Data-Driven Multi-Energy Investment and Management under Earthquakes

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Abstract—Seismic events can severely damage both electricity and natural gas systems, causing devastating consequences. Ensuring the secure and reliable operation of the integrated energy system (IES) is of high importance to avoid potential damage to the infrastructure and reduce economic losses. This paper proposes a new optimal two-stage optimization to enhance the reliability of IES planning and operation against seismic attacks. In the first stage, hardening investment on the IES is conducted, featuring preventive measures for seismic attacks. The second stage minimizes the expected operation cost of emergency response. The random seismic attack is modelled as uncertainty, which is realized after the first stage. An explicit damage assessment model is developed to define the budget set of the uncertain seismic activity. Based on the survivability of transmission lines and gas pipelines of IES, an optimal system investment plan is developed. The problem is formulated as a two-stage distributionally robust optimization (DRO) model, which is tested on an integrated IEEE 30-bus system and 20-node gas network. Case studies demonstrate that the two-stage DRO outperforms robust optimization and a single-stage optimization model in terms of minimizing the investment cost and expected economic loss. This work can help system operators to make economical hardening and operation strategies to improve the reliability of IES under seismic attacks, thus managing a more robust and secure energy system.

Index Terms—Distributionally robust optimization, emergency response, integrated electricity and gas system, reliability.

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I. INTRODUCTION

NATURAL disasters can cause huge power losses of energy systems that threaten the economy [1]. Earthquake is considered as one of the most disruptive natural disasters, which may cause large-scale blackouts without sufficient time for the response due to the weak predictability [2, 3]. The Wenchuan earthquake in May 2008 damaged around 270 transmission lines and 900 substations, leaving 46 million people suffered without electricity. A massive power outage was caused in the 2010 Chile earthquake. Approximately 3GW generation capacity became unavailable, 26% of transmission network substations were damaged, where 93% of residents suffered from a power outage with two weeks [4]. According to existing research, more than 90% of such damage can be avoided if upgraded seismic preventive measures are adopted [5].

To enhance the reliability of power systems against natural disasters, reliability planning has been extensively investigated. Paper [6] proposes a multi-stage and multi-zone based robust optimization (RO) for a bi-level reliability problem considering power line hardening and distributed generation resource placement. Different grid enhancing strategies against extreme weather conditions are considered in [7] in a tri-level framework, which is transformed into an equivalent bi-level problem and solved by a greedy searching algorithm. Paper [8] develops a two-stage stochastic optimization (SO) for reliability planning in a large-scale transmission network to mitigate seismic risk. Optimal capacity expansion is considered as the planning strategy based on explicit damage distribution.

Existing research of seismic attack-based preventive measures mainly contains optimal system expansion and mobile energy storage supplement. To enhance the reliability and protect the system against seismic attacks, paper [8] designs a transmission and expansion scheme, where a SO-based approach is utilized for capturing the uncertain seismic attacks. In [9], mobile power sources are utilized as grid-support resources during seismic attacks for distribution systems. However, the capacity of mobile energy storage and electric vehicles is insufficient for hedging against seismic attacks for transmission systems. Paper [10] investigates the feasibility of energy storage utilization to improve system reliability against seismic attacks, which helps to supply critical loads during and following seismic attacks. Grid hardening, including constructing new lines and facilities, upgrading damaged poles and burying power lines underground, etc, is the most widely-proposed and effective measure to protect systems against

natural disasters [11]. In our paper, reconstruction and upgrade to make systems resistant to earthquakes are modelled as the hardening measures for power lines and gas pipelines. It is assumed that the hardened lines will survive from seismic attacks [6, 8, 12]. The hardening strategy is considered in the first stage of the proposed hierarchical two-stage framework.

Meanwhile, energy infrastructures are becoming more complex and independent, especially with higher attention on the interdependence of different energy carriers. The rapid growth of gas consumption and mushrooming deployment of gas well and electrolysis have boosted the synergetic integration of electricity and natural gas systems. The integrated energy system (IES) can significantly increase energy utilization efficiency. Therefore, enhancing reliability to withstand seismic hazards and mitigate resulting damages is of great vitality for IES. A two-stage robust integrated planning of IES is proposed for enhancing the reliability in [13], which is implemented by replacing power lines by a gas transportation system. Paper [12] optimally minimizes the worst-case electricity and gas load shedding through a tri-level robust planning model with network hardening. Paper [14] proposes a reliability assessment for IES including heating, cooling and distributed generation systems. The proposed assessment is quantified through functionality loss and monetary costs.

However, recent IES planning studies consider the impacts of general natural disasters without specifying the types and ignore the attack assessment model, hardly targeting at mitigating seismic risks [12, 13]. This is impractical as the impacts of natural disasters depend on the grid structure, disaster types, duration and intensity, etc. Different natural disasters could have a very different damage scale that needs specified preventive investment strategies. Thus, it is essential to develop models for assessing seismic risks on IES.

To accommodate the uncertainty of natural disasters, RO and SO have been extensively applied [7, 8, 13]. Nevertheless, RO ensures system robustness while inevitably leads to over conservativeness. SO requires explicit distributions with a large number of samples, which not only produces a high computational burden but also is not always practical. Distributionally robust optimization (DRO) bridges the strengths of RO and SO, which relaxes the assumption of specifying a certain distribution and considers the worst distributions compared to the worst-case oriented RO. An optimal gas-power flow is proposed in [15] by DRO with wind uncertainty. Wasserstein metric is used to select candidate distributions. A two-stage DRO model for IES scheduling is proposed in [16] and compared with traditional adjustable robust optimization, proving that DRO generates less conservative and more economical solutions.

