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Multi-Stage and Multi-Timescale Robust Co-Optimization Planning for Reliable and Sustainable Power Systems

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Clarkson University
8 Clarkson Ave,
Potsdam, New York, 13699

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PRINCIPAL INVESTIGATOR

Jie Li,	Clarkson University	(June 13, 2019 to September 30, 2020)
Lei Wu,	Clarkson University	(October 01, 2016 to December 31, 2018)

TEAM MEMBERS

Jie Li,	Clarkson University	(June 13, 2019 to September 30, 2020)
Lei Wu,	Clarkson University	(October 01, 2016 to December 31, 2018)
Jianhui Wang,	Southern Methodist University	(October 01, 2016 to September 30, 2020)
Bo Zeng,	University of Pittsburgh	(October 01, 2016 to September 30, 2020)

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LIST OF ACRONYMS AND ABBREVIATIONS

AC	Alternating current
ADMM	Alternating direction method of multipliers
CCG	Column-and-constraint generation
CPP	Clean Power Plan
DC	Direct current
DG	Distributed generation
DR	Demand response
DSR	Demand-side resources
ECCG	Extended column-and-constraint-generation
EE	Energy efficiency
EISPC	Eastern Interconnection States' Planning Council
GAMS	General Algebraic Modeling System
GIS	Geographic information system
IEEE	Institute of Electrical and Electronics Engineers
ISO	Independent System Operators
LP	Linear programing
MILP	Mixed-integer linear programming
MIP	Mixed-integer programming
MISO	Midcontinent Independent System Operator
MMCOP	Multi-stage and Multi-timescale robust Co-Optimization Planning
NYISO	New York Independent System Operator
PJM	Pennsylvania-New Jersey-Maryland Interconnection
RPS	Renewable Portfolio Standards
RTO	Regional Transmission Organization
SOCP	Second-order cone programming
UC	Unit commitment
WECC	Western Electricity Coordinating Council

I. Executive Summary

In this project, Clarkson University, in collaboration with Southern Methodist University and University of Pittsburgh, conducted the research to model, design, and implement a sophisticated generation and transmission co-optimization planning decision tool, called Multi-stage and Multi-timescale robust Co-Optimization Planning (MMCOP). The MMCOP decision tool intends to facilitate generation and transmission co-optimization planning of emerging power systems, while mitigating risks and uncertainties in both short-term operation dynamics and long-term policy and technology changes.

Long-term power system planning aims at optimizing asset utilization by investing in a proper mix of various generation technologies and transmission lines to supply the future load growth. Indeed, concerns over environmental sustainability, energy reliability and efficiency, and economic well-being have been driving the transition by expanding existing electric power systems with an increasing deployment of environmentally friendly energy sources such as renewable generation. In particular, the Clean Power Plan (CPP), which is designed to combat climate change and reduce carbon emissions by setting a national limit on carbon pollution from power plants, may dramatically change the landscape of the power industry by further promoting clean energy and phasing out emissions-intensive generation technologies [1]. However, a rapid deployment of variable and uncertain renewable energy sources as well as their geographical disparity bring new challenges across multiple time scales, both of which need to be reflected in the long-term reliable planning and the short-term secure grid operation to achieve a deeper penetration. In addition, novel non-wire alternatives (e.g., demand response (DR), distributed generation (DG), energy efficiency (EE), and smart grid technologies) and the computational complexity for large-scale systems significantly complicate the system planning procedure even further.

However, current state-of-the-art planning technologies [2-6] mostly evaluate decoupled generation and transmission expansions in a queue, and heuristically determine the contributions of renewable generations by subtracting their approximated capacity values from the system peak load or the non-sequential block load duration curve. However, existing conventional planning approaches neglect short-term variability and uncertainty of renewable energy, hourly chronological operation details, and physical nonlinear characteristics of the alternating current (AC) transmission network. In turn, the derived long-term plans may not yield a feasible and optimal short-term dispatch decision. As a result, existing conventional planning approaches may not work properly, and power systems reliability could be in jeopardy.

In observing limitations of existing conventional planning approaches and addressing new challenges of emerging power systems, the main scope of this project is illustrated in Figure 1. Specifically, in designing future power systems by upgrading the existing transmission network and planning new generation and transmission facilities, it is of crucial importance to simultaneously examine the short-term variability and uncertainty, hourly chronological operation details, and nonlinear characteristics of AC transmission network within the co-optimization planning model. With such a decision-making structure and the interdependence between generation and transmission planning, this project developed co-optimization planning models within a multi-stage and multi-timescale framework. In particular, random contingencies, key uncertainty factors, and AC power flows are included to derive expansion plans while considering both long-term reliability and short-term flexibility.

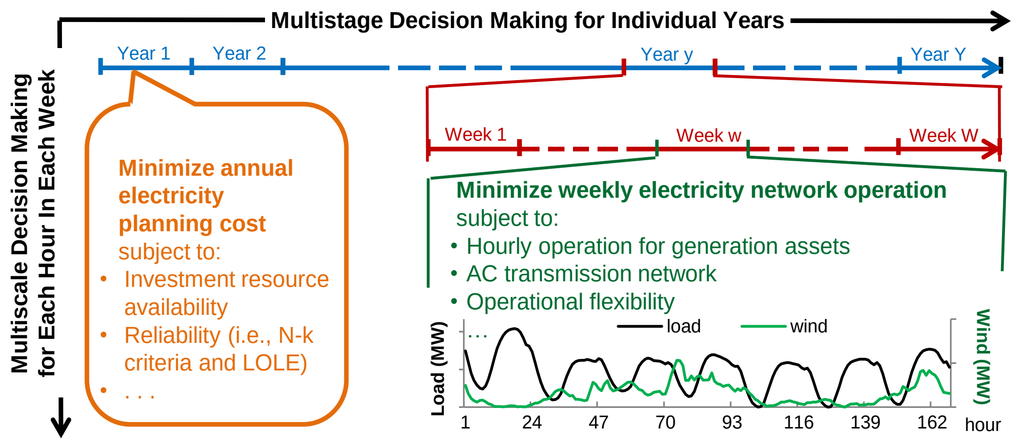


Figure 1. The Multi-stage and Multi-timescale Co-Optimization Planning (MMCOP) framework

Major accomplishments and findings of the project are summarized as follows:

- The team has developed the MMCOP prototype, which integrates the modeling of risks and uncertainties related to the time, location, and type of additional generation technologies, hourly and annual variation of renewable energy sources, long-term reliable planning and short-term economic operation, AC transmission network, and various environmental considerations. The prototype is also equipped with effective solution methodologies, including tight convex approximation and advanced decomposition approaches, to enhance computational efficiency for solving real-world large-scale long-term planning problems.
- The proposed prototype has been extensively tested via several Institute of Electrical and Electronics Engineers (IEEE) benchmark systems and the practical Western Electricity Coordinating Council's (WECC) system to illustrate its effectiveness and efficiency. The tests have shown that: (i) By considering flexible resources especially those non-wire technologies on the demand side and capturing short-term operation status of the power system,

more economically efficient and reliable systems can be planned; (ii) The hybrid stochastic and robust model adopted in the MMCOP prototype can accurately capture various discrete and continuous uncertainties in modern power grid, thus facilitating the long-term planning with significant renewables while ensuring cost effectiveness, reliability, and sustainability; (iii) Extensive studies on the practical WECC system show that the proposed advanced solution approaches have the potential to enhance computational efficiency for solving real-world large-scale long-term planning problems.

