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Distributed Post-Disaster Restoration of Interdependent Infrastructure Networks under Spatially Correlated Regional Hazards

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Abstract: Regional hazards can severely disrupt interdependent infrastructure networks, and post-disaster restoration is further complicated by spatially correlated repair uncertainty and limited data sharing among networks. This paper proposes a distributed post-disaster restoration framework for interdependent power and water networks with a known initial damage set. Spatially correlated repair durations are generated through a Gaussian copula, and a representative scenario set is generated via a scenario reduction method. A two-stage stochastic mixed-integer model determines a repair schedule in Stage 1, while Stage 2 optimizes network operation under each repair-duration scenario. To coordinate different operators under privacy constraints an Alternating Direction Method of Multipliers with embedded Logic-Based Benders Decomposition (ADMM-LBBD) is developed and only the status of dependency-pair nodes is exchanged through shared gate variables in this method. Applied to the Shelby County power-water system, the distributed method converges in 9 ADMM iterations and yields a cumulative satisfied demand of 3635, compared with 561 for the no-repair benchmark and 3994 for centralized coordination. The solution also reveals a consistent power-first, water-follows recovery pattern induced by physical interdependencies. Overall, the proposed method achieves performance within 91% of a centralized solution while preserving data privacy and maintaining tractable computation.

Keywords: Interdependent infrastructure networks, decentralized post-disaster restoration, two-stage stochastic programming, spatial correlation, ADMM-LBBD.

1. Introduction

Natural hazards and human-induced disruptions continue to expose the vulnerability of lifeline infrastructures such as electric power and water supply systems. In modern cities, these infrastructures are operated as tightly coupled networks: while interdependencies improve efficiency in normal conditions, they also create pathways for failure propagation and can amplify disruption impacts through cascading service losses [1]. As a result, effective restoration depends not only on within-network repair prioritization but also on synchronizing enabling components across interdependent systems under realistic decision-making environments [2].

Restoration optimization of interdependent infrastructure networks has therefore attracted substantial attention, yet most formulations remain centralized and assume a single decision-maker with full information who jointly schedules repairs and operations. For coupled power-water systems, recent work has focused on jointly optimizing network restoration plans under multiple sources of uncertainty [3,4], and mean-risk formulations with decomposition-based solution methods have been proposed for interdependent infrastructure restoration [5]. Although such centralized models can produce high-quality schedules, the assumption of unified control is often unrealistic: power and water systems are frequently owned and operated by independent entities, and detailed topology, repair parameters, and operational data are not readily shared due to institutional boundaries and privacy constraints. Decentralized restoration mechanisms, including resource-allocation schemes for interdependent networks [6] and adaptive restoration under imperfect information sharing [7], have begun to address these governance and privacy constraints. Nevertheless, decision-making remains challenging once restoration uncertainty, particularly repair-duration uncertainty, is explicitly considered.

Repair duration is a primary source of restoration uncertainty, and it has been highlighted in the resilience literature [8]. Repair durations depend on evolving field conditions, secondary hazards, transportation accessibility, and resource logistics [9], and thus tend to be geographically clustered [13]. Systematically embedding spatially correlated repair-duration uncertainty into interdependent restoration planning, especially under a distributed framework, remains underexplored.

From an algorithmic standpoint, distributed optimization provides a natural coordination tool under autonomy. The Alternating Direction Method of Multipliers (ADMM) is widely used to enforce consensus by iterating between local subproblems and multiplier updates, with scalability properties for convex problems [10]. Interdependent restoration scheduling, however, is mixed-integer, and ADMM may yield oscillatory or fractional consensus decisions. Therefore, this problem requires additional mechanisms to obtain implementable solutions [11].

To address these gaps, this paper develops a distributed stochastic restoration framework for interdependent power-water networks under spatially correlated repair-duration uncertainty. Repair durations are sampled using a Gaussian-copula construction with discrete marginals and reduced to a representative scenario set via a scenario reduction method [12]. Cross-network coupling is enforced through shared gate variables associated with interdependency pairs, so that only gate status is exchanged. An ADMM embedded with logic-based Benders decomposition (ADMM-LBBD) is proposed to coordinate the two operators while preserving data privacy and to generate implementable restoration schedules. The remainder of the paper presents the modelling framework, the proposed model, the solution methodology, and case studies.

