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An Integrated Planning Strategy for a Power Network and the Charging Infrastructure of Electric Vehicles for Power System Resilience Enhancement

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Abstract: This paper addresses the integrated planning problem of a power network and the charging infrastructure of electric vehicles (EVs) for enhancing power system resilience under various extreme weather scenarios. The planning methodology determines the optimal joint expansion decisions while modeling the benchmark system operation under the $n - k$ resilience criterion. The proposed coordinated planning framework is a robust two-stage/tri-level mixed-integer optimization model. The proposed robust joint planning model includes the construction plan in the first level, identifying the worst-case scenario in the second level, and optimizing the operation cost and load shedding in the final level. To solve this model, a duality-based column and constraint generation (D-CCG) algorithm is developed. Using case studies, both the robust sole transmission planning and joint planning models are demonstrated on the IEEE 30-bus and IEEE 118-bus power systems. Numerical simulations of the benchmark systems validate the effectiveness of the developed framework and the efficiency of the proposed solution approach. Simulation results show the superiority of the proposed robust integrated planning over the sole transmission planning model.

Keywords: power system; resilience enhancement; electric vehicle; load shedding; robust optimization; normal stage; resilience stage; integrated planning; duality-based column and constraint generation (D-CCG) algorithm

1. Introduction

Enhancing power system resilience to resist, adapt, and recover from disruptions caused by extreme weather events has received increasing attention [1]. Extreme weather disasters, such as typhoons, storm surges, hurricanes and earthquakes can cause power outages and subsequent blackouts. This is evidenced by prime examples such as the Great East Japan Earthquake in 2011, Hurricane Sandy on the east coast of the United States in 2012, and the supercell thunderstorms and four tornadoes in South Australia in 2016 [1–3]. It is reported that in South Australia storms brought power outages to

160,000 customers in 2016. This was the largest recorded power outage event in South Australia—in terms of average minutes of lost supply (SAIDI) [3].

The definition of resilience was first presented in 1972 as “a measure of the persistence of systems and of their ability to absorb change and disturbances and still maintain the same relationships between populations or state variables” [4]. For the past several decades, the concept of resilience has been widely researched in many fields such as environment science, economy, psychology, power engineering. In the power system area, different definitions for resilience are available in some existing publications [4–7], and some of them are completely competing with others.

Generally, the existing related research work can be categorized into two groups, according to the difference from reliability. In the first group, resilience represents the ability to withstand low-probability, high-impact incidents in an efficient manner, while ensuring the least possible interruption in the supply of electricity and enabling a quick recovery and restoration to the normal operation state [8].

In the second group, resilience defines the ability of a power grid to respond to unexpected disturbances while maintaining an acceptable operating state. The farthest acceptable deviation from normal operating conditions is defined as minimum normalcy (i.e., maintaining service to all critical loads and assets). Compared with the first group, this definition differentiates itself from reliability by not focusing on the statics surrounding the outcomes of these events but a system response to an unexpected disturbance.

In this work, the definition of the second group is basically followed. The definition of the first group is based on the fact that event probabilities are constant over time. However, in some events such as hacking, the probability changes over time. As a result, this definition is not well-grounded as the corresponding probabilities of events may change over time. The second definition does not depend on event probabilities, but instead the concept of resilience includes two major aspects, the system response to the events, and maintenance of an acceptable operating state, and is more reasonable.

Several conceptual frameworks for enhancing resilience have been proposed in the current literature. Depending on the stages of occurrence of extreme weather events, existing strategies can be categorized into three groups: prior to the event, during the event, and after the event [9].

The prior-to-event strategies are primarily concerned with power system hardening. The main idea of grid hardening is to improve the resilience of a power system through undergrounding power lines, vegetation management, pole reinforcing, stockpiling power lines, etc. [10]. Extensive research has been conducted to develop grid hardening techniques. A targeted hardening strategy was proposed to improve distribution reliability by strengthening poles with a high probability of failure in [2]. An evaluation of using airborne sensors for vegetation management in power-line corridors was presented in [11]. Three management stages were addressed, including the detection of trees, relative positioning with respect to the nearest power line, and vegetation height estimation. In addition to hardening, some designs of intentional islanding, more commonly known as microgrids (MGs), have been perceived as a viable solution to address the challenge of power system resilience [7]. A self-healing strategy for two neighboring islanded MGs that are connected through a normally open interconnecting static switch (ISS) was investigated in [12]. A hierarchical outage management scheme to enhance the resilience of a smart distribution system composed of multiple MGs against unexpected disaster events was proposed in [13].

The strategies during an extreme weather event are rarely mentioned in existing publications. Few examples include an integrated resilience response framework that integrates the preventive and emergency responses for resilience enhancement [14]. The uncertain sequential transition of the system state driven by the evolution of extreme events is modeled as a Markov process in [15], and a proactive operation strategy to enhance system resilience during an unfolding extreme event developed.

After an extreme weather event related with power outages, resilience restoration plays a vital role in system and load restoration, which consequently reduces economic loss [16,17]. A resilience-oriented service restoration method using MGs to restore critical loads after natural disasters is proposed in [18].

In [19], the authors presented a novel distribution system operational model by forming multiple MGs energized by distributed generators (DGs) from a radial distribution system to restore critical loads from the power outage.

Transmission expansion planning (TEP) is based on load forecasting and power supply planning. Normally, TEP determines when, where, and what type of transmission lines, as well as how many circuits to be constructed to achieve the required transmission capacity in the planning horizon while minimizing the total cost of the transmission system [20]. An MG-based integrated planning model of transmission and generation considering the power system reliability and the economic constraints, was studied in [21]. In [22], a comprehensive robust planning model incorporating transmission lines, generators, and FACTS devices with flexibility requirements and different construction periods was developed. A novel integrated expansion planning for natural gas (NG) and electricity considering long-term, multi-area and multi-stage criteria was presented in [23]. However, these planning models did not consider the impact of extreme natural events.

It goes without saying that the ever-increasing number of EVs has become an important issue in power system operation. At the present time, the traditional way of economic and social development, characterized by centralized utilization of fossil fuel energy, is gradually changing. At the same time, the third industrial revolution is transforming the world. As the core technology of the third industrial revolution, the Energy Internet aims at facilitating large-scale utilization and sharing of renewable energy by integrating renewable energy and internet technologies [24]. With EVs, the coupling degree of power systems and transportation systems will deepen continuously in the future. Electrified transportation systems, especially EVs, will be an important part of the Energy Internet.

As flexible and schedulable demand side resources, EVs can be employed in several aspects such as peak load shifting, providing ancillary services, and suppressing power output fluctuations from renewable energy generation. An EV could act as a load or a small generator depending on its charging or discharging state; it is helpful to enhance power system flexibility and hence resilience.

EVs can feed their electric energy back into the power system concerned through the Vehicle to Grid (V2G) technology, and hence be used as distributed power supply for providing ancillary services such as frequency regulation and spinning reserves. With the support of advanced development in power electronics, communication, and control technology, EVs can be used to enhance the capability of the power system against natural disasters by self-adaptation and fault self-healing, and ensure its secure and stable operation. As a result, EVs can play an important role in power system resilience enhancement [25,26] and should be considered in transmission expansion planning so as to well explore their potentials.

The main contributions of this paper include the following three aspects:

- (1) A new approach for coordinated planning of EV charging facilities and the power system concerned is presented.
- (2) In the robust coordinated planning model, the $n-k$ resilience criterion is included.
- (3) The duality-based column and constraint generation (D-CCG) method are presented to solve the developed optimization model.

The rest of this paper is organized as follows. The integrated robust planning methodology is proposed, and the contingency set in terms of the number of damaged electrical components in the power systems is introduced to describe the degree of impact of extreme weather events in Section 2. An integrated resilience enhancement planning framework for a power system is formulated in Section 3. The D-CCG algorithm is presented in Section 4. Two comprehensive case studies are presented in Section 5 and the paper is concluded in Section 6.