- The research findings have been disseminated to the community via our 8 journal publications and 4 technical conference presentations. The list of publications and presentations is detailed in Appendix A. The project team has also interacted with multiple industry partners, seeking opportunities to customize the MMCOP models and computational tools based on their specifications and needs and to provide technical support for promoting co-optimization in their system expansion planning.
- Multiple undergraduate and graduate students at Clarkson University, University of Pittsburgh, and Southern Methodist University participated in this project, receiving training and professional development on areas of power and energy systems, mathematical optimization, and algorithms. One Ph.D. Thesis “Multiple Timescale Power Systems Operation and Planning with Renewable Energy, Demand Side Resource, and Energy Storage” was completed in August 2018 at Clarkson University. Some of the research findings have also been integrated into undergraduate and graduate courses offered at Clarkson University and University of Pittsburgh.

The reminder of this report is organized as follows:

- Section II describes objectives of this project, including the background information that supports the need for this research, the technical challenges addressed by the project, and the project goals;
- Section III details technical approaches adopted in the project to support the generated results and findings;
- Section IV summarizes accomplishments and conclusions out of the project, and recommends future work for the possible continuation of the initiative;
- Appendix A provides the list of publications and presentations for information dissemination/sharing that occurred during the period of project.

II. Objectives

II.1. Background

Generation and transmission planning is the central piece of power system expansion to meet future electricity demand growth. Current state-of-the-art power system planning approaches mostly generate and evaluate decoupled generation and transmission expansion decisions in a sequential fashion. One major reason for the decoupled planning process has been the lack of capabilities to address computational challenges that arise if both generation and transmission expansion plans were done in an integrated way [2-6]. The actual power system under study can have thousands of generators and lines, which make the co-optimization planning problem very difficult to solve. However, such decoupled strategies fail to reflect that generation and transmission assets are closely tied and mutually support each other for delivering electricity to customers. As one can imagine, this artificially separated planning procedure cannot guarantee that the obtained expansion plan is globally optimal, as the coupled nature of power generation and transmission has been ignored. Moreover, they typically neglect short-term hourly operation decisions, which indeed could have serious impacts on the long-term planning. Note that system expansions are primarily driven by the reliability needs in unusual situations and at peak demands that just occur with very short durations. Consequently, it is very likely that a sequential generation and transmission long-term plan while neglecting hourly chronological operational details is of a low quality, leading to expensive or even infeasible short-term operation decisions. To this end, the increasingly interconnected power grid requires an integrated and coordinated expansion plan for generation and transmission sectors while effectively considering hourly chronological operational details.

In addition, in the long-term planning problem, scenario sampling is a commonly used technique to simulate uncertainty factors such as loads, fuel prices, hydroelectric conditions, and renewable generation penetration in the planning years. However, usually only a very limited number of scenarios can be considered to investigate the reliability of the system under a particular expansion plan, and the expansion plan with the least cost and satisfactory reliability can be chosen. For example, it can take power system planners a week to run the commercial production cost simulation model for calculating the operations of the Eastern Interconnection for a single year, considering only one future scenario [7]. This modeling and computational deficiency greatly limits the ability of system planners to explore other possible expansion alternatives and scenarios.

Furthermore, most existing planning models are based on (mixed-integer) linear approximations of nonconvex AC power flow formulations, which clearly bring a great computational advantage. However, such linear approximations may lead to solutions of poor quality or even outside acceptable operational ranges of the AC transmission system.

Various entities involved with power system planning in practice have realized that the above modeling and computational bottlenecks should be and can be overcome. For instance, the Eastern Interconnection States' Planning Council (EISPC) that represents the 39 states, the District of Columbia, the City of New Orleans, and 8 Canadian Provinces located within the Eastern Interconnection has published a white paper on co-optimization of transmission and other supply resources [8]. Although the white paper does not address the above-mentioned challenges in detail, it does point out the need for a coordinated plan. An associated technical conference consisting of experts from academia and industry confirmed the benefits of conducting such a co-optimization expansion plan. However, related research has been confined to small unpractical systems and conceptual discussions [9-17]. Nevertheless, the need for developing stochastic models to address the increasing uncertainty and variability in power system planning has been identified in several government and industry reports including [17].

II.2. The Technical Challenges and Project Goals

This project is aimed at addressing the modeling challenges and computational difficulties associated with co-optimization of generation and transmission planning, and developing the MMCOP tool that can be used by various interested users. At the same time, as the resulting model is a large-scale optimization problem with uncertainties, the required large-scale modeling and simulation capabilities also present a break-through in science and engineering.

Specifically, this project targets on addressing the following modeling challenges and computational difficulties associated with co-optimization of generation and transmission planning:

- **Co-optimization of Generation and Transmission Expansion While Considering Accurate AC Power Flow Modeling**: Co-optimization planning with AC power flow modeling is a significant contribution by itself. Note that the majority of existing planning models are based on (mixed-integer) linear approximations of the nonconvex AC power flow model. Although a clear computational efficiency can be obtained, weak linear approximations could lead to solutions of poor quality with expensive operational cost. In MMCOP, through co-optimization with tighter convex approximations, especially those with the second-order cone programming (SOCP) representations and additional tight cutting planes, a more accurate optimal expansion plan can be identified. It could be far superior to the results calculated sequentially using traditional direct current (DC) power flow approximations.

- **Unprecedented Granularity**: Most of the existing models only consider typical load profiles or simplified load blocks in the planning procedure, while failing to capture temporal operation details of power systems as well as short-term variability from renewable generation resources such as wind power. In MMCOP, we execute unit commitment with hourly time resolution for candidate expansion plans, and in turn accurately capture the system impacts of fast ramps from wind power and other uncertain generation resources.
- **Two-Stage Robust Co-optimization Planning Hedging against Uncertainties as well as N-1/2 and N-1-1 Contingencies**: The current industry practice does not consider multiple scenarios within a single optimization problem as it would be too computationally expensive. Accordingly, the solution obtained from a single scenario may be infeasible in other scenarios and very likely be suboptimal. In comparison, MMCOP considers realistic uncertainty descriptions within a single optimization problem to ensure reliable co-optimization plans that are robust to critical randomness and N-1/2 contingencies under consideration. We also define novel uncertainty descriptions to capture N-1-1 contingencies and design systems with guaranteed performance under consecutive outages.
- **Hybrid Robust and Stochastic Optimization**: By developing a hybrid robust and stochastic optimization framework that utilizes both historical data and include N-K considerations, the co-optimization plans obtained will be both robust and cost-effective. Note that the proposed hybrid robust and stochastic optimization framework would eliminate unrealistic scenarios and reduce the conservativeness level as compared to pure robust optimization models. We will particularly demonstrate the effectiveness of using this hybrid framework to design systems with desired resilience under different outage levels.
- **Fast Computational Methods to Support Industrial Scale Applications**: Most existing computational methods cannot effectively address actual system needs. Our research will lead to a set of practical computational tools using three powerful strategies, including approximation, decomposition, and distributed computation. These tools can effectively calculate large-scale practical systems.