2. Modelling Framework

Natural hazards with regional footprints and spatially correlated impacts on interdependent networks are considered in this work, including earthquakes, typhoon-induced urban flooding, severe icing and snowstorms, and extreme storm surges. Such events generate hazard fields (e.g., ground-motion intensity, wind-rain loads, ice accretion, and water depth) that can simultaneously disrupt a large number of assets. During the emergency phase, supported by rapid reconnaissance and remote sensing, the initial set of failed components can typically be identified within a short time. By contrast, the completion time of repairs at individual damaged sites is difficult to predict, as it is influenced by multiple evolving factors, including secondary perturbations (e.g., aftershocks, re-inundation, and refreezing), access restrictions caused by landslides, standing water, or road closures, and fluctuations in material logistics and crew rostering. Collectively, these factors make repair duration the dominant short-term source of randomness in post-disaster recovery. Accordingly, the initial damage state of the network is treated as known, whereas the repair durations of nodes and links are modeled as random variables. Because disaster impacts and accessibility constraints are often geographically clustered, restoration times typically exhibit spatial correlation and should not be approximated as independent and identically distributed (i.i.d.). To capture this feature, repair durations are represented using a scenario-based discrete distribution. For network k, the repair durations of node i and link (i, j) are defined as:

$$\begin{aligned} D_i^k &= \left\{ d_1^{(i)}, \ldots, d_n^{(i)} \right\}, \pi_i^k \in H^n \\ D_{ij}^k &= \left\{ d_1^{(ij)}, \ldots, d_m^{(ij)} \right\}, \pi_{ij}^k \in H^m \end{aligned} \tag{1}$$

The probability masses π^k associated with the discrete repair-time outcomes can be elicited from prior-event statistics or expert judgement. Spatial correlation in disaster-induced restoration uncertainty is modeled. For each network, a distance matrix $\mathbf{H}$ is constructed over nodes (or, analogously, over links), and separate correlation-strength parameters are specified for nodes and for links. An exponential kernel is adopted to characterize spatial dependence [13].

$$\mathbf{K} = \kappa \exp(-\mathbf{H} / l) + (1 - \kappa)\mathbf{I} \tag{2}$$

This specification implies stronger correlation for assets that are closer in distance and an exponential decay as distance increases, while retaining a small independent-noise component via $(1-\kappa)\mathbf{I}$. Empirically, such a kernel is consistent with locally correlated, rapidly decaying patterns observed in seismic PGA fields, typhoon wind-rain loads, and accreted ice thickness.

Additionally, each interdependent network is modeled as a multi-source, multi-sink maximum-flow network. Network performance is quantified by the total satisfied demand, subject to flow-conservation and arc-capacity limits constraints.

3. Proposed Model

Given a known post-disaster damage state, a restoration problem for interdependent power-water networks is formulated to minimize the penalty associated with unmet demand over a predefined planning horizon. A subset of intermediate nodes is subject to a unidirectional interdependency: specifically, the operational status of a dependent water-system node is constrained to be no higher than that of its paired power-system node. This constraint captures the physical requirement that water pumping and conveyance cannot be provided in the absence of electricity supply.

A two-stage cost-minimization framework is adopted. Conditional on the observed initial damage configuration, Stage 1 determines a here-and-now restoration schedule over the planning horizon, including the repair start times of damaged components (e.g., substations and transmission lines in the power system; pumping stations and pipelines in the water system) and the assignment of limited repair crews. These Stage-1 decisions are scenario-independent and are fixed before the uncertain repair durations are revealed. Uncertainty is represented by the repair durations of damaged components. In Stage 2, after a repair-duration scenario is realized, the resulting component availability trajectories are induced, and network operation is adjusted accordingly. A damaged component is assumed to provide no service until its repair is complete, and temporary stopgap measures (e.g., mobile generators or alternative water deliveries) are not considered. Interdependency constraints explicitly couple the restoration of water-pumping functionality to the restoration of the corresponding power-supply components. The cost function accounts for service-interruption penalties arising from unmet electricity and water demand. Notation for parameters and decision variables is summarized in Table 1.

Table 1. Notations.

