Mapping and Modeling Interdependent Power, Water, and Gas Infrastructures

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Abstract — **Although various aspects of interdependencies among Power, Water, and Gas (PWG) infrastructures have been studied in the last couple of decades, there still exists void of modeling techniques capable of revealing the interdependencies among real-world infrastructures. This paper presents review of the state-of-the-art knowledge on interdependent critical infrastructure (ICI) modeling techniques along with delineation and discussion of interdependencies at transmission and distribution levels among PWG networks. The present study will also outline the suitability of various approaches to work with real-time infrastructure monitoring data that is becoming abundantly available in the recent years. The paper also highlights some directions on future research in interdependency modeling as well as suggestions on improving real-time interdependent models in operational and physical aspects.**

***Index Terms* — Components, Cascading Failure, Interdependent Infrastructure, Power Grid, PWG Networks, Real-time.**

I. INTRODUCTION

UPON reviewing the state-of-the-art knowledge on interdependent critical infrastructures (ICIs), especially Power-Water-Gas (PWG), the variety of modeling techniques that have been previously used becomes clearly apparent. In the literature, most focus has been geared toward how failures are caused and cascaded from one PWG network to another; however, the consequences and the granularity at which such cascading mechanisms have been modeled varied widely. Besides, many researches have quantified interdependencies only between pairs of infrastructures [1]–[3] thereby limiting the breadth of interdependencies in our real-world ICIs. In this study, taking into consideration the two-way cascading effects of power grid on all other infrastructures including water and gas all at once is a priority. Also, as Rinaldi (2004) proposed, there are heuristic approaches to digging deep into the interoperability of PWG networks [4], but poor data acquisition and lack of real-world near-real-time data for model validation causes significant paucity of accuracy in the model. Needless to say, lack of sufficient and reliable data for validation purposes, in turn, will lead to the unlikelihood of temporal analysis focused on how often and how long does it take for a failure to cascade between ICIs. In an attempt to summarize the state-of-the-art knowledge and outstanding challenges with modeling failures in ICIs, this paper will: (i) briefly review the various ICI modeling techniques from the literature; (ii) map the specific dependencies among the PWG infrastructures; and (iii) assesses the suitability of modeling techniques for temporal analysis of cascading failures in ICIs. By addressing these aspects, future directions will be aimed at real-time modeling of large PWG networks with focus on predictive capabilities for real-time decision-making.

II. SUMMARY OF ICI MODELING TECHNIQUES

A. Identification and Literature Review

This section aims at highlighting the most recent reviews on ICI modeling and then identifying various modeling approaches. These methods have been comprehensively reviewed by Ouyang (2014) based on the following criteria: maturity, paradigm, monitoring area, data needs, course of triggered events, types of events, types of interdependencies, design strategies, and modeling focus [5]. Taking into account these criteria in this study, the paper is mainly focused on strengths and weaknesses inherent to the reviewed ICI modeling techniques are summarized. Owing to the growing nature of temporal relevance of ICIs as well as the complexity of interdependencies, suitability of ICI modeling techniques to leverage the currently available real-time monitoring data is discussed [6]–[10].

To begin with, Table 1 lists some of the most recent papers on how interdependencies among critical infrastructures are modeled

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and evaluated based on several metrics. Only those studies published after Ouyang's study [5] are listed in Table 1 to minimize repetition.

Table 1. Summary of ICI Simulation Methods and Modeling Approaches by Recent Scholars

Authors	Objectives and Methods Used
Pengshuai Cui (2016) [11]	A capability-based dependency model of interdependent networks that takes two node-dependency properties (connectivity and dependence links) into account; The general approach closes in on Numerical and Analytical Interpretations and numerical simulations.
Zlontik et al. (2017) [12]	Dynamic scheduling and simulation of coupled gas-electricity networks
Yang et al. (2015) [13]	Systematic modeling framework and simulation platform for coupled gas-power systems as well as analysis of impact of 6 factors (market and system related)
Tien and Chloe (2017) [14]	Methodology to model interdependencies probabilistically using a novel Bayesian network approach
Bing Li (2017) [15]	Framework to model economic impact of cascading failures occurring in power network as well as ranking the criticality of the components in power system
Zhang et al (2016) [1]	Cascading model; redistribution of load in power system to explore vulnerabilities

Based on the review of the studies listed in Table 1, it becomes apparent that nearly all of them are tailored to applying a specific method to a particular network for purposes like vulnerability or resilience assessment. However, real-time data has not been used to develop or validate ICI interdependency models that were previously proposed. Furthermore, a simple selection of modeling approach would not meet the requirements for an accurate real-time interoperability of interdependencies. It is opined that a combination of the following three models is required to have a real-time model that could support operations of ICIs: (i) demand forecasting model, (ii) simulation model and (iii) optimization model [8]. So, this means that a simple selection of modeling approach would not meet the requirements for an accurate real-time interoperability of interdependencies.

B. Outlining the Interdependency Modeling Methods

Various approaches of modeling ICIs have been reviewed in multiple studies [4], [5], [16]–[18]. Different taxonomies have been used by these authors to classify the models. Ouyang (2014) classified them in six broad categories: Empirical (E), Agent-based (AB), System Dynamics (SD), Economic Theory (ET), Network-based (NB) and other approaches which included Dynamic Control System Theory (DCST), Bayesian Network (BN), Petri-net, and Hierarchical Holographic Modeling (HHM) based models [5]. In present work, the first five modeling approaches – empirical, agent-based, system dynamics, economic theory, and network based – have been reviewed and building upon the review of Ouyang (2014) [5], these approaches have been analyzed for their suitability to model interdependencies in PWG considering temporal aspects.