Targeting on addressing the above modeling challenges and computational difficulties associated with co-optimization of generation and transmission planning, the overall objective of this project is to develop a sophisticated decision-making tool

MMCOP for facilitating generation and transmission co-optimization planning of emerging power systems. MMCOP will represent an efficient decision-making tool for augmenting the existing capabilities of power system planner and operators to support collaborative planning, analysis, and implementation of emerging power systems, and to effectively mitigate risks and uncertainties in both short-term operation dynamics and long-term policy/technology changes. MMCOP integrates advanced features for the modeling and simulation of risks and uncertainties related to the time, location, and type of additional generation technologies via the hybrid robust and stochastic optimization framework, hourly and annual variation of renewable energy sources, integrated long-term reliable planning and short-term economic operation, AC transmission network, and various environmental considerations. MMCOP explores innovative solutions via dynamic transmission network reduction, tighter convex approximation as compared to standard SOCP-based AC power flow convexification models, integrated decomposition approaches, and distributed computation methods. MMCOP will enhance reliable and sustainable operation of the existing grid with the most economic integration of additional generation and transmission assets.

The goals of the proposed project include:

- Establishing the MMCOP prototype with the proposed comprehensive modeling features (including co-optimization of generation and transmission planning, generation sizing/sitting and line routing with the consideration of environmental impacts, integrated long-term reliability and short-term economics, full AC power flow, and hybrid robust and stochastic optimization for uncertainty simulation and risk mitigation) and advanced solution methodologies (including dynamic transmission network reduction, tight convex approximation, integrated decomposition approaches, and distributed computation methods);
- Validating the technological viability and effectiveness of MMCOP via standard IEEE testing systems and practical systems, on mitigating risks and uncertainties in co-optimized generation and transmission planning while ensuring reliability, sustainability, and economic benefits;
- Disseminating the research findings via journal publications, conference presentations, training courses, and collaboration and interactions with industry partners to create broader impacts.

III. Technical Approach

The project involves three phases to achieve the project goals of developing the MMCOP for facilitating generation and transmission co-optimization planning of emerging power systems. The objectives for individual phases are listed as follows:

Phase I – Development of MMCOP framework and algorithms;

Phase II – Validation and verification of MMCOP via standard testing systems and practical systems;

Phase III – Dissemination of the results and final reporting.

Technical details adopted in individual phases to achieve the targeted objectives are discussed below in details.

III.1. Phase I. Development of MMCOP Framework and Algorithms

- Generation and Transmission Co-optimization Planning with AC Power Flows

  This project investigates the comprehensive deterministic multi-stage and multi-timescale generation and transmission co-optimization planning model, which explores financially viable and physically feasible planning decisions to ensure sufficient electricity resources and delivery capacities to meet electricity loads. The co-optimization planning model simultaneously studies electricity network configurations along with the detailed characterization of their functionalities (including supply, demand, storage, and transmission constraints), while integrating long-term reliability, short-term flexibility, and hourly chronological operation details in a single analytical framework. The basic framework of the deterministic multi-stage and multi-timescale generation and transmission co-optimization planning model is highlighted as followed, while the full modeling details can be referred to from the team's publication [18] out of this project.

  The proposed co-optimization planning model determines when (which year), where (which bus and route), and what (which type) generators and transmission lines will be built for minimizing the total system cost throughout the planning horizon, as shown in (1). Function C quantifies the annual investment cost associated with new generators and transmission lines, and function F calculates the hourly costs for electricity production and unserved demand; $\boldsymbol{IG}_y$ and $\boldsymbol{IT}_y$ are binary investment variables for generators and transmission lines in year y; N_w is the number of weeks that can be represented by a typical week w in a year; $\boldsymbol{I}_t$ and $\boldsymbol{P}_t$ are unit commitment and generation dispatch related operation decisions in hour t. Typical weeks in each month/season are considered to reflect the impact of distinct temporal operation characteristics of electricity systems.

$$\min_{\boldsymbol{IG}_y,\boldsymbol{IT}_y,\boldsymbol{I}_t,\boldsymbol{P}_t} \sum_y \left[C\left(\boldsymbol{IG}_y, \boldsymbol{IT}_y\right) + \sum_{w\in y} N_w \cdot \sum_{t\in w} F(\boldsymbol{I}_t, \boldsymbol{P}_t) \right] \quad (1)$$

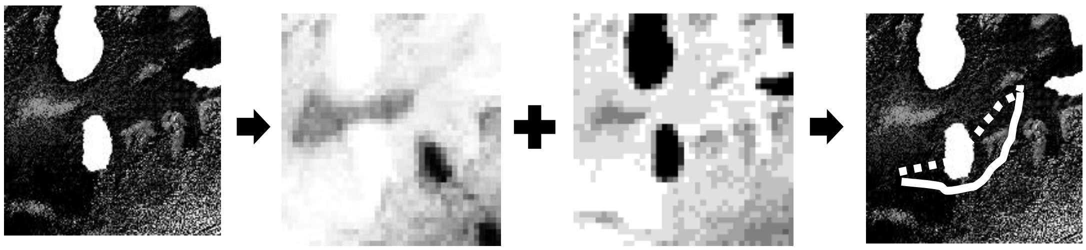
The proposed co-optimization planning model includes the following typical constraints: (i) *Long-term planning constraints* describe site availability, types and capacities of candidate units and transmission lines at each site, as well as commissioning and construction time requirements. Additional constraints would include Renewable Portfolio Standards (RPS) in terms of emission limits and renewable penetration levels for addressing various socio-environmental obstacles; (ii) *Short-term operation constraints* include electricity load balance, system reserve requirements, operation limits of traditional units and renewable resources (including capacity, ramp up/down rate, minimum ON/OFF time limits, etc.), and transmission constraints (power flow limits, etc.); (iii) *Different types of generators*, including regular thermal units, combined-cycle gas-fired units, hydro units, renewable energy, and energy storage devices, will be rigorously represented; (iv) *Network evaluations for normal and pre-selected contingency cases* will be included. Power system operators not only enforce network constraints in the normal situation, but also evaluate the performance in pre-selected (i.e., the most credible) contingency cases to guarantee network security; (v) *Coupling constraints between long-term planning and short-term operation* describe linkages of installation statuses and commitment decisions of units, and installation statuses and power flows of lines.