Notations	Descriptions
f_i^k	Node repair cost parameter of node i in network k
f_{ij}^k	Link repair cost parameter of link (i,j) in network k
M_j^k	Penalty cost for unsatisfied demand of node j in network k
$z_{ij,1}^k$	Link status of link (i,j) in network k at time $t=1$
$z_{i,1}^k$	Node status of node i in network k at time $t=1$
δ_i^k	Node initial damage indicator
δ_{ij}^k	Link initial damage indicator
R^k	Number of repair crews in network k
u_{ij}^k	Link capacity of link (i,j) in network k
θ_j^k	Network node demand of node j in network k
γ_i^k	Network node supply of node i in network k
p_ω	Scenario probability
Ω	Scenario set
O^k , D^k	Supply-node and Demand-node set
V^k	Transit node set
N^k , L^k	Set of nodes and links
Ψ	Dependency pairs across networks
$D_{ij,\omega}^k$	Link repair duration in scenario ω
$D_{i,\omega}^k$	Node repair duration in scenario ω
bud	Repair budget cap
A^k	The input of the structure matrix of the network
Decision variables	
$y_{i,t}^k$	Repair decision variable of node i in network k at time t
$y_{ij,t}^k$	Repair decision variable of link (i,j) in network k at time t
$x_{ij,t,\omega}^k$	Link flow of link (i,j) in network k at time t under scenario ω

$\Delta^k_{j,t,\omega}$	Unmet demand of node j in network k at time t under scenario ω
$z^k_{ij,t,\omega}$	Link status of link (i,j) in network k at time t under scenario ω
$z^k_{i,t,\omega}$	Node status of node i in network k at time t under scenario ω

$$\min Z = \sum_{\omega\in\Omega} p_\omega \sum_{t\in T}\left(\sum_{k\in K}\sum_{j\in D^k} M^k_j \Delta^k_{j,t,\omega}\right) \quad (3)$$

$$\sum_{t\in T}\sum_{k\in K}\left(\sum_{i\in N^k} f^k_i y^k_{i,t} + \sum_{(i,j)\in L^k} f^k_{ij} y^k_{ij,t}\right) \le bud \quad (4)$$

$$\begin{cases}\sum_{t\in T} y^k_{i,t} \le \delta^k_i \\ \sum_{t\in T} y^k_{ij,t} \le \delta^k_{ij}\end{cases}, \forall (i,j)\in L^k, i\in N^k, k\in K \quad (5)$$

$$\begin{cases} z^k_{i,1,\omega} = 1-\delta^k_i \\ z^k_{ij,1,\omega} = 1-\delta^k_{ij}\end{cases}, \forall (i,j)\in L^k, i\in N^k, k\in K \quad (6)$$

$$\begin{cases} z^k_{i,t-1,\omega} \le z^k_{i,t,\omega} \\ z^k_{ij,t-1,\omega} \le z^k_{ij,t,\omega}\end{cases}, \forall (i,j)\in L^k, i\in N^k, k, t\ge 2 \quad (7)$$

$$\begin{cases} z^k_{i,t,w} \le \left(1-\delta^k_i\right) + \sum_{\tau=2}^{t-D^k_{i,w}} y^k_{i,\tau} \\ z^k_{ij,t,w} \le \left(1-\delta^k_{ij}\right) + \sum_{\tau=2}^{t-D^k_{ij,w}} y^k_{ij,\tau}\end{cases} \forall i,k,\omega,\forall t\ge 2 \quad (8)$$

$$\begin{cases} z^k_{ij,t,w} \le z^k_{i,t,w} \\ z^k_{ij,t,w} \le z^k_{j,t,w}\end{cases} \forall (i,j)\in L^k, k, \omega, t \quad (9)$$

$$\sum_i \sum_{\tau=\max\left(2,t-D^k_{i,w}+1\right)}^{t} y^k_{i,\tau} + \sum_{ij}\sum_{\tau=\max\left(2,t-D^{k,E}_{e,w}+1\right)}^{t} y^k_{ij,\tau} \le R^k \quad (10)$$

$$-u^k_{ij} z^k_{ij,t,\omega} \le x^k_{ij,t,\omega} \le u^k_{ij} z^k_{ij,t,\omega}, \forall (i,j), k, \omega, t \quad (11)$$

$$A^k_{j,\cdot} x^k_{\cdot,t,\omega} = 1-\Delta^k_{j,t,\omega}, \forall j\in D^k, \omega, t \quad (12)$$

$$0 \le 1-\Delta^k_{j,t,\omega} \le \theta^k_j z^k_{j,t,\omega}, j\in D^k, \omega, t \quad (13)$$