Empirical modeling approaches build a database to identify and quantify failure patterns in critical infrastructures [19]–[22]. Since these models rely mainly on media reports and ex-post assessments [19], [23], [24], there are internal dependencies and intangible cross-infrastructure dependencies which remain unaccounted in empirical models. Empirical approaches have been used to model cascading failures [25], to identify alternatives for risk mitigation [26]. Generally, metrics used in empirical methods represent the behavior of infrastructure system as a whole [24], [29]. Majority of empirical methods have been used to investigate cascading failures in case of natural disasters or large scale disruptions [19], [22], [24], [28], [29], which are cases of extreme perturbation to the infrastructure systems. Models developed at such large scales are capable of capturing the failure scenarios only at a lower resolution due to the paucity of data and abstraction of processes in concerned infrastructures. Databases prepared for empirical analysis are highly specific to the event and location, so there remains lack of standardized framework even for similar types of failures. Interdependence effects are modeled for historical data that generally lack a quantifiable threshold for the criticality of CIs that makes it difficult to interpolate the impacts for perturbations of lower intensity. Despite having these limitations, empirical methods have proved useful in validation of models based on other approaches. Also, empirical methods are utilized to characterize the resilience of individual components in ICIs in the form of fragility curves [30].

Agent-based approaches have been used widely to model complex systems where each component is regarded as an individual agent and interacts with other agents and environment [31]. For example, NABLE is an agent-based model developed by Sandia National Laboratory which has the capabilities to model the interdependencies among various ICIs and economic firms [32]. Flexible Agent Simulation Toolkit (FAST) [33] and CIMS [34] are other agent-based models developed to study interdependencies.

Agent-based approaches have been used to model physical and logical interdependencies. Methods based on agent-based approach provide a flexible platform to model the interdependency among range of heterogeneous components. Moreover, this approach is deemed useful to model cognitive aspects in decision making at agent level [35] which is a uniqueness of this approach and can be exploited for real-time decision making. Agent-based methods are capable of modeling complex systems exhibiting a large number of interactions between agents. However, the complexity of these models increases significantly in modeling interdependencies considering all critical components.

System Dynamics (SD) based approaches model the interdependencies using causal loop diagram and stock flow diagrams. For example, CIP/DSS is an SD-based model used extensively to study the cascading failures to other infrastructures from disruptions in power supply [34], modeling outbreak of disease [36] and impacts of natural hazards on ICIs [37]. SD-based methods are capable of modeling the dynamics of the non-linear systems with temporal variations. Since quantification of interdependencies among CIs is based on experts' opinion and historical data [38], SD based methods need colossal calibration efforts to model physical interdependencies among real-world CIs. Identification of vulnerable components or a sub-system in an infrastructure is important and is emerging part of studies related to ICIs but standard SD-based methods are not capable of providing an effective platform for that.

Table 2. Pros and Cons of the Identified Methods

Methods	Strengths	Limitations
Empirical	• Used for validation of models based on other approaches • Can be used to model the fragility of components	• Database prepared are highly specific to causes of disruptions • Not able to capture failures/ impact of failure at component level
Agent-based	• Component level mapping is feasible • Capable of modeling complex behaviors • Can be used to model cognitive decision making	• Modeling is complex and data intensive unlike the network based models where topological information are sufficient • Difficult to update the model in case of changes in the network
System Dynamics	• Modeling of non-linear dynamic behavior of CIs is relatively easier • Have been used successfully in developing system level decision support systems	• Reflects the behavior of the CI as a whole; not able to model the dynamics at component level • SD based models need calibration in order to represent real-world systems, which further needs huge amount of data
Economic Theory	• Capable of quantifying the impact of inoperability among different sectors at large scale.	• Only systemic modeling is feasible; component level modeling is not feasible • Economic metrics depend on market dynamics as well; not a true representation of physical interdependencies
Topology based	• Provides a comprehensive method to investigate structural reliability of the systems	• Physical interdependencies among CIs can be modeled only for structural failure • Component criticality is derived more from an empirical framework rather than physics of the system
Flow based	• Capable of modeling the systems based on physics of the system and considering flow constraints of components • Has the potential to provide an efficient and accurate framework to model dynamics at a higher temporal resolution	• Operational data of the CIs is required for validation of the models • Computationally expensive

Economic approaches are based on the input-output economic model proposed by Leontief [39]. Input-output inoperability models (IIM) are utilized to investigate the impact of natural hazards and systemic failures on various industries and economy at a macro level [40]. IIM based model quantify interdependencies and impact of inoperability on various ICIs in terms of financial losses occurring owing to disruptions. Inoperability of similar nature and of the same order may have different monetary impacts depending on the market-dynamics.