2. Resilience Enhancement Strategies

2.1. A Two-Stage/Tri-Level Robust Optimization Model for Resilient Integrated Planning

Two-stage/tri-level robust optimization models, also known as defender–attacker–defender sequential game models, have been widely employed to solve the power system resilience enhancement problems. An integrated resilience response (IRR) framework, which is a two-stage/tri-level robust mixed-integer optimization model, has been proposed to integrate the preventive response and emergency response [14]. With the proposed IRR model, power system resilience enhancement can be achieved. In [27], the authors developed a tri-level optimization strategy to enhance the resilience of power distribution networks to defend against extreme weather events. The objective of this model is to minimize the grid hardening investment and load shedding. In [28], a tri-level robust optimization model for integrated electricity and natural gas system planning was presented for enhancing the power grid resilience in extreme weather conditions.

In this paper, we develop a tri-level robust optimization model for resilient integrated planning as shown in Figure 1. The power system operator decides the transmission network and EV charging system expansion plan in the first level. In the second level, an extreme weather disaster, serving as the attacker, occurs and, disrupts the power system. The damage of the transmission lines and generators is maximized as the worst-case scenario. Finally, as the defender, the power system operator reacts to the worst-case scenario of an extreme event by adjusting the system power flow and load shedding.

Figure 1. The two-stage/tri-level model developed for power system resilience enhancement.

To view the above tri-level optimization model as two-stage robust resilient planning, the first level decision for the planning of transmission and EV charging systems is considered as the first or normal stage. As shown in Figure 1, the optimization of the second and the third levels is formed as the second or resilience stage, in which the optimal power flow and load curtailment are operated to cope with the worst-case contingency scenario.

2.2. Damage from Disasters

Power outage may be caused not only by extreme natural disasters, but also other factors, such as power system failures, man-made damages, terrorist attacks, and even incorrect operations. Following most papers in the literature studying power system resilience, this paper focuses on the resilience of the power system against natural disaster events only [16,29,30].

The damage on electricity infrastructure varies with the type of extreme natural events. For example, storms normally cause damaged transmission lines, whereas flooding mainly affects generators more than other power grid components [31,32]. Natural disasters can damage power system components, and the worst disaster scenario usually leads to the maximum damage. The maximum damage of an extreme weather event can be reflected by the estimated maximum number of damaged electricity components such as transmission lines and generators. Based on the extreme

weather event information, power outages can be predicted by appropriate statistical methods and simulation models.

In case studies, the estimated maximum number of failed components and the percentage of the shed load are 5 and 20%, respectively [14]. However, the presented methodological framework can accommodate any numbers for these two quantities.

In this paper, instead of trying to forecast the occurrence of different types of extreme weather disasters, we focus on the level of damage, in terms of the maximum number of failed components in the power systems denoted by k . Given a predicted k , we define a contingency set that contains all possible damage scenarios that would result in the given damage level in the following equation:

$$\sum_{sl=1}^{n_L} a^l + \sum_{slc=1}^{n_{LC}} a^{lc} + \sum_{sg=1}^{n_G} a^g \geq n_L + n_{LC} + n_G - k. \quad (1)$$

On the right-hand side of Label (1), n_L , n_{LC} , and n_G are the numbers of existing lines, candidate lines and generators in normal operating conditions; and k is the forecasted maximum number of damaged components in power systems. On the left-hand side of Equation (1), the binary variables a^l , a^{lc} and a^g are introduced to describe the operational/outage (1/0) status of existing lines, candidate lines, and generators after a natural disaster, respectively.

3. Mathematical Formulation

A two-stage/tri-level robust integrated planning model of transmission and EV charging system is proposed in this section. A robust resilience-constrained expansion planning model of coordinated transmission and EV charging system is a two-stage problem where construction plans are made in the first stage before the occurrence of an extreme disaster event. In the second stage, the worst-case scenario of the event is considered, under which optimal power flow and load shedding are undertaken to cope with the disaster. If a construction plan of transmission and EV facilities can meet the resilience $n - k$ criterion under the worst-case scenario, it is robust against all possible scenarios. Considering a given resilience $n - k$ criterion, a mathematical formulation of this problem is given as the following mixed-integer tri-level programming problem: the upper level selects a construction plan; the middle level selects the worst-case scenario (in terms of the damage of transmission lines and generators); and the lower level minimizes the operation cost and load shedding, given the construction plan and damage scenario from the two higher levels:

$$\min \left(\sum_{pl \in LC} c_{pl} u_{pl} + \sum_{i \in I} c_i^{EV} x_i \right) \quad \max_{a^G, a^L, a^{LC} \in \Omega(u, x)} \min_{p_{gi}^t, p_{di}^t \in F(u, x, a^G, a^L, a^{LC})} \left(\sum_{gi \in G} \sum_{t \in T} c_{gi}^p p_{gi}^t + \sum_{i \in I} \sum_{t \in T} c_i^d p_{di}^t \right), \quad (2)$$

subject to:

$$\sum_{pl \in LC} c_{pl} u_{pl} \leq \Pi_{LC}, \quad (3)$$

$$\sum_{i \in I} c_i^{EV} x_i \leq \Pi_{EV}, \quad (4)$$

$$(u_{pl}, x_i) \in \{0, 1\}, \quad (5)$$

where

$$\Omega(x) = \left\{ \sum_{j=1}^{n_L} a_j^l + \sum_{j=1}^{n_{LC}} a_j^{lc} + \sum_{j=1}^{n_G} a_j^g \geq n_L + n_{LC} + n_G - k, \right. \quad (6)$$

$$u_{pl} + a^{lc} \geq 1, \quad pl \in LC \quad (7)$$

$$(a^l, a^{lc}, a^g) \in \{0, 1\}, \quad (8)$$

$$F(u, x, a^l, a^c, a^g) = \left\{ \sum_{gi \in G_i} p_{gi}^t - \sum_{pl \in L} \sum_{i \in I} \lambda_{pl,i} p_{f1}^t - \sum_{pl \in L^c} \sum_{i \in I} \lambda_{pl,i} p_{f2}^t =, \right. \\ \left. d_i^t + r_{ch,i}^t / \eta_{ch} - r_{dch,i}^t \eta_{dch} + p d_i^t, \quad \forall i \in I, \quad \forall gi \in G, \forall t \in T \right. \quad (9)$$

$$p_{f1}^t = [a^l] B_{pl}(\theta_{fpl}^t - \theta_{tpl}^t), \quad \forall pl \in L, \forall t \in T, \quad (10)$$

$$p_{f2}^t = [u_{pl}] [a^c] B_{pl}(\theta_{fpl}^t - \theta_{tpl}^t), \quad \forall pl \in L^c, \forall t \in T, \quad (11)$$

$$p_{f1}^{\min} \leq p_{f1}^t \leq p_{f1}^{\max}, \quad \forall pl \in L, \forall t \in T, \quad (12)$$

$$p_{f2}^{\min} \leq p_{f2}^t \leq p_{f2}^{\max}, \quad \forall pl \in L^c, \forall t \in T, \quad (13)$$

$$[a^g] p_{gi}^{\min} \leq p_{gi}^t \leq [a^g] p_{gi}^{\max}, \quad \forall gi \in G, \forall t \in T, \quad (14)$$

$$p d_i^{\min} \leq p d_i^t \leq p d_i^{\max}, \quad \forall i \in I, \forall t \in T, \quad (15)$$

$$\theta_{fpl}^{\min} \leq \theta_{fpl}^t \leq \theta_{fpl}^{\max}, \quad \forall pl \in (L \cup L^c), \forall t \in T, \quad (16)$$

$$\theta_{tpl}^{\min} \leq \theta_{tpl}^t \leq \theta_{tpl}^{\max}, \quad \forall pl \in (L \cup L^c), \forall t \in T, \quad (17)$$

$$SOC_i^t = SOC_i^{t-1} + r_{ch,i}^t - r_{dch,i}^t, \quad \forall i \in I, \forall t \in T, \quad (18)$$

$$[x_i] SOC_i^{\min} \leq SOC_i^t \leq [x_i] SOC_i^{\max}, \quad \forall i \in I, \forall t \in T, \quad (19)$$

$$r_{ch,i}^t \leq r_{ch,i}^{\max}, \quad \forall i \in I, \forall t \in T, \quad (20)$$

$$r_{dch,i}^t \leq r_{dch,i}^{\max}, \quad \forall i \in I, \forall t \in T, \quad (21)$$

$$\sum_{i \in I} p d_i^t \leq \prod_{pd} \quad \forall i \in I, \quad \forall t \in T \quad (22)$$