This paper targets at alleviating the impacts of seismic events on both power lines and gas pipelines of IES. A two-stage DRO model is proposed to enhance the reliability for an IES, where the damage on both power lines and gas pipelines are considered. For simplicity, the keywords ‘distributionally robust’, ‘seismic’, ‘integrated’ and ‘planning’ are picked and this proposed model is referred to DR-SIP. The seismic activities are regarded as uncertain events and the random

damage on power lines and pipelines are regarded as uncertainties, which are handled by DRO. The first stage minimizes the investment cost for hardening IES against seismic attacks. The hardening strategy incorporates strengthening power lines and gas pipelines with earthquake-resistant material and design. After the uncertainty of seismic activities is realized, the second stage minimizes the loss of emergency response through load shedding under the worst potential seismic risks. An improved Benders Decomposition is utilized to solve this IES reliability optimization problem, which is then demonstrated through the extensive case study. The merits of the proposed model are summarized in the case study section.

The main contributions of this paper are as follows:

- 1) A two-stage coordinated reliability enhancement and emergency response modelling incorporating both planning and operation schemes is developed to enhance IES reliability in the worst-distributed seismic attacks.
- 2) It develops a novel assessment model of IES performance against seismic attacks. This probabilistic quantification is estimated by damage scenarios, easily combined with the proposed two-stage DRO model. The coordinated assessment-optimization model enables the design of the optimal enhancement plans for IES.
- 3) It utilizes the novel DRO in IES reliability assessment and enhancement with a tractable reformulation. Historical information on seismic events is efficiently used to reduce solution conservativeness, thus producing more economical investment and operation decisions.

The rest of this paper is organized as follows. Section II proposes the damage assessment of seismic events. Section III designs reliability enhancement strategies. Section IV presents the mathematical formulation for reliability planning and emergency operation. The methodology and solution algorithm are given in section V. Section VI demonstrates case studies and the performance of DR-SIP. Conclusions are drawn in section VII.

II. ASSESSMENT OF SEISMIC DAMAGE ON IES

This section provides the seismic damage modelling for both electricity and natural gas systems, which mainly considers the damages on power lines and gas pipelines. The relationship between damage consequence and seismic level is established in this section. The seismic intensity is described by peak ground acceleration (PGA) and peak ground velocity (PGV), which are mainly related to landslides and surface faulting [17]. The relationship between seismic level, PGA and PGV are summarized in TABLE I [18, 19].

The concept of connection loss (CL) is adopted to quantify the line failures of electricity systems [20] due to the damage on pylons and conductors from seismic events. They destroy conductors and shake pylons and consequently damage power lines. For simplicity, this paper considers the number of damaged power lines, which are modelled as CL. Paper [21] concludes four-line damage states, minor, moderate, extensive and complete, which refers to 4%, 12%, 50% and 80% of CL, indicating the number of damaged power lines in percentage, which correspond to P_{mi} , P_{mo} , P_{ex} and P_{co} in (1).

Fig. 1. Fragility curve of damage states for seismic attacks.

TABLE I
RANGES OF PGA, PGV AND SEISMIC INTENSITY

Intensity	I	II-III	IV	V	VI	VII	VIII	IX
PGA (%g)	<0.17	0.2-1.4	1.4-3.9	3.9-9.2	9.2-18	18-34	34-65	65-124
PGV (cm/s)	<0.1	0.1-1.1	1.1-3.4	3.4-8.1	8.1-16	16-31	31-60	60-116

A random intensity level can cause a certain range of PGA, presented in TABLE I. Based on the fragility curve in Fig. 1, a random PGA can cause an earthquake in one or a combination of different line damage states. For example, when PGA is 0.6g, the line damage state of being complete is 0% and being extensive is 60%, while 100% for being moderate and minor. Thus, the expected number of line failures modelled as CL under a specific PGA is described in (1).

$$N_{ED} = P_{co}CL_{co} + (P_{ex} - P_{co})CL_{ex} + (P_{mo} - P_{ex})CL_{mo} + (P_{mi} - P_{mo})CL_{mi} \quad (1)$$

The steps to specify seismic damages on electricity lines are summarized as:

1. A random seismic intensity level is sampled from the Monte Carlo approach based on an empirical probability density function of seismic intensity level.
2. Based on TABLE I and the sampled intensity level, a certain range of PGA is given. Then Monte Carlo approach is used to pick a random PGA from the PGA range.
3. Based on the fragility curve in Fig. 1 and obtained PGA, the probability of 4 damage states is obtained.
4. Finally, according to equation (1), the expected number of damaged power lines, N_{ED} , is obtained.

To quantify the damage of the natural gas system due to seismic events, similar to CL of the electricity system, failure rate (FR) is defined to represent the number of damage points on gas pipelines [22]. For simplicity, the natural gas system is assumed to operate in the steady-state, ignoring the dynamic gas leakage characteristics of pipelines.

FR can be described with PGV:

$$FR = \gamma(PGV)^{2.25}L \quad (2)$$

The steps to acquire FR of gas pipelines are as follows:

1. As described in step 1 of section A, the same seismic intensity level is obtained.
2. Based on TABLE I and obtained seismic intensity level, a certain range of PGV is given. Then Monte Carlo approach is used to pick a random PGV from the PGV range.
3. According to equation (2), FR is obtained.

III. MATHEMATICAL FORMULATIONS FOR RELIABILITY ENHANCEMENT

Reliability planning and emergency response modelling are presented in this section. To begin with, the proposed reliability enhancement strategy is illustrated. The seismic hardening strategy is considered for power lines and gas pipelines. Linearized DC power flow and Weymouth gas flow equations are employed with load shedding to meet flow constraints. Finally, a two-stage optimization is proposed to minimize hardening costs in the first stage and operation cost in the second stage.