The proposed co-optimization planning model also includes advanced features to address unique characteristics and special needs of the long-term co-optimization planning for emerging power systems, including: (i) *Incorporating AC power flow formulations*: One essential operating characteristic is the nonlinear behavior of AC power flow, which reflects the nonconvex relationship between nodal voltages and net power injections. Nevertheless, the majority of planning tools use (mixed-integer) linear formulations to approximate the AC power flow behavior, e.g., linear programming based DC power flow equations. Although computational efficiency can be realized, such (mixed-integer) linear approximations may lead to transmission expansion plans of a poor quality. To accurately capture the impact of AC power flow in the system planning, our co-optimization framework will incorporate strong convex approximations of AC power flow to produce better cost-effective co-optimization plans. Specifically, SOCP approximation will be adopted in the MMCOP framework, along with novel cutting planes, to achieve a trade-off between computational expense and solution quality; (ii) *Co-optimization planning with topology control for flexibility*: It is often observed that switching off some transmission lines in certain practical scenarios for scheduling maintenance and mitigating a destructive contingency could lead to a better power delivery capability. MMCOP will include necessary modeling components, e.g., binary variables for switching decisions in $F(\boldsymbol{I}_t, \boldsymbol{P}_t)$, to incorporate this feature in our planning solution, especially for newly planned transmission assets. The detailed models on the SOCP-based AC power flow constraints and topology control can be referred to from the team's publications [19, 20, 22-25] out of this project.

- Co-optimization Planning Considering Complicated Environmental Impacts

Investment costs of planning projects, especially the transmission network planning, largely depend on environmental factors such as terrain and climate. In addition, the construction certificate of transmission lines has become even tougher to obtain due to the environmental protection goal. However, traditional transmission network planning approaches usually assume routes of candidate lines are given, which may bring unbearable errors especially in large regions under a variant environment. Indeed, transmission line route design is an important and complex component of the transmission network planning.

The MMCOP incorporates the spatial transmission network planning into the proposed co-optimization planning model. Based on the raster map in geographic information systems (GIS), the model would derive more economical and flexible solutions by exploring routes of candidate lines according to environmental factors and power system reliability requirements. The proposed co-optimization planning model minimizes the investment and operation cost (1) while simultaneously ensuring the feasibility of line paths and the reliability of power systems. Specifically, the investment cost function C in (1) is evaluated while considering environment and altitude information. As shown in Figure 2, the original GIS image map Figure 2.a can be rasterized into an environmental map (shown in Figure 2.b) and an altitude map (shown in Figure 2.c). In turn, associated with different costs for individual cells, the rasterized environmental and altitude maps can accurately reflect the impact of variant environments and altitudes on the optimal line routes. In Figure 2.b and Figure 2.c, the darker the cell, the higher the cost. The optimal route (i.e., the solid line) in Figure 2.d crosses the regions with the lowest cost by considering both environmental and altitude information of each cell. In comparison, the dash line route crosses some high cost areas, if such information of individual sites is neglected. The detailed models on the spatial power network planning considering complicated environments can be referred to from the team's publication [21].



(a) The original GIS image map (b) The rasterized environmental map (c) The rasterized altitude map (d) Optimal route on the GIS map

Figure 2. Map rasterizing

- Co-optimization Model Considering Risks and Uncertainties

As the reliable electricity delivery is of the core value in the entire power industry, the MMCOP framework adopts a hybrid robust and stochastic co-optimization planning model to address various contingencies and uncertainties. Specifically, as load and renewable energy are clearly uncertain, the impact of these uncertainty factors on the co-optimization planning is fundamentally important. Indeed, when the wind level reaches a critical value, the dependency of power systems on wind availability would inevitably result in supply risks. The basic framework of the hybrid robust and stochastic co-optimization planning model is highlighted as followed, while the modeling details can be referred to from the team's publications [18, 22-25] out of this project.

The N-K reliability criterion (with K=1 or 2) is typically adopted by system operators for mitigating supply risks. Indeed, the N-K criterion perfectly fits the concept of robust optimization, which seeks for solutions that protect the system against any N-K joint contingency of generation and transmission assets. On the other hand, on many occasions, plenty of historical load or renewable energy data is available, which may either carry generic patterns and probabilistic information or provide a basis to generate more simulation data. Hence, it would be reasonable to take advantage of available historical data and adopt the scenario-based approach to describe random loads and renewable generations. In turn, together with the uncertainty set $\boldsymbol{A}$ (2) defining N-K contingencies and the scenario set $\boldsymbol{S}$ representing random loads and renewable generations, a hybrid robust and stochastic co-optimization planning model can be derived as in (3), which minimizes the total investment costs, plus the expected costs for electricity production and unserved demand in the worst N-K contingency throughout the planning horizon. Note in (2) that AG_{it} /AL_{lt} equals to one if the corresponding generator/transmission line is on outage at hour t, NG, NL, and NT are the numbers of generators, transmission lines, and hours, K^G and K^L are the numbers of generators and lines that are simultaneously on outage.

$$\boldsymbol{A} := \left\{ \begin{matrix} AG_{it} \in \{0,1\}^{NG\times NT}, AL_{lt} \in \{0,1\}^{NL\times NT}; \\ \sum_i AG_{it} \leq K^G, \forall t; \sum_l AL_{lt} \leq K^L, \forall t \end{matrix} \right\} \tag{2}$$

$$\min_{\boldsymbol{IG},\boldsymbol{IT}} \left\{ C(\boldsymbol{IG},\boldsymbol{IT}) + \max_{\boldsymbol{AG},\boldsymbol{AL}\in\boldsymbol{A}} \underset{s\in\boldsymbol{S}}{E} \left[\min_{\boldsymbol{I}^s,\boldsymbol{P}^s} F(\boldsymbol{I}^s,\boldsymbol{P}^s,\boldsymbol{AG},\boldsymbol{AL}|\boldsymbol{D}=\boldsymbol{D}^s) \right] \right\} \tag{3}$$

- Multi-Area Coordinated Planning under Uncertainty

In a multi-area power system, the growing interconnection of regional electricity networks and the large-scale integration of renewable energy require a coordinated multi-area plan to achieve the overall reliability and economic efficiency. Under such a background, we further study the multi-area coordinated planning model as in (4), which minimizes the total investment costs plus the worst case costs for electricity production and unserved load over all areas. a and b are indices of areas. We point out that in addition to investment and operation constraints for individual areas, equality constraint (5) represents that on any transmission tie-line, power flow exchange $\boldsymbol{PL}_{a\to b}$ from area a to area b is negative to $\boldsymbol{PL}_{b\to a}$.