Network-based approaches model each infrastructure system as a combination of nodes and arcs. Nodes can be categorized into four types – source, sink, transmission nodes and exchange point. Sources are locations in a network where generation of the commodity takes place, sinks are consumption points, transmission nodes represent a junction point with no consumption or generation, and exchange points are a special type of sink where consumption of the commodity is used to facilitate operation in some other infrastructure. Arcs represent the path of flow between two nodes (can be pipe/compressor /transmission line/distribution line). Ouyang (2014) regrouped network-based approaches into topology-based methods and flow-based methods [5]. Topological methods focus on assessing the reliability based on connectivity and structural redundancy in the network while flow-based methods delve deeper to consider the dynamics of the flow within and across the networks. Analytical methods have also been used to investigate cascading failures in ICIs [41], to create fictitious interdependent networks [1], to model redistribution of the load in power network and to quantify the vulnerability of the networks [1]. Most of the analytical models used so far have generalized the nodes and did not take the heterogeneity of the nodes into consideration [6]. In addition, analytical models need calibration in order to conform to real-world networks, which yet again is highly specific to the configuration of the networks. Simulation-based approaches have been more accurate in modeling interdependencies as the majority of simulation methods take into account the properties of different nodes and utilize heterogeneity of the nodes in quantifying system-level responses [2], [42].

Flow-based methods have been used to investigate the internal dynamics and cascading of ICI failures [43], [44]. A common approach in flow-based methods is to identify the exchange points between infrastructures. Flow based model has been used by [12] to investigate the interdependence effects in real-time in a coupled gas network and power system. Pressure variation in gas network owing to fluctuating intraday power demand at gas fired power generators was minimized by the proposed real-time scheduling of gas withdrawal[12]. Gomand et al. (2015) did a similar analysis for interdependent gas and electricity networks using a transient model with one hour time step [45]. Non-linear terms in fundamental equations make the dynamic modeling of the gas network a challenging task [46]. Most of the flow-based models quantify the failure cascades in terms of physical interdependencies. Since these models are derived from the basic laws of conservations, topological information along with boundary conditions may be sufficient to develop the models.

From the above discussion, we can say that the discussed approaches have been useful in studies with different objectives and scopes. While empirical methods are considered a good choice for swift but rough prediction of the consequences of a particular damage across the ICIs, agent-based approaches are capable of modeling multitudes of relationships among various components. SD-based methods have worked more useful than these two approaches in terms of predicting the dynamics of the systems. Since flow based methods are driven by fundamental laws of conservation, requirements of the calibration efforts are not as significant as they are in most of the discussed approaches although lack of real-world operational data of ICIs remains to be a challenge for researchers. The strengths and weaknesses of these reviewed ICI modeling techniques are summarized in Table 2.

III. COMPONENT-LEVEL MAPPING OF PWG

The purpose of this section is to provide a comprehensive outline of how major components in Water, Power, and Gas networks interact leading to operational dependencies. Such mapping would facilitate the modeling of the interdependencies among these infrastructures.

A. Identifying the Major Components

Table 3 outlines the significant components that comprise each of power, water and gas supply infrastructures. In this paper, the target is directed at first order dependencies where a failure or malfunction in one ICI network cause a cascading malfunction in another ICI network.

Table 3. PWG Identified Components [47]–[52]

Network	Components
Water	Pump Station (PS)
	Tanks (T)
	Water Treatment Plants (WTP)
	Valves (wV)
	Water Mains (WM)
	Fire Hydrants (FH)
Gas	Storage Tanks (ST)
	Transmission Line (High pressure) (TLH)
	Compressors (C)
	Regulators (R)
	City Gate Station (CGS)
	Distribution lines (low pressure) (DLL)
	Valves (wV)
Electricity	Circuit Breaker (CB)
	Transformer (Tr)
	Generator (G)
	Transmission Line (TLE)
	Command and Control System (CCS)
SCADA System	Controlling Room (CR)
	Communication Systems (CS)

B. Mapping of Interdependencies among PWG ICIs

Table 4 representing the correlation between components in one infrastructure and other networks based on "First Order" effects. In this context, first order correlation/failures are those that cause direct failures resulting from malfunction of one components to another.

Table 4. Dependencies among ICI Components [53]; The networks written in columns are described in how they are dependent on components provided in rows (Column-on-Row Dependency)

Networks	**Components**	**Power Network**	**Water Network**	**Gas Network**	**SCADA Systems**
Power Network	*Tr*, *G*, *D*		Power Supply for controlling systems, pumps, and other power-driven units	Power for control systems, storage, compressors, and other control units	Power for switches and telecom equipment
	TLE, *CCS*		Transmission lines and controlling system in power network will usually not "directly" cause failures to be cascaded into other networks. No "First Order" Effect		
Water Network	*PS*, *T*	Water for cooling some distributed gas-driven power generating units		No "First Order" Effect	Water for cooling facilities
	P&M, *wV*	No "First Order" Effect		No "First Order" Effect	No "First Order" Effect
	WTP	No "First Order" Effect		No "First Order" Effect	No "First Order" Effect
	WM	No "First Order" Effect		No "First Order" Effect	No "First Order" Effect
Gas Network	*ST*, *TLH*, *C*	Fuel for generators and heating	No "First Order" Effect		Fuel for heat, generators, and facilities
	R, *DLL*	No "First Order" Effect	No "First Order" Effect		No "First Order" Effect
SCADA	*CR*, *CS*	Distribution automation, EMS, and cybersecurity , crew repair telecom	Distribution automation, EMS, and cybersecurity , crew repair telecom	Distribution automation, EMS, and cybersecurity , crew repair telecom	

a) Effects of Power Outage

1) Consequences in Water Distribution Networks

This will lead to the deficiency in power supply to run the pumping stations in water networks. As an example, a typical pump station in a city takes almost 25 horsepower for each pump.