A. Illustration of the Proposed Reliability Enhancement

The proposed reliability-based IES planning consists of adaptation and recovery. The scope of this paper is on reliability planning and emergency response against seismic attacks. The preventive response is ignored as the preventive time after detecting seismic events is only up to a few seconds, which is too short for seismic preventive actions. In reliability planning, system operators make investment plans for seismic hardening on existing energy infrastructures. After the damage caused by seismic disasters, emergency response is implemented by system operators to mitigate the impact. There are two steps in the proposed DR-SIP: the first stage - reliability planning and the second stage - emergency response.

In the first stage, hardening on power lines is considered as the proposed reliability planning measure. In the second stage, the daily operation is implemented in the pre-hardened IES. To maintain the system balance while suffered from uncertain seismic attacks, load shedding is considered.

B. Overall Objective

The first and second-stage objectives are in (3) and (4). In (3), the objective Γ_p represents total hardening investment cost for power lines and pipelines, which are given in the first and second terms, respectively, i.e., $\sum_{i,j \in I} h_{ij}\pi_{ij}$ and $\sum_{m,n \in M} h_{mn}\pi_{mn}$.

In (4), the objective Γ_R is to minimize the emergency response cost. The final term of (4) represents the generation cost of gas wells in the gas system. It is assumed that the system operator curtails electricity and gas load under the worst-distributed seismic attacks to mitigate damage. During real seismic attacks, partial load needs to be curtailed to ensure the overall system supply-load balance. Since seismic attacks cause the unavailability of power lines and pipelines, energy transmission is significantly affected. Apart from load shedding, the generation function is also considered in the emergency response for normal system operation. The first and second terms are the shedding costs of electricity and gas loads. The generation cost function of electricity generators is a quadratic function, which is shown from the third term to the fifth term.

$$\Gamma_p = \sum_{i,j \in I} h_{ij}\pi_{ij} + \sum_{m,n \in M} h_{mn}\pi_{mn} \quad (3)$$

$$\Gamma_R = \sum_{t \in T, d_e \in D_E} \delta_{d_e,t}\pi_{d_e} + \sum_{t \in T, d_g \in D_G} \delta_{d_g,t}\pi_{d_g} + \sum_{t \in T, g_e \in G_E} \lambda_{ge}^a p_{ge,t}^2 + \lambda_{ge}^b p_{ge,t} + \lambda_{ge}^c + \sum_{t \in T, g_g \in G_G} \lambda_{gg} p_{gg,t} \quad (4)$$

The overall objective of the proposed DR-SIP is to minimize the planning cost in the first stage and the emergency response cost in the second stage in (5).

$$\min \Gamma_P + \sup E_P[\Gamma_R] \quad (5)$$

C. Seismic Risk Oriented Reliability Planning

Here, the feasibility set of hardening strategies for electricity network, gas network and the overall IES are shown in (6) to (8) respectively. The maximum number of power lines and pipelines to be hardened are constrained by (6) and (7). Constraint (8) means the total hardening investment cannot exceed the maximum monetary budget.

$$\sum_{i,j \in I} h_{ij} \leq EL_h \quad (6)$$

$$\sum_{m,n \in M} h_{mn} \leq PL_h \quad (7)$$

$$\sum_{i,j \in I} h_{ij} \pi_{ij} + \sum_{m,n \in M} h_{mn} \pi_{mn} \leq IC_{max} \quad (8)$$

D. Emergency Response

Seismic events can have disruptive damage on power lines and gas pipelines, where the damages are considered as uncertainty, represented by binary variables d_{ij} and d_{mn} . In the second stage of DR-SIP, to mitigate the loss of seismic events, electricity and gas load shedding is identified and implemented accordingly to keep the system balance. The sub-objective is to minimize the cost of load shedding and generation as an emergency response. When considering the effects of hardening strategies against seismic damage, the availability of lines needs to be identified and multiplied with the power and gas flow. Reference [12] considers the availability as $1 - \xi + \xi h$, but the term ξh is nonlinear. This paper presents the availability as $\xi + h$ in (14) and (15), which is linear but may cause $\xi + h = 2$ and thus leads to overloading on power lines. For instance, in (14), $(\xi_{ij} + h_{ij})f_{ij,max}$ can be $2f_{ij,max}$. Accordingly, additional constraints are added to ensure the original limits, i.e., $-f_{ij,max} \leq f_{ij,t} \leq f_{ij,max}$.

The DC linearized power flow and Weymouth gas flow are utilized for modelling power flow and gas flow respectively, which are shown in (9) and (10).

$$x_{ij} f_{ij,t} = (\theta_{i,t} - \theta_{j,t}) \quad (9)$$

$$f_{mn,t} |f_{mn,t}| = \gamma_{mn} (Pr_{m,t}^2 - Pr_{n,t}^2) \quad (10)$$

However, this paper considers the availability of asset that will inevitably lead to the nonlinear term $(\xi + h)(\theta_{i,t} - \theta_{j,t})$ and $(\xi + h)(Pr_{m,t}^2 - Pr_{n,t}^2)$. This nonlinearity is linearized based on sufficiently large constants M_{ij} and M_{mn} . Thus, the linearized DC power flow and Weymouth gas flow constraints are used in (11)-(12) and (22)-(23).