$$0 \le A^k_{i,\cdot} x^k_{\cdot,t,\omega} \le \gamma^k_i z^k_{i,t,\omega}, \forall i\in O^k, \omega, t \quad (14)$$

$$A^k_{i,\cdot} x^k_{\cdot,t,\omega} = 0, \forall i\in \mathcal{V}^k, \omega, t \quad (15)$$

$$z^{k_2}_{v_r,t,\omega} \le z^{k_1}_{u_r,t,\omega}, \forall r:(u_r,v_r)\in\Psi, \omega, t \quad (16)$$

$$x^k_{ij,t}, \Delta^k_{j,t} \ge 0, y^k_{ij,t}, y^k_{i,t}, z^k_{i,t}, z^k_{ij,t} \in \{0,1\} \quad (17)$$

Objective (3) minimizes the expected penalty associated with unmet demand over the planning horizon and across all scenarios. Budget feasibility is enforced by constraint (4), while the repair-only-if-damaged and at-most-once rule is imposed by constraint (5). Component availability is initialized from the observed damage state in constraint (6) and must be nondecreasing over time under constraint (7). The linkage between repair starts and restoration completion under scenario-dependent durations is captured by constraint (8), and link availability is further bounded by the availability of its end nodes in constraint (9). An occupancy-style crew limit per period is enforced in constraint (10) by counting all repairs that remain active given their durations.

Operational feasibility is represented through network-flow constraints. Link flows are limited by the product of rated capacity and the corresponding availability indicator in constraint (11). Flow balance at demand nodes is enforced in constraint (12) with a shortage variable, and the served demand is upper-bounded by the nominal demand scaled by node availability in constraint (13). Supply injections are bounded by the corresponding capacities scaled by availability in constraint (14), while zero net injection is enforced at transit nodes in constraint (15). Cross-network interdependency is captured by constraint (16), requiring that the availability of each dependent water node does not exceed that of its paired power node at any time and in any scenario. Variable domains are specified in constraint (17).

Defining the centralized formulation (3)-(17), a distributed variant can be constructed by limiting information exchange to the operational status of pre-identified dependency-node pairs. For each pair (u_r, v_r), period t, and scenario ω, a shared consensus gate variable $s_{r,t,\omega}$ is introduced as an auxiliary coordination variable. It represents whether the dependency pair is activated: the dependent water-side node can be available only if the gate is open, and the gate can open only if the corresponding power-side node is available. The original interdependency constraint (16) is therefore equivalently rewritten as the two gate inequalities (18)-(19). In this way, the direct coupling between the power and water networks is transformed into a consensus form that supports ADMM-LBBD, while requiring only pair-status information to be exchanged.

$$z^{k_2}_{v_r,t,\omega} \le s_{r,t,\omega}, \forall r:(u_r,v_r)\in\Psi,\omega,t \quad (18)$$

$$s_{r,t,\omega} \le z^{k_1}_{u_r,t,\omega}, \forall r:(u_r,v_r)\in\Psi,\omega,t \quad (19)$$

4. Solution Methodology

To optimize the stochastic restoration model, the uncertain repair-duration parameters must be specified. Under the modeling assumptions, joint repair-duration scenarios are generated via a Gaussian copula with discrete marginals, whose dependence structure is parameterized by a correlation matrix constructed from the exponential kernel introduced earlier. Correlated Gaussian vectors are first sampled and then transformed into correlated uniform variates through a probability mapping, after which a discrete inverse transform is applied to obtain node and link repair durations consistent with the marginal discrete supports defined in (1).

Let G denote a correlated Gaussian vector and let $\Phi(\bullet)$ be the standard normal cumulative distribution function applied componentwise. The correlated uniforms are obtained by:

$$U=\Phi(G) \quad (20)$$

Given the marginal discrete probability masses π^k in (1), the repair duration is obtained via an inverse transform mapping. For a node i and a link (i,j), the mapping can be written as:

$$D^k_{i,\omega}=d^{(i)}_r \;\text{ if } \sum_{q=1}^{r-1}\pi^k_i(q)<U_i\le\sum_{q=1}^{r}\pi^k_i(q) \quad (21)$$

$$D^k_{ij,\omega}=d^{(ij)}_r \;\text{ if } \sum_{q=1}^{r-1}\pi^k_{ij}(q)<U_{ij}\le\sum_{q=1}^{r}\pi^k_{ij}(q) \quad (22)$$