The objective function (2) intends to minimize the total cost including the construction cost of the transmission and EV charging facilities, and the damage cost of the power systems under the worst-case scenario. Equations (3) and (4) represent the budget constraints for the transmission and EV charging system investments, respectively. The binary variables in Equation (5) are used to indicate whether an investment is undertaken (e.g., 1 means an investment is undertaken). Equation (6) to Equation (8) define the contingency set that provides all possible contingency scenarios for the given construction plan (in terms of the variables u and x) meeting the resilience $n - k$ criterion. Equation (7) shows that, if a candidate line has not been built, it cannot have an outage (to appear in the contingency set). Equation (9) to Equation (22) define the feasible region that provides an optimal power flow solution under a given construction plan and the worst-case contingency scenario. In Equations (10), (11), (14) and (19), the bracket notation $[.]$ is used to highlight a 0/1 binary variable. Equation (10) represents power flow on existing lines. Equation (11) represents the power flow on candidate lines. Equations (12) and (13) represent power flow limits on existing and candidate transmission lines, respectively. Equation (14) requires the power generation to be within generating limits. Equation (15) limits the amount of load shedding. Equations (16) and (17) limit the phase angles at the sending ends and receiving ends of the power lines, respectively. The charge and discharge process of the EV charging system are presented in Equation (18). Equation (19) imposes the limits for the State-of-Charge (SOC) of EV charging system. The charge and discharge rate limits of EV systems are enforced in Equations (20) and (21). The total load shedding budget is given in Equation (22).

4. Solution Methodology

The duality-based column and constraint generation (D-CCG) algorithm, which upgrades the primality-based column and constraint generation (P-CCG) algorithm [33,34], is applied to the proposed

resilient integrated planning model. The difference between D-CCG and P-CCG lies in the way they reformulate the middle and lower levels into a problem with a single level, called the ‘middle-lower level’. To derive the middle-lower level, P-CCG uses the Karush–Kuhn–Tucker (KKT) conditions for the lower level problem, whereas D-CCG solves the dual problem of the lower level problem. Since, in general, there are fewer constraints and variables introduced by the dual problem than those involved in the KKT conditions, D-CCG is more computationally efficient.

The original problem is decomposed to the master problem and the sub-problem, grouped by the upper level and middle-lower level. The master problem proposed is based on primal cuts, which is more computationally efficient than the Benders’ master problem based on dual cuts. The proposed approach can converge quickly within a few iterations without imposing additional cuts. In this paper, a binary variable with an overbar is the binary variable from the counterpart problem (either the master or the subproblem).

4.1. Subproblem

Given a construction plan described by $\overline{u}_{pl}$ and $\overline{x}_i$ representing the construction of transmission lines and EV charging facilities, respectively, the subproblem (middle level and lower level) intends to determine the worst-case scenario and the optimal power system operation solution under the scenario:

$$\max_{a^G, a^{LC} \in \Omega(u, x)} \min_{p_{gi}^t, p_{di}^t \in F(u, x, a^G, a^{LC})} \left(\sum_{gi \in G} \sum_{t \in T} c_{gi}^p p_{gi}^t + \sum_{i \in I} \sum_{t \in T} c_i^d p_{di}^t \right), \quad (23)$$

$$\sum_{gi \in G_i} p_{gi}^t - \sum_{pl \in L} \sum_{i \in I} \lambda_{pl,i} p_{f1}^t - \sum_{pl \in L^c} \sum_{i \in I} \lambda_{pl,i} p_{f2}^t = d_i^t + r_{ch,i}^t / \eta_{ch} - r_{dch,i}^t \eta_{dch} + p_{di}^t, \quad \forall i \in I, \forall gi \in G, \forall t \in T : u_1, \quad (24)$$

$$p_{f1}^t = [a^l] B_{pl} (\theta_{fpl}^t - \theta_{tpl}^t), \quad \forall pl \in L, \forall t \in T : u_2, \quad (25)$$

$$p_{f2}^t = [\overline{u}_{pl}] [a^{lc}] B_{pl} (\theta_{fpl}^t - \theta_{tpl}^t), \quad \forall pl \in L^c, \forall t \in T : u_3, \quad (26)$$

$$p_{f1}^{\min} \leq p_{f1}^t \leq p_{f2}^{\max}, \quad \forall pl \in L, \forall t \in T : u_4, u_5, \quad (27)$$

$$p_{f2}^{\min} \leq p_{f2}^t \leq p_{f2}^{\max}, \quad \forall pl \in L^c, \forall t \in T : u_6, u_7, \quad (28)$$

$$[a^g] p_{gi}^{\min} \leq p_{gi}^t \leq [a^g] p_{gi}^{\max}, \quad \forall gi \in G_i, \forall t \in T : u_8, u_9, \quad (29)$$

$$p_{di}^{\min} \leq p_{di}^t \leq p_{di}^{\max}, \quad \forall i \in I, \forall t \in T : u_{10}, u_{11}, \quad (30)$$

$$\theta_{fpl}^{\min} \leq \theta_{fpl}^t \leq \theta_{fpl}^{\max}, \quad \forall pl \in (L \cup L^c), \forall t \in T : u_{12}, u_{13}, \quad (31)$$

$$\theta_{tpl}^{\min} \leq \theta_{tpl}^t \leq \theta_{tpl}^{\max}, \quad \forall pl \in (L \cup L^c), \forall t \in T : u_{14}, u_{15}, \quad (32)$$

$$SOC_i^t = SOC_i^{t-1} + r_{ch,i}^t - r_{dch,i}^t, \quad \forall i \in I, \forall t \in T : u_{16}, \quad (33)$$

$$[\overline{x}_i] SOC_i^{\min} \leq SOC_i^t \leq [\overline{x}_i] SOC_i^{\max}, \quad \forall i \in I, \forall t \in T : u_{17}, u_{18}, \quad (34)$$

$$r_{ch,i}^t \leq r_{ch,i}^{\max}, \quad \forall i \in I, \forall t \in T : u_{19}, \quad (35)$$

$$r_{dch,i}^t \leq r_{dch,i}^{\max}, \quad \forall i \in I, \forall t \in T : u_{20}, \quad (36)$$

$$\sum_{i \in I} p_{di}^t \leq \prod_{pd} p_{pd}, \quad \forall i \in I, \forall t \in T : u_{21}, \quad (37)$$

where

$$\Omega(x) = \left\{ \sum_{sl=1}^{n_L} a^l + \sum_{slc=1}^{n_{LC}} a^{lc} + \sum_{sg=1}^{n_G} a^g \geq n_L + n_{LC} + n_G - k, \right. \quad (38)$$

$$u_{pl} + a^{lc} \geq 1, \quad (39)$$

$$(a^l, a^{lc}, a^g) \in \{0, 1\}. \quad (40)$$

The dual problem of the lower level problem can be expressed as:

$$\begin{aligned} \max_{u_1-u_{20}} & \sum_{i \in I} d_i^t u_1 - \sum_{l \in L^c} p_{f1}^{\min} u_4 + \sum p_{f1}^{\max} u_5 + \sum_{pl \in L} p_{f2}^{\min} u_6 + \sum_{pl \in L} p_{f2}^{\max} u_7 \\ & - \sum_{gi \in Gi} [a^g] p_{gi}^{\min} u_8 + \sum_{gi \in Gi} [a^g] p_{gi}^{\max} u_9 - \sum_{i \in I} p d_i^{\min} u_{10} + \sum_{i \in I} p d_i^{\max} u_{11} \\ & - \sum_{fpl \in L} \theta_{fpl}^{\min} u_{12} + \sum_{fpl \in L^c} \theta_{fpl}^{\max} u_{13} - \sum_{tpl \in L} \theta_{tpl}^{\min} u_{14} + \sum_{tpl \in L^c} \theta_{tpl}^{\max} u_{15} - \sum_{i \in I} [\bar{x}_i] SOC_i^{\min} u_{17} \\ & + \sum_{i \in I} [\bar{x}_i] SOC_i^{\max} u_{18} - \sum_{i \in I} r_{ch,i}^{\max} u_{19} - \sum_{i \in I} r_{dch,i}^{\max} u_{20} - \prod_{pd} u_{21}, \end{aligned} \quad (41)$$

$$p_{gi}^t : c_{gi}^p + u_1 - u_8 + u_9 = 0, \quad (42)$$

$$p d_i^t : c_i^d - u_1 - u_{10} + u_{11} + u_{21} = 0, \quad (43)$$

$$p_{f1}^t : -\lambda_{pl,i} u_1 + u_2 - u_4 + u_5 = 0, \quad (44)$$

$$p_{f2}^t : -\lambda_{pl,i} u_1 + u_3 - u_6 + u_7 = 0, \quad (45)$$

$$\theta_{fpl}^t : -[a^l] B_{pl} u_2 - [\bar{u}_{pl}] [a^{lc}] B_{pl} u_3 - u_{12} + u_{13} = 0, \quad (46)$$

$$\theta_{tpl}^t : [a^l] B_{pl} u_2 + [\bar{u}_{pl}] [a^{lc}] B_{pl} u_3 - u_{14} + u_{15} = 0, \quad (47)$$

$$SOC_i^t : -u_{17} + u_{18} = 0, \quad (48)$$

$$r_{ch,i}^t : -u_1 - u_{19} = 0, \quad (49)$$

$$r_{dch,i}^t : u_1 - u_{20} = 0, \quad (50)$$

$$u_4 \sim u_{21} \geq 0. \quad (51)$$

In (41), the objective function contains bilinear terms which are $a^g p_{gi}^{\min} u_8$, $a^g p_{gi}^{\max} u_9$, $x_i SOC_i^{\min} u_{17}$ and $x_i SOC_i^{\max} u_{18}$, and each of them is a multiplication of a binary variable and a continuous variable. Using standard approaches, the bilinear terms $a^g u_8$, $a^g u_9$, $x_i u_{17}$ and $x_i u_{18}$ can be linearized by first replacing them with new variables $\beta_8, \beta_9, \beta_{17}$ and β_{18} , respectively. Then, the following linear constraints are introduced:

$$\beta_8 \geq u_8 - M(1 - a^g), \quad (52)$$

$$\beta_8 \geq 0, \quad (53)$$

$$\beta_9 \geq u_9 - M(1 - a^g), \quad (54)$$

$$\beta_9 \geq 0, \quad (55)$$

$$\beta_{17} \geq u_{17} - M(1 - x_i), \quad (56)$$

$$\beta_{17} \geq 0, \quad (57)$$

$$\beta_{18} \geq u_{18} - M(1 - x_i), \quad (58)$$

$$\beta_{18} \geq 0. \quad (59)$$

Likewise, the bilinear terms $\alpha^l B_{pl} u_2$ and $u_{pl} \alpha^{lc} B_{pl} u_3$ in Equations (46) and (47) can be linearized in a similar manner. First, the terms $\alpha^l u_2$ and $\alpha^{lc} u_3$ are replaced by new variables β_2 and β_3 , respectively. We then introduce additional linear constraints as follows:

$$\beta_2 = u_2 - h_2, \quad (60)$$

$$-Ma^l \leq \beta_2 \leq Ma^l, \quad (61)$$

$$-M(1 - a^l) \leq h_2 \leq M(1 - a^l), \quad (62)$$

$$\beta_3 = u_3 - h_3, \quad (63)$$

$$-Ma^{lc} \leq \beta_3 \leq Ma^{lc}, \quad (64)$$

$$-M(1 - a^{lc}) \leq h_3 \leq M(1 - a^{lc}). \quad (65)$$

Finally, the subproblem is equivalent to the following mixed-integer linear programming problem:

$$\begin{aligned} & \max_{\substack{a^l, a^{lc}, a^g, a^{ev} \\ u_1 - u_{20} \\ \beta_2, \beta_3, \beta_8, \beta_9, \beta_{17}, \beta_{18}}} \sum_{i \in I} d_i^t u_1 - \sum_{l \in L^c} p_{f1}^{\min} u_4 + \sum p_{f1}^{\max} u_5 + \sum_{pl \in L} p_{f2}^{\min} u_6 + \sum_{pl \in L} p_{f2}^{\max} u_7 \\ & - \sum_{gi \in Gi} p_{gi}^{\min} \beta_8 + \sum_{gi \in Gi} p_{gi}^{\max} \beta_9 - \sum_{i \in I} p d_i^{\min} u_{10} + \sum_{i \in I} p d_i^{\max} u_{11} \\ & - \sum_{fpl \in L} \theta_{fpl}^{\min} u_{12} + \sum_{fpl \in L^c} \theta_{fpl}^{\max} u_{13} - \sum_{tpl \in L} \theta_{tpl}^{\min} u_{14} + \sum_{tpl \in L^c} \theta_{tpl}^{\max} u_{15} - \sum_{i \in I} SOC_i^{\min} \beta_{17} \\ & + \sum_{i \in I} SOC_i^{\max} \beta_{18} - \sum_{i \in I} r_{ch,i}^{\max} u_{19} - \sum_{i \in I} r_{dch,i}^{\max} u_{20} - \prod_{pd} u_{21}, \end{aligned} \quad (66)$$

$$p_{gi}^t : c_{gi}^p + u_1 - u_8 + u_9 = 0, \quad (67)$$

$$p d_i^t : c_i^d - u_1 - u_{10} + u_{11} + u_{21} = 0, \quad (68)$$

$$p_{f1}^t : -\lambda_{pl,i} u_1 + u_2 - u_4 + u_5 = 0, \quad (69)$$

$$p_{f2}^t : -\lambda_{pl,i} u_1 + u_3 - u_6 + u_7 = 0, \quad (70)$$

$$\theta_{fpl}^t : -B_{pl} \beta_2 - [\overline{u_{pl}}] B_{pl} \beta_3 - u_{12} + u_{13} = 0, \quad (71)$$

$$\theta_{tpl}^t : B_{pl} \beta_2 + [\overline{u_{pl}}] B_{pl} \beta_3 - u_{14} + u_{15} = 0, \quad (72)$$

$$SOC_i^t : -u_{17} + u_{18} = 0, \quad (73)$$

$$r_{ch,i}^t : -u_1 - u_{19} = 0, \quad (74)$$

$$r_{dch,i}^t : u_1 - u_{20} = 0, \quad (75)$$

$$u_4 \sim u_{20} \geq 0, \quad (76)$$

$$\beta_8 \geq u_8 - M(1 - a^g), \quad (77)$$

$$\beta_8 \geq 0, \quad (78)$$

$$\beta_9 \geq u_9 - M(1 - a^g), \quad (79)$$

$$\beta_9 \geq 0, \quad (80)$$

$$\beta_2 = u_2 - h_2, \quad (81)$$

$$-Ma^l \leq \beta_2 \leq Ma^l, \quad (82)$$

$$-M(1-a^l) \leq h_2 \leq M(1-a^l), \quad (83)$$

$$\beta_3 = u_3 - h_3, \quad (84)$$

$$-Ma^{lc} \leq \beta_3 \leq Ma^{lc}, \quad (85)$$

$$-M(1-a^{lc}) \leq h_3 \leq M(1-a^{lc}), \quad (86)$$

$$\sum_{sl=1}^{n_L} a^l + \sum_{slc=1}^{n_{LC}} a^{lc} + \sum_{sg=1}^{n_G} a^g \geq n_L + n_{LC} + n_G - k, \quad (87)$$