$$\min_{\boldsymbol{IG}_a,\boldsymbol{IT}_a,\boldsymbol{PL}_a} \sum_a \left\{ C(\boldsymbol{IG}_a,\boldsymbol{IT}_a,\boldsymbol{PL}_a) + \max_{\boldsymbol{AG}_a,\boldsymbol{AL}_a\in\boldsymbol{A}} \min_{\boldsymbol{I}_a,\boldsymbol{P}_a} F(\boldsymbol{I}_a,\boldsymbol{P}_a,\boldsymbol{AG}_a,\boldsymbol{AL}_a) \right\} \tag{4}$$

$$\boldsymbol{PL}_{a\to b} = -\boldsymbol{PL}_{b\to a} \tag{5}$$

Note that to compute (4)-(5) as a single optimization model would require data across multiple areas, which may not be readily accessible because of limitations on information privacy and difficulties in complicated models. To this end, we adopt alternating direction method of multipliers (ADMM) based distributed algorithms to relax (5), which will separate (4) into two disjoint formulations that can be computed independent of each other. As a result, by just exchanging the pricing value of that tie-line flow, i.e., the Lagrangian multiplier, we will be able to achieve coordinated transmission planning without sharing private information inside each area. The detailed procedure of using ADMM to solve (4)-(5) can be referred to from the team's publication [26] out of this project.

- Enhancement of Computational Methods for Practical Instances

  The MMCOP includes efficient computation methods to effectively solve complicated models discussed above. Specifically, three strategies of approximation, decomposition, and distributed computation are explored to address the complexities in co-optimization planning models, including: (i) SOCP approach for AC power flow calculation is incorporated into MMCOP to simulate physical Kirchhoff laws that regulate power flows more accurately than a DC power flow model; (ii) The structurally complicated formulations related to the lengthy planning horizon and temporal correlations in load, generation, and transmission aspects will be effectively computed by column-and-constraint generation (CCG) method; (iii) The scale of practical network and spatial correlations will be tackles by decomposition and distributed computation approaches such as ADMM. Technical details of the SOCP based approach, the CCG method, and the ADMM implementation can be referred to from the team's publications [18-26] out of this project.

The entire MMCOP modeling and algorithm is detailed as follows:

- Mathematical Model Description

  The system state model with the detailed formulations on operation costs and constraints used in the MMCOP is first presented, followed by the two-stage robust generation-transmission expansion planning model while considering various uncertainties in the planning horizon.

  - **System State Model**: Load duration curve has been extensively applied in existing planning studies, which is usually modelled via a limited number of load blocks in practice. However, because individual load blocks are regarded as mutually time independent, temporal operation characters, such as correlations of load and wind profiles, cannot be effectively handled. More importantly, temporal operation characters of generating units, such as start-up and shut down costs, minimum on/off time limits, and ramping constraints, cannot be modelled. To this end, the system state model together with a transition matrix is adopted to recover certain chronological operation information (i.e., unit start-up/shut down cost) within the long-term planning problem. That is, with additional binary variables to indicate unit commitment status and transitions among different states, start-up/ shut-down actions along the planning horizon can be reasonably captured, and in turn provide a model with better accuracy.

    The system state model-based optimal operation of power systems with demand-side resources (DSR) programs for each year t within the long-term planning horizon is described as in (6)-(19). The objective function (6) is to minimize the total operation cost of generating units, including variable production cost, fixed no-load cost, start-up cost, and shut-down cost, in addition to load reduction payments of DSR programs and penalty costs of unserved loads. Constraints (7)-(10) represent limits of thermal units, wind farms, DSRs, and line power flows. Nodal power balance is expressed as in (11). Constraint (12) represents the relation between start-up/shut-down decisions and unit commitment statuses in each state. DC power flow is expressed as a function of voltage phase angles (13), where phase angles are limited in (14). The DSR deployment limit in each year t is formulated as in (15), reflecting functionality requirements of physical demands and consumers' non-appreciation on over-discomfort. Constraints (16)-(19) describe boundaries of decision variables. AC constraints could be similarly considered via convex relaxation approaches, which can help enhance the computational performance.

$$OC_t = min \left\{ \begin{array}{c} \sum_{s,g \in G} \left[\begin{array}{c} T_{t,s} \cdot \left(VC_g \cdot p_{g,t,s} + FC_g \cdot y_{g,t,s} \right) + \\ \sum_{s'} N_{t,s,s'} \cdot \left(C_g^{up} \cdot su_{g,t,s,s'} + C_g^{dn} \cdot sd_{g,t,s,s'} \right) \end{array} \right] \\ + \sum_{s,d} T_{t,s} \cdot EC_{t,s} \cdot dr_{d,t,s} + PC_t \cdot \sum_{s,i} T_{t,s} \cdot v_{i,t,s} \end{array} \right\} \quad (6)$$

$$\text{s.t.} \quad P_g^{min} \cdot y_{g,t,s} \le p_{g,t,s} \le P_g^{max} \cdot y_{g,t,s} \qquad \forall g, s \quad (7)$$

$$0 \le p_{w,t,s} \le P_{w,t,s} \qquad \forall w, s \quad (8)$$

$$0 \le dr_{d,t,s} \le DR_{d,t}^{max} \cdot y_{d,t,s} \qquad \forall d, s \quad (9)$$

$$-P_l^{max} \le p_{l,t,s} \le P_l^{max} \qquad \forall l, s \quad (10)$$

$$\sum_{G \in B_g(i)} p_{g,t,s} + \sum_{l \in R(i)} p_{l,t,s} - \sum_{l \in S(i)} p_{l,t,s} + v_{I,t,s} + \sum_{w \in B_w(i)} p_{w,t,s} = \sum_{d \in B_d(i)} \left(P_{d,t,s} - dr_{d,t,s} \right) \qquad \forall i, s \quad (11)$$

$$y_{g,t,s'} - y_{g,t,s} = su_{g,t,s,s'} - sd_{g,t,s,s'} \qquad \forall g, s, s' \quad (12)$$

$$B_l \cdot (\theta_{s(l),t,s} - \theta_{r(l),t,s}) - p_{l,t,s} = 0 \qquad \forall l, s \quad (13)$$

$$-\theta_i^{max} \le \theta_{i,t,s} \le \theta_i^{max}; \quad \theta_{ref,t,s} = 0 \qquad \forall i, s \quad (14)$$

