilization of demand side resources (DSRs) to provide the supply and demand balance, is one of the main activities in future power systems [26, 27]. In this regard, from the societal network viewpoint it is needed to investigate and model the customers' involvement. Further, from the physical network perspective, it is needed to study the power system and the effect of demand response on its operation. It is vital to use DSRs in order to provide electric power in a sustainable way. Consequently, DR resources are known as an essential part of the power market for enhancing the flexibility of the system and achieving the balance between supply and demand [28, 29].

Demand response aggregator aims to motivate customers to modify their electricity demand, when they receive the DR signals [30, 30]. Indeed, these programs are established to encourage end-users to change their consumption considering market signals. The employment of DR programs has become more interesting for both the sellers and buyers, due to peak demand [32-36]. Although, DR programs were firstly considered as a measure for solving the system deficiencies, recently, these programs have been introduced as virtual resources, because of their high benefits and successful experiences [35]. There are different players in the power market who gain benefits from DR potential, including retailers, as well as distribution/transmission network operators [37].

It should be noted that, these programs should cope with different challenges and barriers [26]. Kim et al. [38] have investigated DR challenges. An emerging barrier is that the customers are not willing to have participation for a long time or cannot continuously be responsive to the DR signals [34, 38]. DR service providers are introduced in [34] as the responsible entities to provide DR capacities through managing the potential of responsive customers. By considering these entities, Ref. [34] proposed the problem of "Unit and DR commitment" where the ISO will aggregate the generating units' supply curves and DR service providers' cost functions to optimally operate the system.

Generally, DR programs could be enabled through two frameworks [39]:

a) contract oriented: that enables bilateral trading among players in DR framework;

b) market oriented that classifies players into two major categories: DR buyers (DRBs) and DR sellers/providers (DRSs/DRPs).

Demand response buyers aim at improving their business as well as system reliability. DRSs are entities who sell DR to DRBs. This procedure, could be structured to enable an efficient market mechanism for DR, which is referred to as DR exchange (DRX) market [37]. According to [40, 41], DR is considered as a tradable good in pool-based market. To this end, a DRX operator (DRXO) collects all the demand-side and supply-side functions. Finally, it clears the DR market at an equilibrium point that determines the DR price and quantity [40].

Different models have been proposed in order to investigate the effect of DR on various aspects of power systems. References [42-46] developed the economic models of DR on the basis of price elasticities. Schweppes et al. [47] introduced three models for responsive loads in terms of the structure of demand functions: linear, potential, and exponential. Conejo et al. [48] proposed a model to adjust the customers' load pattern based on electricity prices. A multi-agent framework is proposed in [33] to enable load management in distribution systems. Furthermore, Ref. [49] presented an approach to manage the residential loads.

DR programs could also change the behavior of the electric vehicle drivers (Drivers may change their driving patterns based on the various electricity prices, or DR incentives and penalties) [50, 51]. Another aspect of DR implementation is to maintain the customers' privacy and protect the customers' data against the adversaries' accesses. A retailer should buy electric power from the day-ahead market for its corresponding end-users. On the other hand, it is faced with uncertain load levels to sell electric power to the end-users. Therefore, the retailers should cope with a financial risk due to these price and demand uncertainties. Demand reduction during price spike periods, can help the retailers to be able to mitigate the financial risk levels [52].

Here, a decision making framework is introduced for retailers, in which the optimal amount of purchasing electric power from the pool market, the optimal electricity prices, and the best strategy to participate in the DRX market will be determined. The response of electricity customers to the contract prices could be considered by using piecewise price quota functions. The details of these functions are discussed in [52]. Fig. 3 illustrates the introduced decision making framework for a retailer.

The goal of a retailer is to maximize its estimated profit by leveraging the electricity market as well as DRX market, and is formulated by (1).

$$\begin{aligned} &Max \ \{RB\} \\ &where, \\ &RB = ER + EP + FC + EDR + ES \end{aligned} \tag{1}$$

In which, ER denoted the expected revenue from selling electricity to the clients; EP is the expected costs for purchasing electric power from the wholesale market; FC represents costs of the forward contracts; EDR is the expected cost (or revenue) from buying (or selling) DR in the DRX market; and ES represents the expected cost (or revenue) from buying (or selling) electric power in the spot market.

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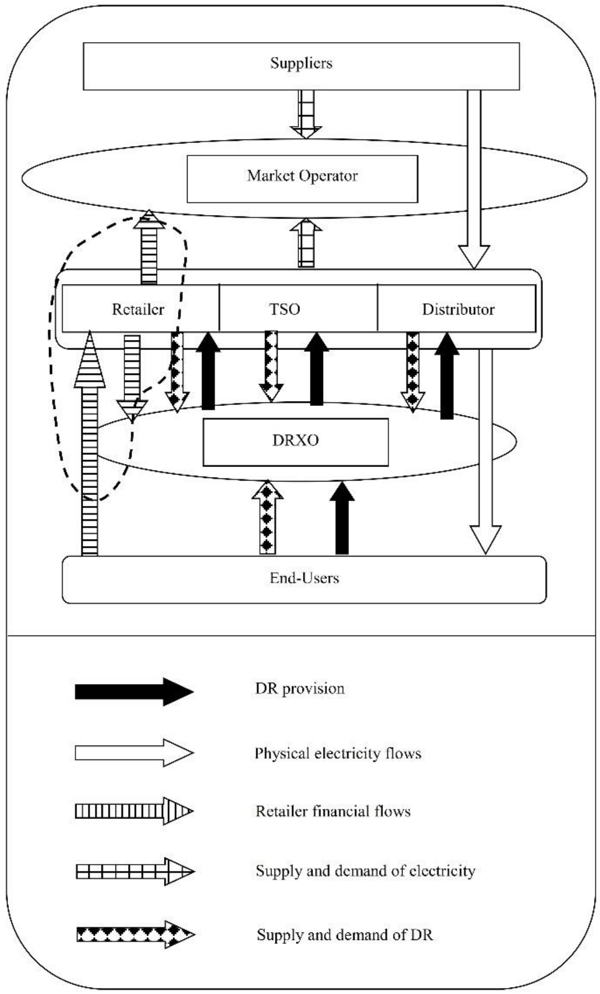