The constraints of electricity and gas well output are in (16) and (17). Equations (18) and (19) show the constraints for electricity and gas load shedding. Equation (20) shows the upper and lower bounds for the pressure square of pipelines. Weymouth gas flow is presented in (21) and (22). The power and gas balance constraints are in (23) and (24).

$$x_{ij} f_{ij,t} \leq (\theta_{i,t} - \theta_{j,t}) + (1 - \xi_{ij} - h_{ij})M_{ij} \quad (11)$$

$$x_{ij} f_{ij,t} \geq (\theta_{i,t} - \theta_{j,t}) - (1 - \xi_{ij} - h_{ij})M_{ij} \quad (12)$$

$$-\pi \leq \theta_{i,j,t} \leq \pi \quad (13)$$

$$-(\xi_{ij} + h_{ij})f_{ij,max} \leq f_{ij,t} \leq (\xi_{ij} + h_{ij})f_{ij,max} \quad (14)$$

$$0 \leq f_{mn,t} \leq (\xi_{mn} + h_{mn})f_{mn,max} \quad (15)$$

$$P_{ge,min} \leq P_{ge,t} \leq P_{ge,max} \quad (16)$$

$$P_{gg,min} \leq P_{gg,t} \leq P_{gg,max} \quad (17)$$

$$0 \leq \delta_{d_e,t} \leq \delta_{d_e,max} \quad (18)$$

$$0 \leq \delta_{d_g,t} \leq \delta_{d_g,max} \quad (19)$$

$$Pr_{min}^2 \leq Pr_t^2 \leq Pr_{max}^2 \quad (20)$$

$$f_{mn,t} \leq \gamma_{mn} ((Pr_{m,t}^2 - Pr_{n,t}^2) + (1 - \xi_{mn} - h_{mn})M_{mn}) \quad (21)$$

$$f_{mn,t} \geq \gamma_{mn} ((Pr_{m,t}^2 - Pr_{n,t}^2) - (1 - \xi_{mn} - h_{mn})M_{mn}) \quad (22)$$

$$\sum_{d_e \in DE} P_{d_e,t} - \delta_{d_e,t} = \sum_{g_e \in GE} P_{g_e,t} + \sum_{ij \in I(ter)} f_{ij,t} - \sum_{ij \in I(ini)} f_{ij,t} \quad (23)$$

$$\sum_{d_g \in DG} P_{d_g,t} - \delta_{d_g,t} + \sum_{gg \in GG} P_{gg,t} = \sum_{mn \in M(ter)} f_{mn,t} - \sum_{g \in M(ini)} f_{mn,t} \quad (24)$$

The Weymouth gas flow is nonlinear, but Pr_t^2 is modelled in the squared form in this paper, which does not require linearization. The nonlinear term $f_{mn,t}^2$ can be linearized by piecewise linear approximation to convert DR-SIP into a MILP problem [23], which is presented as follows. $h(f_{mn,t})$ represents the nonlinear function, $\Delta f_{mn,k}$ is the segment of gas pipeline mn, and $\chi_{mn,t,k}$ is the auxiliary continuous variable.

$$h(f_{mn,t}) \approx h(\Delta f_{mn,1})$$

$$+ \sum_{k \in K} (h(\Delta f_{mn,k+1}) - h(\Delta f_{mn,k})) \chi_{mn,t,k} \quad (25)$$

$$f_{mn,t} = \Delta f_{mn,1} + \sum_{k \in K} (\Delta f_{mn,k+1} - \Delta f_{mn,k}) \chi_{mn,t,k} \quad (26)$$

$$0 \leq \chi_{mn,t,k} \leq 1 \quad (27)$$

IV. SOLUTION PROCEDURE

This section provides the procedure for solving the DR-SIP problem. The abstract forms of matrices and vectors are used to describe the constraints and variables. The ambiguity set for characterizing the seismic damage is constructed with moment information. Finally, the dual formulation is obtained and the proposed improved Benders Decomposition is used to solve the DR-SIP.

A. Abstract Formulation

For notation simplification, the compact form of the DR-SIP is given in (28)-(31). x and y are the first and second-stage decision variables. The uncertain seismic attack is represented by vector ξ . Equation (28) is the overall objective function containing (3) and (4). Vector c consists of the unit hardening cost coefficient π_{ij} and π_{mn} . Equation (29) represents constraints (6)-(8), where vector b contains the allowed number of hardened power lines and pipelines as well as the monetary investment limit. Equation (30) shows the second-stage objective function where vector f corresponds to the coefficients of (4). Equation (31) represents the second-stage constraints shown in (11)-(27).

$$\min_{x \in X} c'x + \sup_{P \in D} E_P[Q(x, \xi)] \quad (28)$$

$$\text{s.t. } Ax \leq b, \quad (29)$$

$$Q(x, \xi) = \min_y f'y \quad (30)$$

$$\text{s.t. } Ex + Fy + G\xi \leq h, \quad (31)$$

B. Distributionally Robust Optimization

The construction of the ambiguity sets for uncertain damage on both power lines and pipelines, i.e., ξ_{ij} and ξ_{mn} , are proposed in this section. Moment information is widely used most for characterizing uncertainties and this paper utilizes the first moment for building ambiguity set. Since the damage probability can be obtained from historical data, thus μ_{EL} and μ_{PL} representing the estimated damage probability of power lines and pipelines, are used as the mean vectors. Compared with paper [24] which incorporates mean the vector and covariance matrix in the ambiguity set, this paper only utilizes the mean vector due to the data limit of distributional information. However, this paper provides a practical guide for characterizing uncertain rare events, such as natural disasters and contingency issues. The ambiguity sets are presented as follows.

$$D_{EL} = \left\{ f(\xi_{ij}) \middle| \begin{array}{l} P\{\xi_{ij} \in \Xi_{EL}\} = 1 \\ E\{\xi_{ij}\} = \mu_{EL} \end{array} \right\} \quad (32)$$

$$D_{PL} = \left\{ f(\xi_{mn}) \middle| \begin{array}{l} P\{\xi_{mn} \in \Xi_{PL}\} = 1 \\ E\{\xi_{mn}\} = \mu_{PL} \end{array} \right\} \quad (33)$$