$$\sum_s T_{t,s} \cdot y_{d,t,s} \le DR_{d,t}^c \qquad \forall d \quad (15)$$

$$y_{g,t,s} \in \{0,1\} \qquad \forall g, s \quad (16)$$

$$y_{d,t,s} \in \{0,1\} \qquad \forall d, s \quad (17)$$

$$0 \le su_{g,t,s,s'}, sd_{g,t,s,s'} \le 1 \qquad \forall g, s, s' \quad (18)$$

$$v_{i,t,s} \geq 0 \qquad \forall i, s \tag{19}$$

In the system state model (6)-(19), d, l, g, w, and t are indices of DSR programs, transmission lines, thermal units, renewable units, and years; i and j are indices of buses; s and s' are indices of system states; $s(l)$ and $r(l)$ are indices of sending and receiving buses of line l. $dr_{d,t,s}$ is demand reduction of DSR d in state s of year t; $p_{l,t,s}$ is power flow of line l in state s of year t; $p_{g,t,s}$ and $p_{w,t,s}$ are power outputs of thermal unit g and renewable unit w in state s of year t; $sd_{g,t,s,s'}$ and $su_{g,t,s,s'}$ are shutdown and startup indicators of unit g from state s to state s' in year t; $v_{i,t,s}$ is unserved load on bus i in state s of year t; $x_{d,t}$, $x_{g,t}$, and $x_{l,t}$ are binary indicators describing whether DSR program d, unit g, and line l is deployed in year t; $y_{d,t,s}$ is binary indicator describing whether DSR program d is called in state s of year t; $y_{g,t,s}$ is commitment status of unit g in state s of year t; δ^{+} and δ^{-} are binary indicators describing if an uncertainty term reaches its positive and negative bounds; $\theta_{i,t,s}$ is voltage phase angle of bus i in state s of year t; $(\cdot)^{u}$ is decision variables in response to uncertainties. B_l is susceptance of transmission line l; C_g^{up} and C_g^{dn} are startup and shutdown costs of unit g; $DR_{d,t}^{c}$ is annual maximum number of hours that load reduction of DSR d is allowed at year t; $DR_{d,t}^{max}$ is load reduction capacity of DSR d in year t; $EC_{t,s}$ is incentive payment to DSRs in state s of year t; FC_g and VC_g are fixed and variable production costs of unit g; IC_d is annualized investment cost of DSR program d; IC_g and IC_l are annualized investment costs of unit g and line l; M is a very large positive number; NT and NS are numbers of years and states in each year; $N_{t,s,s'}$ is number of transitions from state s to s' in year t; OC_t and PC_t are system operation cost and penalty cost in year t; $P_{d,t,s}$ and $P_{w,t,s}$ are demand and renewable energy forecasts in state s of year t; $T_{t,s}$ is duration of state s in year t; A is devaluation rate; Δ is budget level of uncertainty variables; $(\cdot)^{max/min}$ is maximum/minimum value of a quantity; $(\hat{\cdot})$ indicates solution to a variable; $(\cdot)^{+}$ and $(\cdot)^{-}$ are positive and negative deviations of an uncertainty factor. $\boldsymbol{B}_g(i)$ and $\boldsymbol{B}_w(i)$ are sets of thermal and renewable units at bus i; $\boldsymbol{B}_d(i)$ is set of demands connected to bus i; $\boldsymbol{D}, \boldsymbol{G}$, and $\boldsymbol{L}$ are sets of existing DSR programs, units, and lines; $\boldsymbol{D}^{C}, \boldsymbol{G}^{C}$, and $\boldsymbol{L}^{C}$ are sets of candidate DSR programs, units, and lines; $\boldsymbol{F}(s)$ and $\boldsymbol{T}(s)$ are sets of system states transited from and to state s, $\boldsymbol{R}(i)$ and $\boldsymbol{S}(i)$ are sets of transmission lines ending and starting at bus i.

- **Robust Generation and Transmission Expansion Planning Model with DSRs**: The multi-period robust generation and transmission expansion planning problem is formulated as in (20)-(31). The robust counterpart (20) is expressed in a two-stage structure, in which investment decisions x are determined in the first stage. After x are revealed, the most economically inefficient scenarios under uncertainties are detected in the second stage and fed back to the first stage for adjusting planning decisions, where y and z respectively represent binary and continuous variables in the second stage.

  The objective function (20) is to minimize the total cost, including investment cost (21) of candidate assets and total operation cost (22) of multiple years within the planning horizon. Investment cost (21) contains construction costs of new generators and lines, and deployment costs of new DSR programs. Deployment costs of DSRs can be in the form of installation and upgrade costs of demand side infrastructure and associated technological equipment (such as direct load control devices, smart meters, in-home displays, and communication facilities), acquisition costs, and incentives for enrolment. Other one-time expenses that usually occur once instead of repeatedly in each year, such as deploying IT systems for settlement and conducting market research for program design, could also be included as part of investment cost. In addition, complicated environment could be reflected via investment costs of generators/ transmission lines in (21) and/or modeled as forbidden zones in (23), i.e., by setting certain $\boldsymbol{x}_{g,t}$ and $\boldsymbol{x}_{l,t}$ as zero.

  Feasible region of investment decision variables is denoted as in (23), in which investment variables of existing assets are fixed to 1 while those of candidate assets will be optimized. Uncertainties from load/wind forecasts are formulated as a polyhedral uncertainty set (24), which is associated with the operation problem. In (24), uncertainty budget levels Δ_d and Δ_w control ranges of uncertainties considered in the robust optimization model. That is, a larger value of uncertainty budget indicates that a more severe uncertainty situation with a larger fluctuation will be considered. Specifically, when uncertainty budget is 0, the uncertainty set is reduced to singleton without any uncertainty being considered; While the maximum budget value of $NT \times NS$ corresponds to the entire hypercube, in which all uncertainties in all time intervals are considered.

  Feasible set of the operation problem is shown as in (25)-(31), in which uncertain wind and load deviate from their forecast values as indicated in (26) and (29). Capacity limits of candidate assets are restricted by their investment decisions, which are formulated as coupling constraints (25), (27)-(28), and (30) that link planning and operation decisions.

$$\min_{\boldsymbol{x}\in X}\left\{IC(\boldsymbol{x})+\max_{\boldsymbol{u}\in U}\min_{\boldsymbol{y},\boldsymbol{z}\in\Omega(\boldsymbol{x},\boldsymbol{u})} OC\,(\boldsymbol{y},\boldsymbol{z})\right\} \tag{20}$$

$$IC(\boldsymbol{x})=\sum_t\left\{\frac{1}{(1+\alpha)^t}\cdot\left[\sum_{g\in G^C} IC_g\cdot x_{g,t}+\sum_{l\in L^C} IC_l\cdot x_{l,t}+\sum_{d\in D^C} IC_d\cdot x_{d,t}\right]\right\} \tag{21}$$

$$OC(\boldsymbol{y},\boldsymbol{z})=\sum_t 1/(1+\alpha)^t\cdot OC_t \tag{22}$$

$$\boldsymbol{X}=\left\{\boldsymbol{x}:\begin{array}{c} x_{g,t},x_{l,t},x_{d,t}\in\{0{,}1\},\ \ \forall g\in G^c,\forall l\in L^c,\forall d\in D^c;\\ x_{g,t}=x_{l,t}=x_{d,t}=1,\quad \forall g\in G,\forall l\in L,\forall d\in D;\\ x_{g,t-1}\le x_{g,t},x_{l,t-1}\le x_{l,t},x_{d,t-1}\le x_{d,t},\forall t,g,l,d \end{array}\right\} \tag{23}$$