$$\left[\overline{u_{pl}} \right] + \left[a^{lc} \right] \geq 1, \quad (88)$$

$$(a^l, a^{lc}, a^g) \in \{0, 1\} \quad (89)$$

4.2. Master Problem

At the k^{th} iteration, for any $m < k$, variables $a^{l(m)}, a^{lc(m)}, a^{g(m)}$ can be obtained from the sub-problem, thus the master problem is expressed as follows:

$$\min_{u,x} \left(\sum_{pl \in L^C} c_{pl} u_{pl} + \sum_{i \in I} c_i^{EV} x_i + \alpha \right), \quad (90)$$

$$\sum_{pl \in L^C} c_{pl} u_{pl} \leq \Pi_{LC'}, \quad (91)$$

$$\sum_{i \in I} c_i^{EV} x_i \leq \Pi_{EV'}, \quad (92)$$

$$\alpha \geq \left(\sum_{gi \in G} \sum_{t \in T} c_{gi}^p p_{gi}^{t(m)} + \sum_{i \in I} \sum_{t \in T} c_i^d p d_i^{t(m)} \right), \quad (93)$$

$$\sum_{gi \in G_i} p_{gi}^{t(m)} - \sum_{pl \in L} \sum_{i \in I} \lambda_{pl,i} p_{f1}^{t(m)} - \sum_{pl \in L^C} \sum_{i \in I} \lambda_{pl,i} p_{f2}^{t(m)} =$$

$$d_i^t + r_{ch,i}^{t(m)} / \eta_{ch} - r_{dch,i}^{t(m)} \eta_{dch} + p d_i^{t(m)}, \quad m = 1, \dots, k-1, \quad (94)$$

$$p_{f1}^{t(m)} = \left[\overline{a^l}^{(m)} \right] B_{pl} (\theta_{fpl}^{t(m)} - \theta_{tpl}^{t(m)}), \quad m = 1, \dots, k-1, \quad (95)$$

$$p_{f2}^{t(m)} = \left[u_{pl} \right] \left[\overline{a^{lc}}^{(m)} \right] B_{pl} (\theta_{fpl}^{t(m)} - \theta_{tpl}^{t(m)}), \quad m = 1, \dots, k-1, \quad (96)$$

$$p_{f1}^{\min} \leq p_{f1}^{t(m)} \leq p_{f2}^{\max}, \quad m = 1, \dots, k-1, \quad (97)$$

$$p_{f2}^{\min} \leq p_{f2}^{t(m)} \leq p_{f2}^{\max}, \quad m = 1, \dots, k-1, \quad (98)$$

$$\left[\overline{a^g} \right] p_{gi}^{\min} \leq p_{gi}^{t(m)} \leq \left[\overline{a^g} \right] p_{gi}^{\max}, \quad m = 1, \dots, k-1, \quad (99)$$

$$p d_i^{\min} \leq p d_i^{t(m)} \leq p d_i^{\max}, \quad m = 1, \dots, k-1, \quad (100)$$

$$\theta_{fpl}^{\min} \leq \theta_{fpl}^{t(m)} \leq \theta_{fpl}^{\max}, \quad m = 1, \dots, k-1, \quad (101)$$

$$\theta_{tpl}^{\min} \leq \theta_{tpl}^{t(m)} \leq \theta_{tpl}^{\max}, \quad m = 1, \dots, k-1, \quad (102)$$

$$SOC_i^{t(m)} = SOC_i^{t-1(m)} + r_{ch,i}^{t(m)} - r_{dch,i}^{t(m)}, \quad m = 1, \dots, k-1, \quad (103)$$

$$[x_i]SOC_i^{\min} \leq SOC_i^{t(m)} \leq [x_i]SOC_i^{\max}, \quad m = 1, \dots, k-1, \quad (104)$$

$$r_{ch,i}^{t(m)} \leq r_{ch,i}^{\max}, \quad m = 1, \dots, k-1, \quad (105)$$

$$r_{dch,i}^{t(m)} \leq r_{dch,i}^{\max}, \quad m = 1, \dots, k-1, \quad (106)$$

$$\sum_{i \in I} p d_i^{t(m)} \leq \prod_{pd'} \quad m = 1, \dots, k-1. \quad (107)$$

Equation (96) is involved with the nonlinear problem that can be transformed to the following constraint by introducing big M parameters:

$$\left| p_{f2}^{t(m)} - \left[\overline{a^{lc}}^{(m)} \right] B_{pl}(\theta_{fpl}^{t(m)} - \theta_{tpl}^{t(m)}) \right| \leq (1 - u_{pl})M, \quad m = 1, \dots, k-1. \quad (108)$$

4.3. Solution Algorithm

By linearizing the bilinear variables $\beta_2, \beta_3, \beta_8, \beta_9, \beta_{17}$ and β_{18} using the Big-M method, the subproblem can be transformed into a mixed-integer linear programming (MILP) problem. In addition, the master problem is also an MILP problem. They can both be solved using commercial solvers such as CPLEX and GUROBI. The solution algorithm is described below.

Solution Algorithm: Duality-based column and constraint generation (D-CCG) algorithm

Step 0: Initialization. Set the transmission plan variable $\overline{u}_{pl} = 0$ and EV charging system plan variable $\overline{x}_i = 0$; iteration count $k = 0$, the lower bound $LB = -inf$, the upper bound $UB = inf$.

Step 1: $k = k + 1$, Solve the sub-problem and determine the optimal solutions, update the UB using $\min(UB, \sum_{pl \in L^C} c_{pl} \overline{u}_{pl} + \sum_{i \in I} c_i^{EV} \overline{x}_i + VALUE(dual_obj))$, where $VALUE(dual_obj)$ is the computed value of the dual objective function of the lower level problem, expressed by (41) or (66).

Step 2: Based on the variables $\overline{a^l}, \overline{a^{lc}}, \overline{a^s}$ from the sub-problem, solve the master problem and update LB with $LB = \max(LB, \sum_{pl \in L^C} c_{pl} \overline{u}_{pl} + \sum_{i \in I} c_i^{EV} \overline{x}_i + \alpha)$.

Step 3: If $UB - LB \leq \varepsilon$, ($\varepsilon = 10^{-2}$), return the corresponding result and terminate. Otherwise, create variable $\overline{x}_i$ and add the constraints (93)–(107) to the master problem and go to Step 1.

5. Case Studies

The proposed joint planning model of transmission lines and EV charging system considering resilience enhancement is illustrated with two cases based on the IEEE 30-bus system [35] and IEEE 118-bus system [36]. We assume a unit's generating cost as a linear function of the form $c_{gi}^t p_{gi}^t$, which is widely used in the literature of power systems [37,38]. The parameters for the transmission investment are taken from [23]. Other parameters used in the two case studies are listed in Table 1.

The two case studies have been solved by the developed resilience enhancement model (2)–(22), and by the proposed D-CCG algorithm. By changing the maximum number of failed components of power systems k from 1 to 5, the worst-case weather scenario for each k is simulated in the test cases. For these five cases, five different, maximum system load shedding parameter $\prod_{pd}$ values of 0%, 5%, 10%, 15%, and 20% of the total system load are assigned, respectively. The developed robust planning framework is tested by the IEEE 30-bus and IEEE 118-bus power systems. In case studies, the estimated maximum number of failed components is given to be 5, while the shed load is 20% of the total load [14], since the two test systems are not large in size. It is concluded by simulation results that: (1) the advantage of coordinated power grid and EV charging facility planning over sole transmission planning is significant, (2) the benefits of the developed robust coordinated planning are demonstrated, and (3) the efficiency of the proposed D-CCG method is superior to the P-CCG one.