As described in section II, the estimated damage level determines the number of damaged components. Accordingly, Ξ_{EL} and Ξ_{PL} are required as the support of seismic damage. The mean vector defined in equations (32) and (33) are obtained from $\frac{N_{ED}}{N_{pwr}}$ and $\frac{FR}{N_{gas}}$, respectively, where N_{pwr} and N_{gas} are the total number of power lines and pipelines in the proposed IES.

$$\Xi_{EL} = \left\{ \sum_{i,j \in I} \xi_{ij} = N_{ED} \right\} \quad (34)$$

$$\Xi_{PL} = \left\{ \sum_{m,n \in M} \xi_{mn} = FR \right\} \quad (35)$$

The variables of the optimization problem are the probability densities in (32) and (33). The optimization problem contains a finite number of constraints and an infinite number of variables, which is non-tractable. By transforming it from the primal form into the dual form, the problem becomes tractable.

The second-stage objective function $\sup_{P \in D_{EL}, D_{PL}} E_P[Q(x, \xi)]$ can be represented by $S(x)$, where $P(\xi)$ is the probability density function.

$$S(x)^{primal} = \max_{P(\xi) \in D_{EL}, D_{PL}} \int_{\Xi} Q(x, \xi) P(\xi) d\xi \quad (36)$$

$$\text{s.t. } P(\xi) \geq 0, \forall \xi \in \Xi \quad (37)$$

$$\int_{\Xi} P(\xi) d\xi = 1 \quad (38)$$

$$\int_{\Xi} \xi P(\xi) d\xi = \mu \quad (39)$$

Based on dual theory [25], when the strong duality holds, the dual form of (36) is transformed to (40). Accordingly, the results of (40) are equal to those of (36) [26, 27]. Now, the dual form has an infinite number of constraints and a finite number of variables after the dual formulation, which is easier to solve. The dual variables Ψ and ψ_0 are associated with constraints (38) and (39).

$$S(x)^{dual} = \min_{\Psi, \psi_0} \Psi \mu + \psi_0 \quad (40)$$

Fig. 2. Flow chart of Benders Decomposition method.

$$\text{s.t. } \Psi\xi + \psi_0 \geq Q(x, \xi) \quad (41)$$

$$\forall \xi \in \Xi$$

Then, the dual formulation (40) is substituted into (28) and the following reformulations can be obtained:

$$\min_{\Psi, \psi_0} c'x + \Psi \mu + \psi_0 \quad (42)$$

$$\text{s.t. } Ax \leq b, \quad (43)$$

$$\Psi\xi + \psi_0 \geq Q(x, \xi), \forall \xi \in \Xi \quad (44)$$

C. Improved Benders Decomposition

An improved Benders Decomposition is applied to solve the DR-SIP in a master-subproblem framework, summarized in the flowchart in Fig. 2. Under the acceptable optimality gap, the master problem and subproblem are solved separately with the update of upper and lower bounds. Equation (44) is regarded as the Benders cut with respect to ξ . A Benders cut is formulated and added to the set in each iteration. Firstly, equations (42)-(44) are relaxed and only a subset of Benders cut is incorporated. The set of Benders cut becomes larger until the real gap between lower and upper bounds is smaller than the optimality gap. The master problem and primal subproblem are shown in (45)-(46) and (47)-(48).

$$\min_{\Psi, \psi_0} c'x + \Psi \mu + \psi_0 \quad (45)$$

$$\text{s.t. } Ax \leq b, \quad (46)$$

$$\max_{\Psi} Q(x^*, \xi) - \Psi^* \xi \quad (47)$$

$$\text{s.t. } Ex + Fy + G\xi \leq h, \quad (48)$$

The Benders Decomposition framework is given in Fig. 2. In addition, the approaching of optimality gap is enhanced through separating the Benders cut into primal and dual forms. To begin with, the new dual variable τ is introduced to represent the dual form of (30). Accordingly, (30) and (31) can be represented in the following closed form:

$$\max \tau'(h - Ex - G\xi_s) \quad (49)$$

$$\text{s.t. } F'\tau \leq f, \tau \geq 0 \quad (50)$$

Equation (47) is recast as (51) based on the new dual variable τ .

$$\max \tau'(h - Ex - G\xi_s) - \Psi^* \xi \quad (51)$$

$$\text{s.t. } F'\tau \leq f, \tau \geq 0 \quad (52)$$

It is worth noting that the term $\Psi^* \xi$ in (51) is nonlinear because it contains the product of dual variable Ψ^* and binary variable ξ . Although it can be solved by some nonlinear solvers, linearization is still required to ensure a more efficient and global solution. McCormick inequality is used to relax this nonconvex problem, where ϑ_{ij} is used to represent $\tau_i G_{ij} \xi_j$.

$$\vartheta_{ij} \geq G_{ij} \tau_i - M(1 - \xi_j) \quad (53)$$

$$\vartheta_{ij} \geq -M \xi_j \quad (54)$$

Therefore, the dual subproblem can be written as:

$$\max \tau'(h - Ex) - \vartheta - \Psi^* \xi \quad (55)$$

$$\text{s.t. } F'\tau \leq f, \tau \geq 0 \quad (56)$$

$$\vartheta_{ij} \geq G_{ij} \tau_i - M(1 - \xi_j) \quad (57)$$

$$\vartheta_{ij} \geq -M \xi_j \quad (58)$$

The primal Benders cut is based on the primal formulation of (30) and (31), which means at each iteration, the addition of primal Benders cut yields a new set of y^* with respect to ξ^* . The primal form of steps 3 and 5 of Benders framework are shown below:

Step-3-primal: Solve the subproblem (55)-(58), record the optimal solution ξ^* and the optimal objective value O^* . Set $UB = LB - \psi_0^* + O^*$.