This construction maps cumulative probability intervals to discrete support points, thereby producing a discrete repair duration for each node or link while preserving the dependence structure induced by the copula. The scenario-generation procedure can be summarized as follows: (i) construct correlation kernels for nodes and links; (ii) draw correlated Gaussian samples and transform them into correlated uniforms; (iii) map each uniform realization to a discrete duration using the marginal probability masses in Eq.(1) through the inverse transform in Eqs.(21)-(22); (iv) stack all node and link durations to form one joint restoration-time scenario; and (v) repeat steps (ii)-(iv) M times to obtain the raw scenario set. With this construction, spatially proximate assets tend to exhibit jointly high (or low) uniform values and, consequently, clustered long (or short) repair durations.

Because the raw scenario set can be large, scenario reduction is applied to obtain a compact representative set. A fast forward selection is performed in the high-dimensional space of stacked repair durations, and probabilities are updated by backward probability redistribution: each discarded scenario is assigned to its nearest retained representative, and its probability mass is added to that representative. The resulting M scenarios preserve key features and representative extreme patterns with substantially reduced computational burden [12].

After scenario reduction, a distributed optimization framework based on the Alternating Direction Method of Multipliers (ADMM) is therefore adopted, in which each infrastructure solves its own subproblem and coordination is achieved through a small set of coupling constraints and consensus gate updates. However, applying ADMM directly to the present restoration model is challenging. The formulation contains extensive binary and logical decisions (repair starts and availability), time-coupled occupancy constraints, and interdependency gating, yielding a large-scale nonconvex mixed-integer problem for which classical ADMM provides no convergence guarantees. In addition, the conventional splitting requires solving two large MILPs per iteration (one per network), and the computational burden grows rapidly with the number of scenarios [12].

To address these limitations, an ADMM-LBBD is employed. At each iteration, a master problem is solved for each network, retaining discrete repair and availability decisions, while continuous flows are removed and represented by Benders cuts. The cut coefficients are obtained from dual solutions of small single-period network-flow LP subproblems, and the accumulated cuts are carried forward to progressively strengthen the masters.

As an illustrative case for the water network, the master problem takes the following form:

$$\begin{aligned}\max \sum_{\omega\in\Omega} p_\omega \sum_{t=2}^{T} g^W_{t,\omega} - \\ \frac{\rho}{2}\sum_{\omega}\sum_{r}\sum_{t}\left(s^W_{r,t,\omega}-\left(S_{r,t,\omega}-U^W_{r,t,\omega}\right)\right)^2\end{aligned} \quad (23)$$

$$\vartheta^W_{t,\omega} \le \left(a^{W,N}_{t,\omega}\right)^\top z^{W,N}_{:,t,\omega} + \left(a^{W,E}_{t,\omega}\right)^\top z^{W,E}_{:,t,\omega} \quad (24)$$

Eqs. (4)-(10) and Eq. (18) (25)

The single-period subproblem is defined as:

$$Q_{t,\omega}^{k}(z) = \max - \sum_{j \in D^k} M_j^k \Delta_{j,t,\omega}^k \tag{26}$$

$$\text{Eqs. (11)-(15) and Eq. (17)} \tag{27}$$

Let α^+, α^- denote the dual multipliers for the link-capacity bounds, and let μ and λ denote, respectively, the dual multipliers for the demand upper bound and the supply upper bound. The resulting dual program implies the following valid upper bound:

$$Q_{t,\omega}^{k}(z) \le \left(a_{t,\omega}^{k,N}\right)^{\top} z_{\cdot,t,\omega}^{k,N} + \left(a_{t,\omega}^{k,E}\right)^{\top} z_{\cdot,t,\omega}^{k,E} \tag{28}$$

$$a_{t,\omega}^{k,N}(i) = \begin{cases} \gamma_i^k \lambda_i, & i \in O^k \\ \theta_j^k \mu_j, & i \in D^k \\ 0, & i \in V^k \end{cases} \tag{29}$$

$$a_{t,\omega}^{k,E}(\ell) = u_\ell^k \left(\alpha_\ell^+ + \alpha_\ell^-\right) \tag{30}$$

At this stage, within a single ADMM iteration, the cut-augmented master and the collection of decomposed single-period subproblems together define a tractable decomposition of the large-scale mixed-integer restoration problem. During ADMM iterations, the cut-augmented masters are solved under continuous consensus gate variables, while coupling is handled via the consensus gate variable through augmented-Lagrangian updates. After the ADMM iterations stabilize, the consensus gate is discretized (e.g., by a fixed threshold consistent with the projection rule), and each network solves a final cut-augmented MILP that reinstates integrality for repair-start and availability logic, yielding an implementable restoration schedule. The complete ADMM-LBBD procedure is presented below:

Step 1: Initialize the consensus gate s at a neutral value (e.g., 0.5) and relax it as continuous. Set $U^W = U^P = 0$.