$$\boldsymbol{U}=\left\{\boldsymbol{u}:\ \begin{array}{c} P^u_{d,t,s},P^u_{w,t,s}\in\mathbb{R}^{NT\times NS},\delta^{\pm}_{d,t,s},\delta^{\pm}_{w,t,s}\in\{0{,}1\}^{NT\times NS},\\ P^u_{d,t,s}=P_{d,t,s}+\delta^+_{d,t,s}\cdot\tilde{P}^+_{d,t,s}+\delta^-_{d,t,s}\cdot\tilde{P}^-_{d,t,s},\\ P^u_{w,t,s}=P_{w,t,s}+\delta^+_{w,t,s}\cdot\tilde{P}^+_{w,t,s}+\delta^-_{w,t,s}\cdot\tilde{P}^-_{w,t,s},\\ \sum_{t,s}(\delta^+_{d,t,s}+\delta^-_{d,t,s})\le\Delta_d,\delta^+_{d,t,s}+\delta^-_{d,t,s}\le 1,\\ \sum_{t,s}(\delta^+_{w,t,s}+\delta^-_{w,t,s})\le\Delta_w,\delta^+_{w,t,s}+\delta^-_{w,t,s}\le 1,\\ \forall d,w,t,s \end{array}\right\} \tag{24}$$

$\Omega(\boldsymbol{x},\boldsymbol{u})=\{$

$$P_g^{min}\cdot y_{g,t,s}\cdot x_{g,t}\le p_{g,t,s}\le P_g^{max}\cdot y_{g,t,s}\cdot x_{g,t}\qquad \forall t,s,\forall g\in G\cup G^C \tag{25}$$

$$0\le p_{w,t,s}\le P^u_{w,t,s}\qquad \forall w,t,s \tag{26}$$

$$0\le dr_{d,t,s}\le DR^{max}_{d,t}\cdot x_{d,t}\cdot y_{d,t,s}\qquad \forall t,s,\forall d\in D\cup D^C \tag{27}$$

$$-P_l^{max}\cdot x_{l,t}\le p_{l,t,s}\le P_l^{max}\cdot x_{l,t}\qquad \forall t,s,\forall l\in L\cup L^C \tag{28}$$

$$\sum_{g\in B_g(i)} p_{g,t,s}+\sum_{l\in R(i)} p_{l,t,s}-\sum_{l\in S(i)} p_{l,t,s}+v_{i,t,s}+\sum_{w\in B_w(i)} p_{w,t,s}$$
$$=\sum_{d\in B_d(i)}\left(P^u_{d,t,s}-dr_{d,t,s}\right)\qquad \forall i,t,s \tag{29}$$

$$-M\cdot\left(1-x_{l,t}\right)\le B_l\cdot\left(\theta_{s(l),t,s}-\theta_{r(l),t,s}\right)-p_{l,t,s}$$
$$\le M\cdot\left(1-x_{l,t}\right)\qquad \forall t,s,\forall l\in L\cup L^C \tag{30}$$

Constraints (12) and (14)-(19) (31)}

In addition, nonlinear terms in (25) and (27) can be equivalently linearized to facilitate calculation. For instance, the nonlinear term $y_{g,t,s}\cdot x_{g,t}$ in (25) can be equivalently represented as a linear form (32)-(34) with an extra binary variable $q_{g,t,s}$.

$$q_{g,t,s}\le y_{g,t,s} \tag{32}$$

$$q_{g,t,s} \le x_{g,t} \tag{33}$$

$$\mathbf{q_{g,t,s}} \ge \mathbf{y_{g,t,s}} + \mathbf{x_{g,t}} - \mathbf{1} \tag{34}$$

- Solution Methodology

  An extended column-and-constraint-generation (ECCG) algorithm is developed to solve the proposed two-stage robust optimization problem, by decomposing the original problem into one planning master problem and one operation sub-problem. The ECCG algorithm can effectively solve the proposed robust problem with mixed-integer recourse, while mitigating the issue of traditional CCG approach that relies on time-consuming enumeration of integer variables and might be inefficient for practical applications.

  - **Investment Master Problem and Operation Sub-problem**: The proposed model is a two-stage robust optimization problem with mixed-integer recourse, with each stage representing a multi-period decision-making process. That is, in the first stage, annual investment decisions of generation and transmission assets and DSR programs are determined, and operational decisions for each state in each year are then made in the second stage. ECCG algorithm is deployed to decompose the original problem into one master problem and one sub-problem. Specifically, in each iteration, master problem determines investment decisions with one augmented scenario, i.e., new variables and constraints corresponding to the new scenario obtained from sub-problem. Sub-problem detects the worst scenario within the constructed uncertainty set. With $\boldsymbol{x}$ and η representing decision variables in the master problem, as well as $\boldsymbol{y}^r$ and $\boldsymbol{z}^r$ being binary and continuous variables related to the worst case identified in sub-problem at iteration r, the master problem is shown as in (35).

$$\begin{aligned}
&\min_{\boldsymbol{x},\eta} \; IC(\boldsymbol{x}) + \eta \\
&\text{s.t.} \quad \boldsymbol{x} \in \boldsymbol{X} \\
&\qquad \eta \ge OC(\boldsymbol{y}^r, \boldsymbol{z}^r); \quad \boldsymbol{y}^r, \boldsymbol{z}^r \in \Omega(\boldsymbol{x}, \boldsymbol{u}^r), \forall r \\
&\qquad \boldsymbol{y}^r \in \{0,1\}, \; \boldsymbol{z}^r \ge \mathbf{0}, \forall r
\end{aligned} \tag{35}$$

  With revealed decisions $\boldsymbol{x}^*$ from the master problem, the worst-case scenario is identified in the sub-problem (36).

$$V(\boldsymbol{x}^*) = \max_{\boldsymbol{u} \in \boldsymbol{U}/\{\boldsymbol{u}^1,\dots,\boldsymbol{u}^r\}} \; \min_{\boldsymbol{y},\boldsymbol{z} \in \Omega(\boldsymbol{x}^*,\boldsymbol{u})} OC\,(\boldsymbol{y}, \boldsymbol{z}) \tag{36}$$

- **Approximate Technique to Solve Sub-problem**: Sub-problem (36) is a bi-level max-min problem with binary variables in the inner level. This type of problems can be solved by traditional CCG, in which inner-level binary variables are handled by an inner CCG algorithm relying on enumeration. However, traditional CCG is shown to be computationally inefficient for practical-size problems. An ECCG strategy described as follows is used to efficiently solve the bi-level max-min sub-problem.