This implies a power advocating for 18 kW is demanded for each pump to operate. In that case, power shortage or outage will cause pump station to run slower, which results in pumps not being able to operate properly, thus failing to meet the water demands in the network and causing less efficiency in water system. Water demands not being satisfied would have further impacts depending on the type of consumers in the area being served. For example, loss of water would have much severe impact on a hospital than on a movie theater in the same neighborhood.

2) Consequences in Gas Network

Gas transmission networks have a highly sophisticated instrumentation and monitoring system which is controlled in real-time by SCADA system [50]. Control systems and compressors in gas network may need continuous supply of electricity. Majority of compressors in transmission networks use a part of the gas for compression purposes in reciprocating compressors, there still remains the need of electricity for the instrumentations in control systems [50].

3) Consequences in SCADA System

Shortly after the power outage, generally the first cascading failure will appear in SCADA system where all the units including Controlling Room and Communication Systems rely deeply on continuous power supply. Switches and telecommunication equipment serving the automation, emergency signaling as well as crew repair communication will run into critical issues. Although SCADA end points (namely known as "Remote Terminal Units") universally use battery backup systems to obviate the need for reliance on power grid [54], there is still the risk for backup failure which propagates the failure per se from power to SCADA system.

b) Failure in Water Distribution Networks

Huge amount of water is required in power-plants for cooling purpose [55] but since these plants withdraw water from lakes, rivers and other huge water bodies, their reliance on typical water distribution networks is negligible. Similarly, water is required in processing plants of natural gas. However, our main concern in this study falls in water distribution network which accounts for potable water supply right after it flows out of the treatment plants all the way down to end users. Water-demand of processing units is out of the scope of water distribution networks. Nevertheless, as there are distributed gas-driven power generation units in distribution lines, though limited proportionally, water is still needed for cooling these units at smaller scale than production level. Also, SCADA system is another section that requires water for preventing overheating in its units.

1) Consequences in SCADA System

Water circulation for cooldown purposes in SCADA facilities and units plays an essential part in assuring that the interdependency SCADA provides in between all other networks is well maintained. Particularly, "thermal noise" is a phenomenon whereby all transmission media and communication equipment including passive devices will experience if cooling systems are not present [56]. The higher the temperature of the components or the medium, the greater the level of thermal noise, and in turn, the higher the thermal noise is, the less efficient the transmission processes through RTUs[6] and PLCs[7] would be [56]. Thus, air or water coolants are required to keep the SCADA units and room allowably cool.

c) Failure in Gas Compressors and Transmission Lines

1) Consequences in Power Network

Since gas provides a substantial amount of energy to power grids in terms of running the plants, disruption amid the transmission phases in basic components like distribution-level gas processing units or compressors would have adverse effects on the operation of power components [57]. Through the year 2040, the U.S. electricity system will have demanded 340 GW of new generating capacity, 63 percent of which is planned to be supplied by natural gas plants [58]. Thus, a thorough understanding of the gas-power interdependency at componential level is required to optimize the production rate. One important unit lies in the combustion section where natural gas enters the turbine. There, cooling intake air temperatures are required to remain steady and proper through water droplets into the intake air, or simply thrusting the air into other cooling systems can improve the efficiency of the plant, thanks to the additional water use [59]. Therefore, this complex interdependency embraces all PWG networks to make sure gas processing units and storage tanks are well feeding energy into the power components like, basically generators, and transformers [58]. Hence, irregularity in generation unit through power grid will cause damage to electric units in other networks, like sensors and actuators as well as pumps in water network and SCADA units [59].

2) Consequences in SCADA System

Since gas-driven SCADA units are somewhat rare, there exists a minor interdependency between what might occur in gas network and what will consequently result in SCADA system. In case there is a separate in-house generator for SCADA room, gas will play more vital a role in providing energy to it [58].

[6] Remote Terminal Units

[7] Programmable Logic Controllers

d) Failure in Gas Distribution Lines and Regulators

Regulators accounts for reducing gas flow pressure to a predetermined extent [60]. This pressure reduction is subject to a hefty energy loss by containment through pressure regulators [60]. Failures in distribution lines and regulators affect the downstream end consumers which is mainly used for heating and cooking purposes. Majority of the gas-fired power plants have their own dedicated regulators and abstraction lines which withdraw gas directly from high pressure transmission lines. Therefore, first order effect has not been considered in this study.

In water distribution network majority of pumping units run on electricity. Diesel driven pumps have been most preferred back-up units in pumping stations and do not use gas for pumping purposes.

e) Failure in SCADA Components

Inasmuch as SCADA is the cornerstone of interdependent networks, any associated failure in its components will sooner or later causes other networks to fail one after another. In case units and slots at communication system in a SCADA room malfunction, the interoperability of PWG networks will be called into question. If data is not consecutively transmitted among networks via SCADA system, real-time applicability of PWG networks will be disrupted. Also, SCADA is well associated with human factors of interdependent systems; therefore, emergency response or operator/crew repair correspondence will be defective, so SCADA node failures make it impossible for human operators and centralized automated control systems to monitor and control a particular power node. SCADA node failures bring about the disintegration of communications network components; as a result, crew members/operators will be unable to compile data from particular components of the power network [54].