Step 2: Solve, in turn, the master problems of the water and power networks. Decision variables include repair starts, availability states, and the local gate variables.

Step 3: For each period-scenario pair (t,ω), solve the single-period LP. If $\Phi_{t,\omega}^k(z) < g_{t,\omega}^k - \varepsilon$, append the corresponding cut to the cut pool.

Step 4: Update the consensus gate and scaled dual variables via the standard ADMM update.

Step 5: Compute primal and dual residuals; if both fall below tolerances, declare convergence; otherwise return to Step 2.

Step 6: After ADMM convergence, fix the consensus gate and solve, for each network, the final cut-augmented MILP, continuing cut separation until no new cuts are generated (or the violation is sufficiently small).

Step 7: Obtain the optimized results.

Figure 1 illustrates the flowchart of the proposed framework, including the inputs, outputs, optimization model and the solution method.

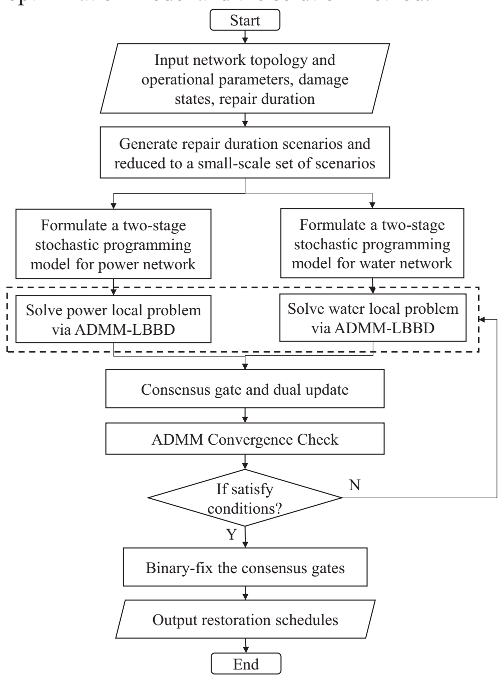

Fig. 1. Flowchart of the proposed framework.

5. Case Study

The proposed model and solution method are evaluated on an interdependent power-water network representative of Shelby County. The power system includes 60 nodes and 76 links (5 generation nodes and 5 demand nodes), and the water system includes 49 nodes and 71 links (5 supply nodes and 5 demand nodes). Fifteen pre-identified dependency pairs connect the two networks (30 paired nodes in total). The initial damage set is treated as known: in each network, 20 nodes and 20 links are damaged, and a subset of dependency pairs is forced to fail on both sides. Uncertain repair durations are represented by a scenario set generated via spatially correlated sampling and subsequently reduced to a set of 15 representative scenarios; thus, a finite collection of repair-time realizations is obtained for the observed damage configuration. The restoration horizon comprises 12 periods, and the per-period crew capacity is set to three for each network. Coordination is implemented in a distributed manner using ADMM-LBBD.

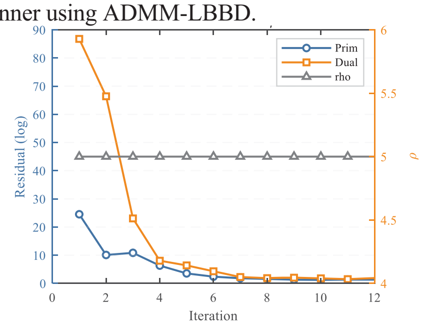

Fig. 2. The convergence of the ADMM-LBBD.