Step-5-primal: Add Benders cut:

$$Ex + Fy^* + G\xi^* \leq h, \quad (59)$$

$$\psi_0 \geq f'y^* - \Psi \xi^* \quad (60)$$

To obtain the dual Benders cut, the dual form of (44) is given in (61). The dual form of steps 3 and 5 of Benders framework are summarized as:

Step-3-dual: Solve the dual subproblem (55)-(58), record the optimal solution ξ^* and τ^* and the optimal objective value O^* . Set $UB = LB - \psi_0^* + O^*$.

Step-5-dual: Add Benders cut:

$$\psi_0 \geq \tau'^*(h - Ex - G\xi^*) - \Psi \xi^* \quad (61)$$

V. CASE STUDIES

This section presents the numerical case studies of the proposed DR-SIP on an integrated electricity and gas system. The IES consists of the standard IEEE 30 busbars electricity system and a 20-node gas network, shown in Fig. 3. The gas network includes 2 gas wells and 14 gas demands. A gas turbine is connected between bus 2 of the electricity network and node 2 of the gas network. The hardening investment cost is set as \$4500 and \$5500 for each power line and gas pipeline, respectively. The technical parameters of gas wells and electricity generators are given in TABLES II and III. All numerical tests are executed on a personal computer with an Intel Core i7-8700 CPU with a 16 GB RAM. Coding is completed in MATLAB platform with MOSEK solver. Three cases are performed to optimize DR-SIP. The only difference between cases 2 and 1 is the addition of the planning stage before the seismic attacks.

TABLE II
PARAMETERS OF GAS WELLS

Node No.	$P_{ig,max}$ (kcf/h)	$P_{ig,min}$ (kcf/h)	λ_{ig}
1	3000	1000	2.2
8	6000	1000	2

TABLE III
GENERATOR PARAMETERS

Bus No.	$P_{ig,min}$ (MW)	$P_{ig,max}$ (MW)	R_{ie}^+, R_{ie}^- (MW)	a_{ie}	b_{ie}	c_{ie}
1	50	200	20	0.004	2	6
2	20	80	16	0.002	2	6
5	15	50	10	0.006	1	8
8	10	35	7	0.008	3	10
11	10	30	10	0.025	3	18
13	12	40	16	0.025	3	18

Fig. 3. Proposed test system.

- Case 1: Single-stage emergency response without considering hardening investment for IES.
- Case 2: Two-stage model including reliability enhancement planning and emergency response for IES.
- Case 3: Two-stage model for IEEE 30-bus system.

Section A presents comparisons of each case. Sections B and C illustrate the optimal hardening plan and computational results for case 2. Section D compares the numerical performance of case 2 between DRO and RO. Section E highlights the merits of the proposed model.

A. Case Comparisons

TABLE IV shows the operation and total cost for cases 1 and 2 with the increasing seismic intensity level. For case 1, without hardening investment, the total cost is the same as the operation

TABLE IV
COMPARISON BETWEEN CASE 1 AND 2

Intensity level	Case 1		Case 2	
	Expected operation cost (10 ³ \$)	Total cost (10 ³ \$)	Expected operation cost (10 ³ \$)	Total cost (10 ³ \$)
I	30	30	30	362
II~III	30	30	30	362
IV	33	33	30	362
V	43	43	38	370
VI	56	56	42	374
VII	71	71	54	448
VIII	263	263	77	872
IX	402	402	125	920

Fig. 4. Load shedding cost of three cases under different seismic intensity levels.

Fig. 5. The frequency of line hardened.

cost. For case 2, the total cost is the sum of operation and investment cost. The predefined investment budget for case 2 is 10 lines. When the intensity level is under level III, the expected line damage obtained from the seismic risk assessment model is around 0, thus the operation cost for both cases 1 and 2 is the same as generation cost. When the intensity level is above III, operation cost increases since more load shedding is conducted. The investment cost of case 2 also increases from 332×10^3 to 795×10^3 even though the investment budget is fixed. The reason is that when more lines are damaged, DR-SIP invests on more important lines, which causes 139% increase of investment cost when intensity is up to level IX. When the intensity is above level VII, the investment cost remains constant as the 10 most vital lines to be hardened are found.

It is to be noted that the operation cost in case 1 is always higher than that in case 2, i.e., the gap is from 10% under level IV to 220% under level IX, since more load shedding is made without hardening investment to protect lines. With the increasing intensity level, the total cost of case 1 is increasing faster than that of case 2. When the intensity level is I, the total

TABLE V
OPTIMAL HARDENING PLAN UNDER DIFFERENT PLANNING BUDGET

Planning budget	Optimal hardening plan
1	1-2
2	1-2, 1-3
3	1-3, 3-4, 2-6
4	1-2, 2-4, 2-5, 6-9
5	1-2, 2-5, 2-6, 12-13, 12-15
6	1-2, 2-4, 4-12, 12-13, 12-15, 25-27
7	1-2, 2-4, 4-12, 12-13, 12-15, 25-27, 2-N8
8	1-2, 2-4, 2-5, 5-7, 4-12, 12-13, 12-15, 8-28
9	1-2, 2-4, 2-5, 5-7, 4-12, 12-13, 12-15, 8-28, 2-N8
10	1-2, 2-4, 2-5, 5-7, 4-12, 12-13, 12-15, 8-28, 2-N8, N8-N9
15	1-2, 2-4, 2-5, 5-7, 4-12, 12-13, 12-15, 12-16, 16-17, 10-17, 10-21, 27-30, 8-28, 2-N8, N8-N9
20	1-2, 2-5, 2-6, 4-6, 6-7, 6-10, 4-12, 12-13, 12-15, 10-21, 10-22, 15-23, 22-24, 23-24, 28-27, 8-28, 6-28, 2-N8, N8-N9

Fig. 6. Electricity and gas load shedding under different investment cost.

cost of case 1 is only 8% of case 2, which reflects that only implementing load shedding without hardening investment is much more economical. However, under level IX, the ratio is up to 44%, which shows that emergency response under seismic attacks without hardening planning causes huge economic loss.