The proposed solution algorithm is implemented in MATLAB (version, Manufacturer, City, US State abbrev. if applicable, Country) with GUROBI (version, Manufacturer, City, US State abbrev. if applicable, Country) on a computer with an Intel Core i7 2.60 GHz CPU (City, US State abbrev. if applicable, Country) and 8 GB of memory. The maximum time limit is specified to be 1 h, and “NA” means that the method fails to attain the coordinated planning scheme within the specified maximum time limit.

Table 1. Settings of parameters.

C_i^{EV}	C_{gi}^p	C_i^d	Π_{LC}	Π_{EV}	Π_{pd}	$SOC_i^{\min}$	$SOC_i^{\max}$	$r_{ch,i}^{\max}$	$r_{dch,i}^{\max}$
$\$4 \times 10^6$	$\$4 \times 10^9/\text{MWh}$	$\$65/\text{MWh}$	$\$41 \times 10^6$ (case A); $\$187 \times 10^6$ (case B)	$\$150 \times 10^6$ (case A); $\$450 \times 10^6$ (case B)	[0%, 5%, 10%, 15%, 20%] of PD	20%	100%	25%	25%

Note: (1) SOC = State of Charge; (2) PD = Power Demand.

5.1. IEEE 30-Bus System

In this case, the proposed robust integrated planning framework is implemented on the IEEE 30-bus network. The benchmark system consists of six generators, 41 transmission lines, 21 system loads, and a set of 41 candidate lines available for transmission expansion. This case study summarizes the construction expansion planning, the load shedding, and system operation cost of the two frameworks including (1) the robust sole transmission planning and (2) the robust coordinated planning of transmission and EV charging facilities. The results of the robust transmission expansion planning is given in Table 2.

Table 2. IEEE 30-bus power system: Robust sole transmission planning.

k	Π_{pd}	Transmission Expansion Plan (Line No.)	Load Shedding (MW)	System Operation Cost ($\$10^6$)
1	0% of PD	34	0	247.6627
2	5% of PD	9, 10, 22, 23, 29, 39	0.1075	328.3223
3	10% of PD	5, 8, 9, 10, 22, 25, 27, 29, 36, 39, 40	0.1514	571.4586
4	15% of PD	9, 10, 21, 37	0.2270	896.6736
5	20% of PD	21, 37	0.3027	1160.3542

Note: PD = Power Demand.

Table 2 illustrates the transmission expansion plans, load shedding, and system operation costs when the estimated maximum number of damaged electrical components (transmission lines and generators) is changed from $k = 1$ to $k = 5$. According to the table, there is a sharp increase in the number of transmission lines expanded from $k = 1$ to $k = 3$, which indicates that the expansion plan grows as the number of k increases. However, the number of expanded transmission lines drops drastically from 11 lines to 4 lines when the value of k increases from 3 to 4. Given the small size of the test problem, when $k \geq 4$, the damage incurred in the worst-case scenario is too significant such the most cost-effective plan is not to construct too many new lines (only to see them to be brought down later). Building new transmission lines can increase the power transfer capability and enhance the system resilience. However, in some cases, such as when $k = 4$, load-shedding is more economical and represents a better choice, compared with transmission expansion.

When $k = 1$, the formulation of (1) is reduced to $\sum_{sl=1}^{n_L} a^l + \sum_{slc=1}^{n_{LC}} a^{lc} + \sum_{sg=1}^{n_G} a^g \geq n - 1$, where $n = n_L + n_{LC} + n_G$. For the conventional $n - 1$ security criterion, no system load loss is permitted. This can be observed from Table 2 that the power system does not have to shed any load when $k = 1$. We can see that the load shed increases dramatically as the uncertain maximum number of failed components in the power systems rises, as expected.

The corresponding operating cost of the proposed planning framework under different k is given in Table 2. It is clear that the operating cost gradually increases from \$247.6627 million to \$1160.3542 million as k increases from 1 to 5, due to the increased system load shedding.

Table 3 shows the numerical results of the coordinated planning of transmission and EV charging facilities. It indicates that, when EV charging facilities are built, the number of transmission lines expanded will decrease with a lower level of load shedding and a lower system operation cost (except when $k = 1$), indicating the importance of using EV batteries as a flexible energy source for resilience enhancement. This result further illustrates the advantage of the coordinated planning of transmission and EV charging facility expansions. When $k = 1$, the operation cost is the same in both Tables 2 and 3 because the robust coordinated planning does not influence the operating cost under the conventional $n - 1$ security criterion.

Table 3. IEEE 30-bus power system: Robust coordinated planning.

k	Π_{pd}	Transmission Expansion Plan (Line No.)	EV Charging System Expansion Plan (EV Stations no.)	Load Shedding (MW)	System Operation Cost (\$10 ⁶)
1	0% of PD	34	-	0	247.6627
2	5% of PD	10, 22, 23, 29, 39	10, 14, 21	0.1073	322.1863
3	10% of PD	9, 10, 22, 25, 27, 36, 39, 40	1, 10, 14, 19, 21, 25	0.1508	570.9903
4	15% of PD	10, 21, 37	10, 20	0.2265	891.6861
5	20% of PD	21	10	0.3023	1154.9273

To demonstrate the advantages of the developed robust coordinated planning over the non-expansion resilience enhancement planning (NEP), the NEP model is formulated as the following tri-level programming problem: the upper level includes generator dispatch; the middle level selects the worst-case scenario; and the lower level minimizes the operation cost and shed load:

$$\min \left(\sum_{gi \in G} \sum_{t \in T} c_{gi}^p p_{gi}^t + \max_{a^G, a^L \in \Omega(u, x)} \min_{p_{gi}^t, pd_i^t \in F(a^G, a^L)} \left(\sum_{gi \in G} \sum_{t \in T} c_{gi}^p p_{gi}^t + \sum_{i \in I} \sum_{t \in T} c_i^d pd_i^t \right) \right), \quad (109)$$

subject to:

$$\Omega(x) = \left\{ \sum_{j=1}^{n_L} a_j^l + \sum_{j=1}^{n_G} a_j^g \geq n_L + n_G - k, \right. \quad (110)$$

$$\left. (a^l, a^g) \in \{0, 1\} \right\}, \quad (111)$$

$$F(a^l, a^g) = \left\{ \sum_{gi \in G_i} p_{gi}^t - \sum_{pl \in L} \sum_{i \in I} \lambda_{pl,i} p_{f1}^t = d_i^t + r_{ch,i}^t / \eta_{ch} - r_{dch,i}^t \eta_{dch} + pd_i^t, \quad \forall i \in I, \quad \forall gi \in G, \quad \forall t \in T, \right. \quad (112)$$

$$p_{f1}^t = [a^l] B_{pl} (\theta_{fpl}^t - \theta_{tpl}^t), \quad \forall pl \in L, \quad \forall t \in T, \quad (113)$$

$$p_{f1}^{\min} \leq p_{f1}^t \leq p_{f1}^{\max}, \quad \forall pl \in L, \quad \forall t \in T, \quad (114)$$

$$[a^g] p_{gi}^{\min} \leq p_{gi}^t \leq [a^g] p_{gi}^{\max}, \quad \forall gi \in G_i, \quad \forall t \in T, \quad (115)$$

$$[a^g] p_{gi}^{\min} \leq p_{gi}^t \leq [a^g] p_{gi}^{\max}, \quad \forall gi \in G_i, \quad \forall t \in T, \quad (116)$$

$$pd_i^{\min} \leq pd_i^t \leq pd_i^{\max}, \quad \forall i \in I, \quad \forall t \in T, \quad (117)$$

$$\theta_{fpl}^{\min} \leq \theta_{fpl}^t \leq \theta_{fpl}^{\max}, \quad \forall pl \in L, \quad \forall t \in T, \quad (118)$$

$$\theta_{tpl}^{\min} \leq \theta_{tpl}^t \leq \theta_{tpl}^{\max}, \forall pl \in L, \forall t \in T, \quad (119)$$

$$SOC_i^t = SOC_i^{t-1} + r_{ch,i}^t - r_{dch,i}^t, \quad \forall i \in I, \forall t \in T, \quad (120)$$

$$[x_i]SOC_i^{\min} \leq SOC_i^t \leq [x_i]SOC_i^{\max}, \quad \forall i \in I, \forall t \in T, \quad (121)$$

$$r_{ch,i}^t \leq r_{ch,i}^{\max}, \quad \forall i \in I, \forall t \in T, \quad (122)$$

$$r_{dch,i}^t \leq r_{dch,i}^{\max}, \quad \forall i \in I, \forall t \in T, \quad (123)$$

$$\sum_{i \in I} pd_i^t \leq \prod_{pd}, \quad \forall i \in I, \quad \forall t \in T. \quad (124)$$