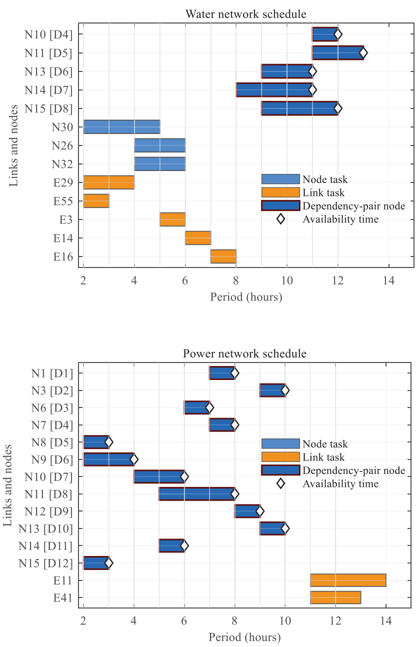

Fig. 3. Restoration schedules of two networks.

Figure 2 shows the convergence of the ADMM-LBBD. The primal residual (Prim) quantifies the gate consensus mismatch, and the dual residual (Dual) measures the step-to-step change of the consensus gate. Both the primal and dual residuals decrease rapidly and stabilize after 9 iterations, indicating satisfactory convergence of the ADMM-LBBD algorithm.

Figure 3 shows the distributed restoration schedules of the water and power networks. It shows that the dependent water-side node does not become available earlier than its paired power-side node. This provides direct visual evidence for the power-first, water-follows pattern induced by the interdependency constraints.

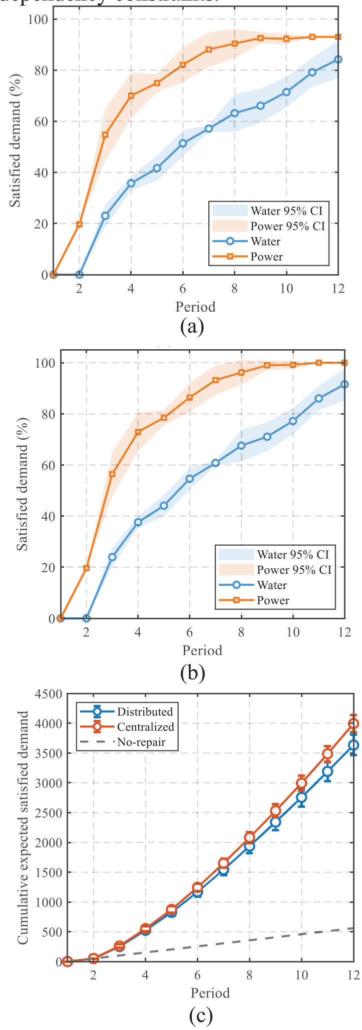

Fig. 4. Performance Comparison.

Figures 4(a) and 4(b) show the demand-satisfaction trajectories under the distributed and centralized restoration schedules, respectively. The curves represent the sample means of the expected demand satisfaction obtained from 20 independent repetitions of scenario sampling, scenario reduction, and optimization, while the shaded bands indicate the corresponding 95% confidence intervals. In both cases, satisfied demand increases steadily over time, and power restoration generally proceeds faster than water restoration. Figure 4(c) compares the cumulative restoration performance of the distributed, centralized, and no-repair strategies over the same 20 repeated runs. At the final period, the distributed approach achieves an expected cumulative satisfied demand of 3635, compared with 561 for the no-repair benchmark and 3994 for centralized coordination. Although the centralized method performs slightly better, the distributed method remains close to the centralized benchmark and substantially outperforms the no-repair case. Moreover, the relatively narrow 95% confidence interval of the distributed method indicates stable performance across repeated runs.

6. Conclusion and Future Work

A distributed post-disaster restoration framework is developed for interdependent power-water networks under spatially correlated hazards. Repair-duration uncertainty is modeled via Gaussian-copula scenario sampling and reduced to a compact representative set. A two-stage stochastic mixed-integer formulation is coordinated through shared gate variables, requiring only dependency-pair status to be exchanged. Computational tractability is achieved using an ADMM-LBBD method that combines cut-augmented relaxed masters with single-period flow LP. In the Shelby County case, the distributed method converges in 9 ADMM iterations and achieves a cumulative satisfied demand of 3635, compared with 561 for the no-repair benchmark and 3994 for centralized coordination. This corresponds to 91.0% of the centralized performance on this metric.

Future work will focus on (i) extending uncertainty beyond repair durations to include damage states and transportation accessibility; and (ii) generalizing coordination mechanisms and privacy guarantees to multi-operator settings with heterogeneous information-sharing policies.

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