Following this further, other data-based components and parameters in PWG networks such as water pump pressure, gas pressure and temperature, and/or power ampere and voltage will be rendered useless or unreliable and this will make problematic the parametric predictions and design as well as cyber security or design for future reliability and resilience of all PWG networks [48]. In this case, Rafael Vida et al. (2014) presented a contagion matrix where they proved malware and virus spreading across all PWG networks would cause cascading defection in data acquisition and management throughout interdependent networks [61].

IV. TEMPORAL ASPECTS OF INTERDEPENDENCIES

In this section, literature review on temporal aspects of interdependencies is presented and challenges in this regard will be put forth.

One of the challenging issues that networks need to be called into discussion is real-time or near real-time operations of PWG grids. Cheng et al. (2014) presented their model "individually" on water distribution network, attempting to measure pressure head and flow rate at 15-minute time intervals [62]. Similarly, Quevedo et al. (2010) put forward their operational real-time parameters, mostly flow rate and head, for every 10 minutes of demand patterns by relying on over 200 control points, sectors, and/or sensors [63]. Identically, in power smart grid, Hu et al. (2018) practiced the real-time aspects of a mutual interaction between utility company and multiple users to monitor daily power usage by each end user at an hourly interval [64]. Also, Mohagheghi et al. (2018) proposed an algorithm whereby a real-time mid-voltage power distribution network is optimized through an ad-hoc case study [65]. Liu et al. (2017) suggested an approach to a distributed real-time optimal power flow control that is both meant to refine the system frequency and keep the generator power as close to the optimal operational parameters as possible in case of any perturbations [66]. However, very little research has been done to take into account the temporal aspects of PWG networks and their interdependencies altogether. First, two aspects of temporality should be regarded for yielding results: (i) operational parameters including power usage in power grid, pressure head and flow rate in water grid as well as pressure and temperature parameters in gas network, so as to clarify how fluctuations in an operational parameter in one infrastructure cascades into the disturbance in those in another infrastructure at a specific interval of time (e.g. a drop in water pressure head may take up to hours to cascade into power generators and cause drop in produced voltage) (ii) physical parameters and proximity collocation of components in networks including the interactions between interdependent components across the ICIs. Notwithstanding, the number of parameters regarded in different research attempts [7]–[10], [62], [63], [67]–[70] needs to significantly increase in order to reach out to an extremely accurate interdependent real-time model, although the model analysis will be computationally expensive.

More specifically, according to Table 4, if a cascading failure is to break out because of power shortage/outage and break into pump station component in water network, the two abovementioned aspects (operational and physical) should be parameterized. Hence, if "a" is assumed to be the power needed to run a pump (e.g. 25 horsepower/pump) and "b" is the amount of water needed for cooldown process of a power plant (20-60 gallons/every kilowatt hour) reciprocally and interdependently, a newfangled model is demanded to both assume (i) the formulation of "a" and "b" as the operational aspects of the two networks and their affiliated mutual interactions as well as the physical consequence these two components will have on each other; including but not limited to the roughness and reliability of connecting pipe in between the two components and/or the pump efficiency rate due to the failure from power generator that might cause backward flow or water hammer within pump station connections. After identifying the physical and operational interactions and parameters that a cascading failure might cause among PWG networks, time steps for monitoring these interactions in real-time should be considered. The perfect real-time model is to reduce the time of monitoring process of a failure from point A in one infrastructure all the way to point B from minutes/hours [63], [64] to seconds. All in all, the modeling challenges in this case turn out to be the integration of PWG network simulation models in a time-synchronized manner. Also, common optimization models for addressing parameters like reliability and costs or other control objectives should be bound in a real-time manner with the simulation model in a way that they work for very large networks at substantially short expansions of time. For now, individual models in the literature regarding updating simulation dynamics are taking on time steps of roughly as low as 5 to 15 minutes [6], [7], [62], [71], but this needs to decrease to less than a minute for multiple iterations for the purpose of high accuracy. What's more, the uncertainties associated with the interdependent networks need to be studied and partly assumed and eventually trained based on real-time monitoring data in order to come up with accurate models [72]. For example, pipe roughness, diameter changes, pump efficiency are of those dynamic uncertain parameters that make the modeling process more challenging and uncertain. It is proposed that such uncertainties can be addressed by leveraging real-world monitoring data and training computational intelligence algorithms.

V. CONCLUSION AND FUTURE WORK

This paper sheds light on different aspects of interdependent infrastructures. First, a comprehensive literature review of the state-of-the-art knowledge on what has been done thus far regarding the ICI modeling of PWG networks was presented along with the strengths and weaknesses of the modeling techniques. Subsequently, a mapping of interdependencies among PWG systems is presented. Lastly, challenges with modeling the temporal aspects of cascading failures in PWG networks are brought up and suggestions are made to develop suitable modeling techniques. Future work should be geared toward the substantial reduction in the duration of time steps to support real-time monitoring as well as identifying as many interdependently operational and physical parameters among PWG networks as possible.

VI. REFERENCES

[1] Y. Zhang, N. Yang, and U. Lall, "Modeling and simulation of the vulnerability of interdependent power-water infrastructure networks to cascading failures," *J. Syst. Sci. Syst. Eng.*, vol. 25, no. 1, pp. 102–118, 2016.

[2] L. Duenas-Osorio, J. I. Craig, and B. J. Goodno, "Seismic response of critical interdependent networks," *Earthq. Eng. Struct. Dyn.*, vol. 36, no. 2, pp. 285–306, 2007.