From Table 4, it is clear that both the robust sole planning and the coordinated planning can reduce the load shed significantly. For example, when $k = 2$, the non-expansion resilience enhancement model will lead to 0.3189 MW load loss so as to maintain the security of the power system, while the robust sole model only needs to shed 0.1075 MW of load, and the system resilience could be further enhanced by using the robust coordinated planning. This indicates the benefits of the proposed transmission expansion plan (TEP) with respect to system reliability.

Table 4. Load shed of the IEEE 30-bus power system under different k 's.

k	$\prod_{pd}$	Load Shed (MW)		
		Non-Expansion Resilience Enhancement Model	Robust Sole Transmission Planning	Robust Coordinated Transmission Planning
1	0% of PD	0	0	0
2	5% of PD	0.3189	0.1075	0.1073
3	10% of PD	0.4769	0.1514	0.1508
4	15% of PD	0.6243	0.2270	0.2265
5	20% of PD	0.7721	0.3027	0.3023

Table 5 lists the computing time of D-CCG and P-CCG for the IEEE 30-bus power system under different k 's. As can be seen, for all instances, the computational time of D-CCG is less than 116.02 s. In contrast, P-CCG is only successful for k up to 3 since tighter security criteria lead to intractable contingency-dependent models. Moreover, D-CCG is considerably faster than P-CCG when k takes 2 and 3. These results clearly demonstrate the superiority of D-CCG over P-CCG from a computational speed perspective.

Table 5. Computation time of D-CCG and P-CCG for the IEEE 30-bus power system under different k 's.

k	Computational Time(s) for Robust Sole Transmission Planning	
	D-CCG	P-CCG
1	1.76	1.82
2	5.68	8.43
3	107.47	388.31
4	54.28	NA
5	116.02	NA

Note: D-CCG = duality-based column and constraint generation algorithm; P-CCG = primality-based column and constraint generation algorithm.

Table 5 also shows that the computational time grows from 1.76 s for $k = 1$ to 107.47 s for $k = 3$. However, the computing time declines significantly when k increases from 3 to 4. This seeming counter-intuitive result comes from the much lesser expansion plans under $n - 4$ resilience criterion. In the proposed D-CCG algorithm, a higher k value and a larger number of new built lines could

lead to more computational loop iterations. Although k rises from 3 to 4, the new built lines decrease dramatically from 11 for $k = 3$ to 4 for $k = 4$; this is why $k = 4$ results in a significantly less computing time of 54.28 s compared to the $k = 3$ row of 107.47 s.

5.2. IEEE 118-Bus Power System

In the second case study, we will use the IEEE 118-bus power system as a benchmark for the proposed coordinated planning. The IEEE 118-bus power system consists of 55 thermal generators, 186 transmission lines and 186 candidate transmission circuits.

Table 6 compares the number of built lines under different k values. As in the first case, the $n - 3$ security criterion results in the most transmission lines added than the other cases. We can find that for, $k \leq 3$, the number of the expansion plans grows as k increases. Three lines are built for $k = 1$, whereas the $n - 3$ resilience criterion leads to 34 new expansion lines. When $k \geq 3$, the number of the constructed lines decreases from 34 to 4 as k increases from 3 to 5. Table 6 also shows that a higher k value leads to a higher load shed and system operation costs, and this is consistent with the results presented in Table 2.

Table 6. IEEE 118-bus power system: Robust sole transmission planning.

k	Π_{pd}	Number of Transmission Lines Built	Load Shedding (MW)	System Operation Cost (\$10 ⁶)
1	0% of PD	3	0	7272.5
2	5% of PD	4	0.2121	7474.0
3	10% of PD	34	0.3216	7803.6
4	15% of PD	4	0.4652	9054.3
5	20% of PD	4	0.5574	9876.5

Building new transmission lines can increase the power transfer capability and enhance the system resilience. However, in some cases, such as when $k = 4$, load-shedding is more economical and represents a better choice, compared with transmission expansion. This result is demonstrated in both Tables 2 and 6 with the number of new built lines and the amount of the shed system load included. It is shown in Tables 2 and 6 that the $n - 4$ resilience criterion leads to a solution with much more load shed under the specified Π_{pd} , compared to the $n - 3$ criterion. In addition, it is found that $k = 3$ represents the maximum level of resilience, which leads to the largest number of new lines to be built. This result demonstrates that shedding load is a better choice than building new lines under the $n - 4$ criterion. This is because a larger value of Π_{pd} results in a higher level of load shedding. Moreover, it should be noted that, for $k > 3$, the attained result exhibits that it is more economical to shed load than to build new lines under a higher level of the permitted Π_{pd} , which is specified to be 15% of the total load.

A noticeable trend is the steady increase in load shedding from $k = 1$ to $k = 5$ to cope with more contingency events. Similar to Case A, no load loss is allowed for the $n - 1$ criterion.

Table 6 also provides information on the operation costs of the proposed three-level robust approaches, which indicates that tighter security criteria will lead to higher system operation costs.

Table 7 demonstrates that the robust coordinated planning of transmission and EV charging facilities can significantly reduce the load shedding and operation costs, compared to the sole transmission model. Finally, it is worth noting that, although the sole transmission planning results in lower construction costs, it always yields higher operation costs stemming from more load shedding.

Table 7. IEEE 118-bus power system: Robust coordinated transmission planning.

k	Π_{pd}	Number of Built Transmission Lines	Number of Built EV Charging Systems	Load Shedding (MW)	System Operation Cost (\$10 ⁶)
1	0% of PD	3	0	0	7272.5
2	5% of PD	3	4	0.2118	7468.3
3	10% of PD	27	23	0.3210	7984.1
4	15% of PD	5	3	0.4643	9039.8
5	20% of PD	4	2	0.5565	9855.4

From Table 8, we can see again that both the sole transmission planning and the coordinated transmission planning could avoid a large portion of the load to be shed. For example, when $k = 2$, non-expansion has to shed 0.6432 MW, while the sole expansion planning and coordinated expansion planning have to shed only 0.2121 MW and 0.2118 MW, respectively.

Table 8. Load shed of the IEEE 118-bus power system under different k 's.

k	Π_{pd}	Load Shed (MW)		
		Non-Expansion Resilience Enhancement Model	Robust Sole Transmission Planning	Robust Coordinated Transmission Planning
1	0% of PD	0	0	0
2	5% of PD	0.6432	0.2121	0.2118
3	10% of PD	0.7653	0.3216	0.3210
4	15% of PD	0.9243	0.4652	0.4643
5	20% of PD	1.0721	0.5574	0.5565

As can be seen from Table 2 to Table 8, when EV charging facilities become available, the number of new transmission lines to be built is reduced together with a decreased operation cost. This illustrates the advantage of the coordinated planning, compared with the sole transmission planning model. The EV infrastructure requires high investment costs and the payback period is long, but it leads to low operation costs incurred by less penalty of load curtailment. Building EV infrastructure is helpful for improving power grid resilience.