When generation cannot satisfy all original load due to broken lines caused by seismic attacks, load shedding is made to maintain the system balance, which inevitably leads to huge load shedding cost. Fig. 4 depicts the load shedding cost for three cases under different seismic intensity levels. Higher load shedding cost is regarded as the system is more vulnerable when facing seismic attacks. It shows that case 1 yields the highest load shedding cost in all intensity levels, which reaches 350×10^3 \$. This figure also shows that case 2 requires less load shedding than case 3, with the cost in case 3: 169×10^3 \$ and in case 2: 90×10^3 \$. The potential reason is that: i). Gas wells provide more supplies to the IES; ii) The IES network is more complex that can defend more severe seismic attacks; iii) Underground pipelines are more reliable than power lines, which is pre-set in the mean value vector in ambiguity set.

With increasing intensity levels, the cost difference between each case is becoming larger. When intensity level is IX, the cost of case 2 and 3 are only 26% and 48% of case 1 respectively. Overall, it can be observed that the integration of electricity and gas networks makes the system more reliable against seismic attacks.

B. Optimal Hardening Plan

The impact of increasing the budget on both planning and operation is given in TABLE V and the intensity level is set as

TABLE VI
COMPUTATIONAL RESULTS UNDER DIFFERENT PLANNING BUDGET

Planning Budget	Investment cost ($10^3\$$)	Expected operation cost ($10^3\$$)	Electricity load shedding (MWh)	Gas load shedding (Sm^3)
1	50	132	3800	35
2	116	72	813	25
3	125	72	787	24
4	141	72	779	23
5	158	72	763	23
6	191	71	752	21
7	224	71	727	20
8	257	71	684	17
9	285	65	640	17
10	314	65	612	16
15	446	62	429	12
20	587	55	315	9

TABLE VII
COMPARISON WITH ROBUST OPTIMIZATION

Case	Robust optimization		Distributionally robust optimization	
	Expected operation cost ($10^3\$$)	Total cost ($10^3\$$)	Expected operation cost ($10^3\$$)	Total cost ($10^3\$$)
1	90	90	71	71
2	72	495	54	448
3	102	544	95	516

Fig. 7. Convergence rate of the Benders Decomposition method.

Fig. 8. Convergence result between 42th and 90th iterations.

TABLE VIII
COMPARISON BETWEEN TBD AND IBD

Method	Investment cost ($10^3\$$)	Iteration	Computation time (hrs)
TBD	330	145	3.8
IBD	332	90	2.1

level V. However, when a large number of damaged lines with few hardening lines considered, e.g., budget=1, may probably cause an infeasible solution. Since there are still many lines damaged without previously hardened, causing the congestion and unbalance among transmission lines. Line 1-2 is almost considered in all the budget ranges since both buses 1 and 2 contain the two largest generators and the power can be transmitted to buses 3, 5, 6 and gas bus 1. Line 2-4 is the second most frequent line to harden as the second largest generation of bus 2 needs to be securely transmitted to bus 4, which is connected with buses 3, 6 and 12. Fig. 5 shows the times for most frequent lines being hardened when the planning budget is under 20. It is concluded that buses 2 and 12 are the most significant buses that involved most frequently. As observed in Fig. 3, bus 2 connects with 5 buses with a generator and load. Bus 12 connects with 5 buses with a load.

C. Computational Results Under Different Planning Budgets

In TABLE VI, it shows that a larger planning budget directly leads to more investment cost, but also improves the reliability and accordingly reduces load shedding cost. When the budget increases from 1 to 2, the investment cost increases dramatically by $66 \times 10^3\$$. The reason is that when the budget is extremely insufficient, e.g., budget=1 or 2, the two most important lines 1-2 and 1-3 are chosen. Lines 1-2 and 1-3 are not only connected with large generators but also have large line ratings, and thus the hardening cost is high. Due to the hardening of lines 1-3, it survives from seismic attack by protecting 2980MWh electricity load and 10Sm^3 gas load from shedding. When the budget increases above 2, the investment cost and load shedding change slowly. Fig. 6 shows the load shedding curve for both electricity and gas with respect to different investment cost. When the investment cost increases, both electricity and gas load shedding decreases. The additional investment cost increasing from $50 \times 10^3\$$ to $116 \times 10^3\$$ helps to prevent load shedding greatly for both the electricity and gas networks. When the investment cost is above $116 \times 10^3\$$, the impact on load shedding is less effective.

D. Comparison with Robust Optimization

RO as a benchmark method is compared with the proposed DRO method in terms of mathematical performance in cases 1, 2 and 3. From TABLE VII, it can be observed that RO yields higher costs in all the three cases. Overall, the total cost and operation cost of DRO are 13% and 18% less than those of RO respectively. The reason is that RO always considers line damages that cause the most severe load shedding. Therefore, in the first stage, RO makes decisions on hardening investment to protect the system before the potential worst damage. In the second stage, under the worst seismic attack, load shedding is made while the whole system flow balance is ensured.