[3] M. Shahidehpour, Yong Fu, and T. Wiedman, "Impact of Natural Gas Infrastructure on Electric Power Systems," *Proc. IEEE*, vol. 93, no. 5, pp. 1042–1056, 2005.

[4] S. M. Rinaldi, "Modeling and simulating critical infrastructures and their interdependencies," *37th Annu. Hawaii Int. Conf. Syst. Sci. 2004. Proc.*, p. 8 pp., 2004.

[5] M. Ouyang, "Review on modeling and simulation of interdependent critical infrastructure systems," *Reliab. Eng. Syst. Saf.*, vol. 121, pp. 43–60, 2014.

[6] A. Agathokleous, S. Xanthos, and S. E. Christodoulou, "Real-time monitoring of water distribution networks," *Water Util. J.*, vol. 10, pp. 15–24, 2015.

[7] N. Fontana, M. Giugni, L. Glielmo, G. Marini, and F. Verrilli, "Real-time control of a PRV in water distribution networks for pressure regulation: Theoretical framework and laboratory experiments," *J. Water Resour. Plan. Manag.*, vol. 144, no. 1, pp. 1–14, 2018.

[8] F. K. Odan, L. F. Ribeiro Reis, and Z. Kapelan, "Real-Time Multiobjective Optimization of Operation of Water Supply Systems," *J. Water Resour. Plan. Manag.*, vol. 141, no. 9, p. 04015011, 2015.

[9] B. M. Brentan, E. Luvizotto, M. Herrera, J. Izquierdo, and R. Pérez-García, "Hybrid regression model for near real-time urban water demand forecasting," *J. Comput. Appl. Math.*, vol. 309, pp. 532–541, 2017.

[10] E. C. A. C. M. F. and C. Modica4, "Unsteady Flow Modeling of Pressure Real-Time Control in Water Distribution Networks," *J. Water Resour. Plan. Manag. © ASCE, ISSN 0733-9496*, vol. 143, no. 9, pp. 1–10, 2017.

[11] P. Cui, P. Zhu, C. Shao, and P. Xun, "Cascading failures in interdependent networks due to insufficient received support capability," *Phys. A Stat. Mech. its Appl.*, vol. 469, pp. 777–788, 2017.

[12] A. Zlotnik, L. Roald, S. Backhaus, M. Chertkov, and G. Andersson, "Coordinated Scheduling for Interdependent Electric Power and Natural Gas Infrastructures," *IEEE Trans. Power Syst.*, vol. 32, no. 1, pp. 600–610, 2017.

[13] H. Yang, J. Qiu, S. Zhang, M. Lai, and Z. Y. Dong, "Interdependency assessment of coupled natural gas and power systems in energy market," *Int. J. Emerg. Electr. Power Syst.*, vol. 16, no. 6, pp. 525–536, 2015.

[14] I. Tien, A. Musaev, D. Benas, A. Ghadi, S. Goodman, and C. Pu, "Detection of damage and failure events of critical public infrastructure using social sensor big data," *IoTBD 2016 - Proc. Int. Conf. Internet Things Big Data*, no. IoTBD, pp. 435–440, 2016.

[15] B. Li, B. Gjorgiev, and G. Sansavini, "A genetic algorithm based calibration approach on validating cascading failure analysis," *2017 IEEE Power Energy Soc. Gen. Meet.*, pp. 1–5, 2017.

[16] S. M. Rinaldi, J. P. Peerenboom, and T. K. Kelly, "Identifying, understanding, and analyzing critical infrastructure interdependencies," *IEEE Control Syst. Mag.*, vol. 21, no. 6, pp. 11–25, 2001.

[17] M. Iturriza, L. Labaka, J. M. Sarriegi, and J. Hernantes, "Modelling methodologies for analysing critical infrastructures," *J. Simul.*, pp. 1–16, Jan. 2018.

[18] R. Setola and M. Theocharidou, "Modelling Dependencies Between Critical Infrastructures," 2016, pp. 19–41.

[19] T. McDaniels, S. Chang, K. Peterson, J. Mikawoz, and D. Reed, "Empirical Framework for Characterizing Infrastructure Failure Interdependencies," *J. Infrastruct. Syst.*, vol. 13, no. 3, pp. 175–184, Sep. 2007.

[20] D. Mendonça and W. A. Wallace, "Impacts of the 2001 World Trade Center Attack on New York City Critical Infrastructures," *J. Infrastruct. Syst.*, vol. 12, no. 4, pp. 260–270, Dec. 2006.

[21] E. Luiijf, A. Nieuwenhuijs, M. Klaver, M. van Eeten, and E. Cruz, "Empirical Findings on Critical Infrastructure Dependencies in Europe," Springer, Berlin, Heidelberg, 2009, pp. 302–310.

[22] S. E. Chang, T. McDaniels, and C. Beaubien, "Societal Impacts of Infrastructure Failure Interdependencies: Building an Empirical Knowledge Base," in *TCLEE 2009*, 2009, pp. 1–10.

[23] S. E. Chang, T. L. McDaniels, J. Mikawoz, and K. Peterson, "Infrastructure failure interdependencies in extreme events: power outage consequences in the 1998 Ice Storm," *Nat. Hazards*, vol. 41, no. 2, pp. 337–358, Apr. 2007.