The superior performance of the proposed D-CCG over P-CCG of the IEEE 118-bus power system is illustrated in Table 9, where the computing time for both methods was presented. It is clear that D-CCG attained the optimal solution within the time allowed. On the other hand, due to the dimensionality issue characterizing the contingency-dependent models, P-CCG is only capable of solving the expansion planning problem for $k = 1$. For $k \geq 2$, P-CCG is unable to attain an acceptable solution within the given maximum computational time constraint. The number of newly built transmission lines decreases sharply from 34 lines for $k = 3$ to 4 lines for $k = 4$. As a result, the dramatic drop of the number of the expansion lines leads to much less computational time for $k = 4$ compared to $k = 3$.

Table 9. Computation time of D-CCG and P-CCG for the IEEE 118-Bus Power System under different k 's.

k	Computational Time (s) for Robust Sole Transmission Planning	
	D-CCG	P-CCG
1	8.56	291.54
2	26.76	NA
3	2261.99	NA
4	805.26	NA
5	2716.97	NA

6. Conclusions

In this work, an integrated planning strategy for a power network and the charging infrastructure of electric vehicles is presented for power system resilience enhancement. A comprehensive integrated model is introduced with a two-stage/tri-level resilience formulation attained, and concentrated charging/discharging of EVs is considered in the presented model.

The developed integrated planning model can accommodate uncertain extreme weather scenarios. A two-stage/three-level robust planning model is developed for the joint expansion planning framework, with security constraints respected. In the proposed model, the maximum number of failed electrical components (transmission lines and generators) is employed to describe the impact extents of extreme weather disasters. The developed coordinated planning model is solved by a D-CCG algorithm. Through numerical studies of IEEE standard test systems, it is demonstrated that the presented robust coordinated planning model is more advantageous than the sole transmission planning model with respect to load shedding and system operation costs. Simulation results also show that EVs can contribute power system resilience enhancement. Less load shedding can be achieved by employing EVs. Numerical results reveal the computational superiority of the proposed D-CCG method over the conventional P-CCG one.

Author Contributions: F.Y. proposed the methodological framework and mathematical model, and performed the simulations; J.W. modified and improved the mathematical model; F.W. examined the mathematical model, analyzed the results, reviewed the manuscript and provided suggestions; C.-L.T. and X.Z. examined the mathematical model, reviewed the manuscript and provided suggestions; Q.W. initiated this project, and analyzed the results. All authors discussed the simulation results and agreed for submission.

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Nomenclature

A. Set and Indices

I	Index set of all buses.
G	Index set of generators.
T	Index set of time horizon.
L	Index set of transmission lines.
L^c	Index set of candidate lines.
$\Omega(u, x)$	A contingency set defined by an integrated construction plan of (u, x) .
$F(u, x, a^G, a^L, a^{LC})$	A feasible region defined by a construction plan of (u, x) and the status of all transmission lines, candidate lines and generators.

B. Parameters

Π_{LC}	Maximum budget for transmission lines investment.
Π_{EV}	Maximum budget for electric vehicle charging systems investment.
Π_{pd}	Maximum system load shedding.
B_{pl}	Susceptance of transmission line pl .
c_{pl}	Investment cost for candidate line pl .
c_i^{EV}	Investment cost for EV charging system at bus i .
c_{gi}^p	Unit generating cost of generator g at bus i .
c_i^d	Unit cost of load curtailment at bus i .
PD	Total system power load.
$p_{f1}^{\max}$	Upper bound (vector) of power flow on existing lines.
$p_{f1}^{\min}$	Lower bound (vector) of power flow on existing lines.
$p_{f2}^{\max}$	Upper bound (vector) of power flow on candidate lines.

$p_{f2}^{\min}$	Lower bound (vector) of power flow on candidate lines.
$p_{gi}^{\max}$	Maximum generation of generator g at bus i .
$p_{gi}^{\min}$	Minimum generation of generator g at bus i .
$pd_i^{\max}$	Maximum system load shedding at bus i .
$pd_i^{\min}$	Minimum system load shedding at bus i .
$\theta_{fpl}^{\max}$	Maximum phase angle at the sending end of line pl .
$\theta_{fpl}^{\min}$	Minimum phase angle at the sending end of line pl .
$\theta_{tpl}^{\max}$	Maximum phase angle at the receiving end of line pl .
$\theta_{tpl}^{\min}$	Minimum phase angle at the receiving end of line pl .
$SOC_i^{\max}$	Maximum state of charge of EV charging system at bus i .
$SOC_i^{\min}$	Minimum state of charge of EV charging system at bus i .
$r_{ch,i}^{\max}$	Maximum amount of charge of EV at bus i .
$r_{dch,i}^{\max}$	Maximum amount of discharge of EV at bus i .
η_{ch}	Efficiency factor of EV charge.
η_{dch}	Efficiency factor of EV discharge.
$\lambda_{pl,i}$	Parameter that is equal to 1 if the power flow on line pl is from the sending end of the line, and is -1 otherwise.

C. Decision Variables

u_{pl}	Binary variable indicating whether the candidate line pl is built or not.
x_i	Binary variable indicating whether EV charging system at bus i is built or not.
θ_{fpl}^t	Phase angle at the sending end of line pl in period t .
θ_{tpl}^t	Phase angle at the receiving end of line pl in period t .
p_{f1}^t	Power flow (vector) of transmission lines in period t .
p_{f2}^t	Power flow (vector) of candidate lines in period t .
SOC_i^t	State of charge of EV charging system at bus i in period t .
a^l	Binary (vector) variable indicating the status of all existing lines.
a^{lc}	Binary (vector) variable indicating the status of all candidate lines.
a^g	Binary (vector) variable indicating the status of all generators.
pd_i^t	Load shedding at bus i in period t .
p_{gi}^t	Power generation of generator g at bus i in period t .
$r_{ch,i}^t$	The amount of charge of EV at bus i in period t .
$r_{dch,i}^t$	The amount of discharge of EV at bus i in period t .

D. Dual Variables

u_1	Dual variable associated with power balance equation.
u_2	Dual (vector) variable associated with power flow on existing lines.
u_3	Dual (vector) variable associated with power flow on candidate lines.
u_4	Dual (vector) variable associated with lower limits of power flow on existing lines.
u_5	Dual (vector) variable associated with upper limits of power flow on existing lines.
u_6	Dual (vector) variable associated with lower limits of power flow on candidate lines.
u_7	Dual (vector) variable associated with upper limits of power flow on candidate lines.
u_8	Dual (vector) variable associated with lower limits of power flow on generator outputs.
u_9	Dual (vector) variable associated with upper limits of power flow on generator outputs.
u_{10}	Dual (vector) variable associated with lower limits of load-shedding at all buses.
u_{11}	Dual (vector) variable associated with upper limits of load-shedding at all buses.
u_{12}	Dual (vector) variable associated with lower limits of phase angles at sending ends of lines.
u_{13}	Dual (vector) variable associated with upper limits of phase angles at sending ends of lines.
u_{14}	Dual (vector) variable associated with lower limits of phase angles at receiving ends of lines.

u_{15}	Dual (vector) variable associated with upper limits of phase angles at receiving ends of lines.
u_{16}	Dual (vector) variable associated with state of charge of EV charging systems.
u_{17}	Dual (vector) variable associated with lower limits of state of charge of EV charging systems.
u_{18}	Dual (vector) variable associated with upper limits of state of charge of EV charging systems.
u_{19}	Dual (vector) variable associated with upper limits of the charging amounts of EV charging systems.
u_{20}	Dual (vector) variable associated with upper limits of the discharge amounts of EV charging systems.
u_{21}	Dual (vector) variable associated with total system load shedding.

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