E. Computational Performance

The proposed Benders Decomposition is denoted as improved Benders Decomposition (IBD) as it considers both primal and dual Benders cuts to accelerate the algorithm. The traditional Benders Decomposition is denoted as (TBD). In Figs. 7 and 8, the convergence result of IBD is given. Intensity level V is applied. It can be seen that 90 iterations are required for converging within the optimality gap. Eventually, the upper and

lower bounds converge at \$332000. The comparison between IBD and TBD is given in TABLE VIII in terms of computational performance. The resulted investment costs are \$330000 and \$332000 under TBD and IBD, respectively. The proposed IBD significantly outperforms than TBD on computation time and convergence iteration times, which are 2.1 hours and 90 times. This result implies the improved computational efficiency of the proposed IBD.

F. Discussion on Numerical Results

Three cases are extensively investigated and the resulting difference shows that case 2, i.e., the two-stage model including reliability enhancement planning and emergency response for IES, outperforms cases 1 and 3. Compared with case 1 which only contains the emergency response to maintain system power balance, case 2 provides a more secure and reliable operation scheme with 54% less load shedding cost. In comparison with case 3 which is implemented on the electricity system without gas system integration, case 2 produces better solutions with less load shedding and investment cost. Since the interdependency between electricity and gas systems enables coordinated energy flow to maintain both power and gas balance, it is effective to reduce load shedding and ensure the security of IES. The benefits of using the newly developed DRO over RO for all three cases are also analyzed, which results in reduced expected operation cost and total cost. The reason is that DRO captures the uncertainty of seismic attacks through partial distribution information of uncertainties via ambiguity sets, i.e., moment information. It considers more specific uncertainty information than RO and accordingly produces less-conservative results.

The extensive case study and analysis illustrate the advantages of DR-SIP, which are:

- 1) DR-SIP is a hybrid optimization model containing both planning and operation schemes. It not only provides an optimal hardening plan to enhance reliability against seismic attacks but takes actions to maintain supply and demand balance via load shedding, ensuring the security for IES in two stages.
- 2) The impact of seismic attacks on IES is assessed by considering historical data of seismic events in a probabilistic manner. Thus, the impact of seismic attacks can be easily included in the optimization model for reliability enhancement.
- 3) The developed two-stage DRO method is less conservative than RO because the statistical information of the uncertainty of seismic attacks is utilized.
- 4) This paper demonstrates that the integrated planning model can further improve the reliability of electricity systems, following the trend multi-vector energy system integration.

VI. CONCLUSION

In this paper, a two-stage DRO method is developed to enhance the reliability of an IES under seismic attacks with combined planning and operation strategies. The proposed method provides optimal hardening plans for specific power lines and gas pipelines under different seismic intensity levels and investment budgets. Through extensive case study demonstrations, the key findings are as follows: i) In the first stage, DR-SIP effectively determines the most vital lines to harden. In the second stage, DR-SIP optimally shed loads in order to keep system balance and minimize the system

operation cost; ii) With RO that considers the most extreme event and serious damage, the proposed DRO provides less conservative results for both planning and operation stages with 13% less cost; iii) Investment plan with a higher budget is more likely to yield a reliable IES with high-reliability performance; iv) The optimal hardening plan is effective for protecting transmission lines and loads and IES is more reliable than electricity network against seismic attacks.

This method can help system operators to make economical hardening and operation strategies to improve the reliability of integrated energy systems under seismic attacks.

NOMENCLATURE

A. Sets

T	Set for time periods.
I	Set for power lines.
M	Set for gas pipelines.
G_E	Set for electricity distributed generators.
G_G	Set for gas wells.
D_E	Set for electricity loads.
D_G	Set for gas loads.

B. Parameters

$CL_{co}, CL_{ex}, CL_{mo}, CL_{mi}$	Connection loss for complete, extensive, moderate and minor seismic level.
γ	Failure rate constant for gas pipelines.
π_{ij}, π_{mn}	Unit hardening cost for power lines and gas pipelines.
EL_h, PL_h	Maximum number of hardening power lines and pipelines.
IC_{max}	Maximum monetary budget.
x_{ij}	Reactance of power line ij.
$f_{ij,max}, f_{mn,max}$	Maximum power flow of line ij and gas flow of pipeline mn.
$P_{ge,min}, P_{ge,max}$	Minimum and maximum power output of electricity generators.
$\delta_{de,max}, \delta_{dg,max}$	Maximum limit for electricity and gas load shedding.
$P_{de,t}, P_{dg,t}$	Electricity and gas load demand at time t.
$P_{gg,min}, P_{gg,max}$	Minimum and maximum output of gas wells.
Pr_{min}, Pr_{max}	Minimum and maximum pressure.
γ_{mn}	Coefficient for Weymouth equation.

C. Variables

$P_{co}, P_{ex}, P_{mo}, P_{mi}$	Probability of being complete, extensive, moderate and minor seismic attacks under a randomly chosen seismic level.
P_{ED}	Expected connection loss.
h_{ij}, h_{mn}	Binary variables indicate if power line (i,j)/pipeline (m,n) is hardened.
$\theta_{i,t}, \theta_{j,t}$	Phase angle at electricity bus i and j
x_{ij}	Reactance of power line ij.
$f_{ij,t}, f_{mn,t}$	Power and gas flow of power line ij and gas pipeline mn at time t.
$P_{ge,t}, P_{gg,t}$	Electricity distributed generation and gas well output at time t.
$\delta_{de,t}, \delta_{dg,t}$	Electricity and gas load shedding at time t.
Pr_t	Gas pressure at time t.

D. Uncertainty

ξ_{ij}, ξ_{mn}	Binary variable indicates if power line (i,j)/pipeline (m,n) is damaged.
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a_{ij} , a_{mn} Binary variable indicates if power line (i,j)/pipeline (m,n) is available.

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