[24] J. E. Bigger, M. G. Willingham, F. Krimgold, and L. Mili, "Consequences of Critical Infrastructure Interdependencies: Lessons From the 2004 Hurricane Season in Florida," *Int. J. Crit. Infrastructures*, vol. 5, no. 3, pp. 199–219, 2009.

[25] I. B. Utne, P. Hokstad, and J. Vatn, "A method for risk modeling of interdependencies in critical infrastructures," *Reliab. Eng. Syst. Saf.*, vol. 96, no. 6, pp. 671–678, Jun. 2011.

[26] G. H. Kjølle, I. B. Utne, and O. Gjerde, "Risk analysis of critical

infrastructures emphasizing electricity supply and interdependencies," *Reliab. Eng. Syst. Saf.*, vol. 105, pp. 80–89, Sep. 2012.
[27] R. Zimmerman, "Decision-making and the vulnerability of interdependent critical infrastructure," in *2004 IEEE International Conference on Systems, Man and Cybernetics (IEEE Cat. No.04CH37583)*, vol. 5, pp. 4059–4063.
[28] Y. Kajitani and S. Sagai, "Modelling the interdependencies of critical infrastructures during natural disasters: a case of supply, communication and transportation infrastructures," *Int. J. Crit. Infrastructures*, vol. 5, no. 1/2, p. 38, 2009.
[29] M. Rong, C. Han, and L. Liu, "Critical Infrastructure Failure Interdependencies in the 2008 Chinese Winter Storms," in *2010 International Conference on Management and Service Science*, 2010, pp. 1–4.
[30] S. Dunn, S. Wilkinson, D. Alderson, H. Fowler, and C. Galasso, "Fragility Curves for Assessing the Resilience of Electricity Networks Constructed from an Extensive Fault Database," *Nat. Hazards Rev.*, vol. 19, no. 1, p. 04017019, Feb. 2018.
[31] J. H. Holland, "Complex Adaptive Systems," *Daedalus; Winter Res. Libr. pg*, vol. 121, no. 1, 1992.
[32] D. A. Schoenwald, D. C. Barton, and M. A. Ehlen, "An Agent-Based Simulation Laboratory for Economics and Infrastructure Interdependency."
[33] M. J. North, "Toward Strength and Stability," *Soc. Sci. Comput. Rev.*, vol. 19, no. 3, pp. 307–323, Aug. 2001.
[34] D. D. Dudenhoeffer, M. R. Permann, and M. Manic, "CIMS: A framework for infrastructure interdependency modeling and analysis," *Proc. - Winter Simul. Conf.*, no. Clinton 1996, pp. 478–485, 2006.
[35] M. A. Niazi and A. Hussain, *Cognitive Agent-based Computing-I*, vol. 1. Dordrecht: Springer Netherlands, 2013.
[36] J. M. Fair *et al.*, "An Integrated Simulation of Pandemic Influenza Evolution, Mitigation and Infrastructure Response," in *2007 IEEE Conference on Technologies for Homeland Security*, 2007, pp. 240–245.
[37] L. J. Steinberg, N. Santella, and C. B. Zoli, "The Role of Critical Infrastructure Modeling in Promoting Resilience INTRODUCTION: CIPDSS Validation Study as an Occasion for Monitoring Resilience."
[38] E. Canzani, "Modeling Dynamics of Disruptive Events for Impact Analysis in Networked Critical Infrastructures," *Proc. 13th Int. Conf. Inf. Syst. Cris. Response Manag. ISCRAM 2016.*, no. May, 2016.
[39] W. W. Leontief, "Input-Output Economics," 1951.
[40] K. G. Crowther, Y. Y. Haimes, and G. Taub, "Systemic Valuation of Strategic Preparedness Through Application of the Inoperability Input-Output Model with Lessons Learned from Hurricane Katrina," *Risk Anal.*, vol. 27, no. 5, pp. 1345–1364, Dec. 2007.
[41] S. V. Buldyrev, R. Parshani, G. Paul, H. E. Stanley, and S. Havlin, "Catastrophic cascade of failures in interdependent networks," *Nature*, vol. 464, no. 7291, pp. 1025–1028, 2010.
[42] I. Hernandez-Fajardo and L. Dueñas-Osorio, "Probabilistic study of cascading failures in complex interdependent lifeline systems," *Reliab. Eng. Syst. Saf.*, vol. 111, pp. 260–272, 2013.
[43] L. K. Nozick, M. A. Turnquist, D. A. Jones, J. R. Davis, and C. R. Lawton, "Assessing the performance of interdependent infrastructures and optimising investments," *Int. J. Crit. Infrastructures*, vol. 1, no. 2/3, p. 144, 2005.
[44] S. Delamare, A. A. Diallo, and C. Chaudet, "High-level modelling of critical infrastructures' interdependencies," *Int. J. Crit. Infrastructures*, vol. 5, no. 1/2, p. 100, 2009.
[45] O. Gomand, A. Antenucci, B. Li, and G. Sansavini, "Modelling interdependent electric power and gas networks in the context of cascading failures," in *Safety and Reliability of Complex Engineered Systems*, CRC Press, 2015, pp. 4413–4421.
[46] Y. Chen, W. Wei, F. Liu, and S. Mei, "A multi-lateral trading model for coupled gas-heat-power energy networks," *Appl. Energy*, vol. 200, pp. 180–191, 2017.