Figure 3. The decision making framework of a retailer

The details of the cost terms of the objective function are completely described in [52]. The cost to purchase DR from the DRX market could be formulated by (2):

$$\sum_{n}\sum_{t} l_{R,n}^{DRX}(t) \times \pi_{n}^{DRX}(t), \qquad \forall t \in T, \;\; n \in \Gamma \qquad (2)$$

The notation of this equation is represented as follows:

T	scheduling time horizon;
Γ	set of DRPs;
t	number of time-steps (hours);
n	number of DRPs (customer groups);
db	number of DRBs;
$l_{db,n}^{DRX}(t)$	value of purchased DR from n^{th} DRP by db^{th} DRB at time t [MW];
$\pi_{n}^{DRX}(t)$	DR supply cost of n^{th} DRP at hour t;

Assuming a linear model as the DR cost function, equation (3) formulates the DR supply curve of each DRP.

$$\pi_{n}^{DRX}(t) = \alpha^{n} l_{n}^{DRX}(t) + \beta^{n}, \qquad \forall t \in T, \;\; n \in \Gamma \qquad (3)$$

Where, l_{n}^{DRX} denotes the amount of sold DR by n^{th} DRP [MW], and α^{n} and β^{n} are constant coefficients. β^{n} could be defined as $\beta^{'}(1-\theta_{n})$, in which, θ_{n} indicates the willingness of a customer to have participation in DR (it is related to the customers' type and its value is among [0-1]). Since higher values of θ_{n} is equivalent with the more willing to participate in DR, increment of this parameter will decrease the DR costs. Hence, higher values of α^{n} and β^{n}, show the less motivation of DRPs to be responsive to the DR calls. Similarly, by considering the retailer, TSO and distributor as the buyers of DR, Table I indicates their functions to purchase DR from the DRX market.

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Table 1
DRBs' curves to purchase DR

DRBs	DR purchasing functions
Retailer	$\rho^R = a^R \times DR^R + b^R$
TSO	$\rho^T = a^T \times DR^T + b^T$
Distributor	$\rho^D = a^D \times DR^D + b^D$

In which, *R*, *T* and *D* indicate the retailer, TSO and distributor, respectively.
Generally, two types of constraints could be considered for this problem:

- *Balancing constraints*

Sum of electric power demand (purchased) and enabled DR need to be equal to total electric demands of the clients.

- *load and price permissible threshold constraints*

The lower and upper limits of purchased load and DR capacities, as well as electricity and DR prices, should be considered for the sake of achieving a more practical model. Such restrictions could be formulated by (4)-(9).

$$0 \le l_n^{DRX}(t) \le l_n^{DRX,max}, \qquad \forall n \in \Gamma, \ t \in T \quad (4)$$

$$l_{DA}(t) \ge o \qquad t \in T \quad (5)$$

$$\pi_n^{DRX}(t) \ge o \qquad \forall n \in \Gamma, \ t \in T \quad (6)$$

$$\pi_n^{cu}(t) \ge 0 \qquad \forall n \in \Gamma, \ t \in T \quad (7)$$

$$p^{forward}(t, fc) \ge 0 \qquad \forall t \in T, \quad fc \in N^f \quad (8)$$

$$\zeta(t, fc) \ge 0 \qquad \forall t \in T, \quad fc \in N^f \quad (9)$$

The notation of the above-mentioned equations is provided as follows:

fc	Indicator for the number of forward contracts;
$l_n^{DRX,max}$	Maximum DR capacity of n^{th} DRP;
$l_{DA}(t)$	Value of purchased load from the wholesale market [*MW*];
$\pi_n^{cu}(t)$	Selling electricity price to customer group *n* at hour *t* [*\$/MWh*];
$p^{forward}(t, fc)$	Amount of load according to the fc^{th} forward contract at hour *t* [*MW*];
$\zeta(t, fc)$	Price of fc^{th} forward contract at hour *t* [*\$/MWh*].

Conclusion

This paper first investigated the concept of smart cities to provide hardware and software platforms and to enable novel functionalities. The ultimate goal of smart cities is to improve the quality of life while making sure all technologies are deployed in a sustainable manner. The paper identified power systems as one of the major players in future smart cities. As power system modernization plays a pivotal role in city smartification, interdependent power and energy networks can expedite the path towards intelligent infrastructures by supplying reliable and sustainable energy to the end-users. This paper further focused on the promises of modern power systems for future smart cities. According to this aim, the current practices are explained for the transition from conventional fossil-fuel-based power systems towards smart grids which are more reliable, secure, and environmental-friendly. Also, the paper explored potential advantages and contributions of modern power systems in smart cities. As a use-case of promising technologies in power systems that affect the future smart cities, demand response programs and their implementation are investigated.

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