[47] C. Bohan, "Introduction to Water Distribution Systems," *Dep. Environ. Conserv.*, pp. 147–194, 2012.
[48] C. Heracleous, P. Kolios, C. G. Panayiotou, G. Ellinas, and M. M. Polycarpou, "Hybrid systems modeling for critical infrastructures interdependency analysis," *Reliab. Eng. Syst. Saf.*, vol. 165, no. August 2016, pp. 89–101, 2017.
[49] T. Report, "Interdependence of the Electricity Generation System and the Natural Gas System and Implications for," no. May, 2013.
[50] S.M. Folga, "Natural Gas Pipeline Technology Overview," *Environ. Sci. Div.*, 2007.
[51] S. Spradley, S. Edwards, J, R. Leffer, H. Underhill, and R. Callahan, "People and Processes: Current State of Telecommunications and Electric Power Interdependencies," *Telecommun. Electr. Power Interdepend. Task Force*, vol. January, 2006.
[52] W. Systems, "DISASTER RESILIENCE FRAMEWORK," *Water Wastewater Syst. Introd. 9. Water Wastewater Syst. San Diego CA Work.*, pp. 1–32, 2015.
[53] GITA, "The Geospatial Dimensions of Critical Infrastructure and Emergency Response White Paper Series," no. 1, pp. 1–9, 2008.
[54] R. Kurz, M. Lubomirsky, and K. Brun, "Gas compressor station economic optimization," *Int. J. Rotating Mach.*, vol. 2012, 2012.
[55] "Electricity's Thirst for a Precious Resource: A Report of the Energy and Water in a Warming World Initiative."
[56] I. Mukherjee and I. A. Gadoura, "Low-Thermal Noise Input-Filter Design for DC/DC Power Regulators," *IFAC Proc. Vol.*, vol. 44, no. 1, pp. 12201–12206, Jan. 2011.
[57] B. C. Erdener, K. A. Pambour, R. B. Lavin, and B. Dengiz, "An integrated simulation model for analysing electricity and gas systems," *Int. J. Electr. Power Energy Syst.*, vol. 61, pp. 410–420, 2014.
[58] Center for climate and energy solutions C2ES, "Leveraging Natural Gas to Reduce Greenhouse Gas Emissions," no. June, p. 116, 2013.
[59] M. Doyle and H. Fell, "Fuel prices, restructuring, and natural gas plant operations," *Resour. Energy Econ.*, vol. 52, pp. 153–172, May 2018.
[60] E. G. Rami, B. Jean-Jacques, G. Pascal, and M. François, "Stability study and modelling of a pressure regulating station," *Int. J. Press. Vessel. Pip.*, vol. 82, no. 1, pp. 51–60, Jan. 2005.
[61] R. Vida, J. Galeano, and S. Cuenda, "Vulnerability of state-interdependent networks under malware spreading," *Phys. A Stat. Mech. its Appl.*, vol. 421, pp. 134–140, Mar. 2015.
[62] W. P. Cheng, T. C. Yu, and G. Xu, "Real-time model of a large-scale water distribution system," *Procedia Eng.*, vol. 89, pp. 457–466, 2014.
[63] J. Quevedo *et al.*, "Validation and reconstruction of flow meter data in the Barcelona water distribution network," *Control Eng. Pract.*, vol. 18, no. 6, pp. 640–651, Jun. 2010.
[64] M. Hu, J.-W. Xiao, S.-C. Cui, and Y.-W. Wang, "Distributed real-time demand response for energy management scheduling in smart grid," *Int. J. Electr. Power Energy Syst.*, vol. 99, pp. 233–245, Jul. 2018.
[65] E. Mohagheghi, A. Gabash, M. Alramlawi, and P. Li, "Real-time optimal power flow with reactive power dispatch of wind stations using a reconciliation algorithm," *Renew. Energy*, vol. 126, pp. 509–523, 2018.
[66] Y. Liu, Z. Qu, H. Xin, and D. Gan, "Distributed Real-Time Optimal Power Flow Control in Smart Grid," *IEEE Trans. Power Syst.*, vol. 32, no. 5, pp. 3403–3414, 2017.
[67] M. Romano and Z. Kapelan, "Adaptive water demand forecasting for near real-time management of smart water distribution systems," *Environ. Model. Softw.*, vol. 60, pp. 265–276, 2014.
[68] B. M. Brentan, E. L. Jr., I. Montalvo, J. Izquierdo, and R. Pérez-García, "Near Real Time Pump Optimization and Pressure Management," *Procedia Eng.*, vol. 186, pp. 666–675, 2017.
[69] Y. Ishido and S. Takahashi, "A new indicator for real-time leak detection in water distribution networks: Design and simulation validation," *Procedia Eng.*, vol. 89, pp. 411–417, 2014.
[70] U. Shamir and E. Salomons, "Optimal Real-Time Operation of Urban Water Distribution Systems Using Reduced Models," *J. Water Resour. Plan. Manag.*, vol. 134, no. 2, pp. 181–185, 2008.
[71] P. F. Boulos, L. Jabonsen, J. Heath, and S. Kamojjala, "Expanded Summary Real-time modeling of water distribution systems : A case study," *J. AWWA*, 2014.
[72] A. Vassiljev, M. Koor, and T. Koppel, "Real-time demands and calibration of water distribution systems," *Adv. Eng. Softw.*, vol. 89, pp. 108–113, 2015.