  (i) With respect to the master problem solution $\boldsymbol{x}^*$, binary variables in the recourse sub-problem are relaxed as continuous, and the corresponding linear programing (LP) relaxation problem is calculated to derive a solution $\boldsymbol{u}^*$. This is done by converting the bi-level max-min into a single-level maximization problem via duality theory, and further linearizing bilinear terms via outer approximation. Detailed formulations of the LP relaxed bi-level sub-problem and its single-level equivalence are provided as follows. Symbols bracketed in the end are dual variables of corresponding constraints.

$$\max_{\boldsymbol{u}\in\boldsymbol{U}} min \left\{ \begin{array}{c} \sum_{s,g\in G}\left[\begin{array}{c} T_{t,s}\cdot\left(VC_g\cdot p_{g,t,s}+FC_g\cdot y_{g,t,s}\right) \\ +\sum_{s'}N_{t,s,s'}\cdot\left(C_g^{up}\cdot su_{g,t,s,s'}+C_g^{dn}\cdot sd_{g,t,s,s'}\right)\end{array}\right] \\ +\sum_{s,d}T_{t,s}\cdot EC_{t,s}\cdot dr_{d,t,s}+PC_t\cdot\sum_{s,i}T_{t,s}\cdot v_{i,t,s}\end{array}\right\}$$

s.t. $$P_g^{min}\cdot y_{g,t,s}\cdot\hat{x}_{g,t}\le p_{g,t,s}\le P_g^{max}\cdot y_{g,t,s}\cdot\hat{x}_{g,t} \qquad \left(\mu_{g,t,s}^{(1)},\mu_{g,t,s}^{(2)}\right)$$

$$0\le p_{w,t,s}\le P_{w,t,s}^{u} \qquad \left(\mu_{w,t,s}^{(3)},\mu_{w,t,s}^{(4)}\right)$$

$$0\le dr_{d,t,s}\le DR_{d,t}^{max}\cdot\hat{x}_{d,t}\cdot y_{d,t,s} \qquad \left(\mu_{d,t,s}^{(5)},\mu_{d,t,s}^{(6)}\right)$$

$$-P_l^{max}\cdot\hat{x}_{l,t}\le p_{l,t,s}\le P_l^{max}\cdot\hat{x}_{l,t} \qquad \left(\mu_{l,t,s}^{(7)},\mu_{l,t,s}^{(8)}\right)$$

$$\sum_{g\in B_g(i)}p_{g,t,s}+\sum_{l\in R(i)}p_{l,t,s}-\sum_{l\in S(i)}p_{l,t,s}+\sum_{w\in B_w(i)}p_{w,t,s}+v_{i,t,s} = \sum_{d\in B_d(i)}\left(P_{d,t,s}^{u}-dr_{d,t,s}\right) \qquad \left(\mu_{i,t,s}^{(9)}\right)$$

$$-M\cdot\left(1-\hat{x}_{l,t}\right)\le B_l\cdot\left(\theta_{s(l),t,s}-\theta_{r(l),t,s}\right)-p_{l,t,s}\le M\cdot\left(1-\hat{x}_{l,t}\right) \qquad \left(\mu_{l,t,s}^{(10)},\mu_{l,t,s}^{(11)}\right)$$

$$y_{g,t,s'}-y_{g,t,s}=su_{g,t,s,s'}-sd_{g,t,s,s'} \qquad \left(\mu_{g,t,s,s'}^{(12)}\right)$$

$$-\theta_i^{max}\le\theta_{i,t,s}\le\theta_i^{max},\quad \theta_{ref,t,s}=0 \qquad \left(\mu_{i,t,s}^{(13)},\mu_{i,t,s}^{(14)}\right)$$

$$\sum_s T_{t,s}\cdot y_{d,t,s}\le DR_{d,t}^{c} \qquad \left(\mu_t^{(15)}\right)$$

$$0 \le y_{g,t,s}, y_{d,t,s}, su_{g,t,s,s'}, sd_{g,t,s,s'} \le 1$$

$$\left(\mu_{g,t,s}^{(16)}, \mu_{g,t,s}^{(17)}, \mu_{d,t,s}^{(18)}, \mu_{d,t,s}^{(19)}, \mu_{g,t,s,s'}^{(20)}, \mu_{g,t,s,s'}^{(21)}, \mu_{g,t,s,s'}^{(22)}, \mu_{g,t,s,s'}^{(23)}\right)$$

$$v_{i,t,s} \ge 0 \qquad \left(\mu_{i,t,s}^{(24)}\right)$$

Its single level equivalent formulation is detailed as follows. Symbols bracketed in the end are original primal variables of corresponding constraints.

$$\max_{\boldsymbol{u} \in \boldsymbol{U}} \sum_s \left\{ \begin{array}{c} \sum_g \left[\mu_{g,t,s}^{(17)} + \sum_{s'} \left(\mu_{g,t,s,s'}^{(21)} + \mu_{g,t,s,s'}^{(23)}\right)\right] + \sum_w P_{w,t,s}^u \cdot \mu_{w,t,s}^{(4)} \\ +DR_{d,t}^c \cdot \mu_t^{(15)} + \sum_d \mu_{d,t,s}^{(19)} \\ + \sum_l \left[P_l^{max} \cdot \hat{x}_{l,t} \cdot \left(\mu_{l,t,s}^{(7)} + \mu_{l,t,s}^{(8)}\right) + M \cdot \left(1 - \hat{x}_{l,t}\right) \cdot \left(\mu_{l,t,s}^{(10)} + \mu_{l,t,s}^{(11)}\right)\right] \\ + \sum_i \left[\theta^{max} \cdot \left(\mu_{i,t,s}^{(13)} + \mu_{i,t,s}^{(14)}\right) + \left(\sum_{d \in B_d(i)} P_{d,t,s}^u\right) \cdot \mu_{i,t,s}^{(9)}\right] \end{array} \right\}$$

s.t.

$$-\mu_{g,t,s}^{(1)} + \mu_{g,t,s}^{(2)} + \mu_{i,t,s}^{(9)} \le T_{t,s} \cdot VC_g, g \in B_g(i) \qquad (p_{g,t,s})$$

$$\hat{x}_{g,t} \cdot \left(P_g^{min} \cdot \mu_{g,t,s}^{(1)} - P_g^{max} \cdot \mu_{g,t,s}^{(2)}\right) + \sum_{s'} \mu_{g,t,s,s'}^{(12)} - \sum_s \mu_{g,t,s,s'}^{(12)} - \mu_{g,t,s}^{(16)} + \mu_{g,t,s}^{(17)} \le T_{t,s} \cdot FC_g \qquad (y_{g,t,s})$$

$$-\mu_{w,t,s}^{(3)} + \mu_{w,t,s}^{(4)} + \mu_{i,t,s}^{(9)} \le 0,\ w \in B_w(i) \qquad (p_{w,t,s})$$

$$-\mu_{d,t,s}^{(5)} + \mu_{d,t,s}^{(6)} + \mu_{i,t,s}^{(9)} \le T_{t,s} \cdot EC_{t,s},\ d \in B_d(i) \qquad (dr_{d,t,s})$$

$$-DR_{d,t}^{max} \cdot \hat{x}_{d,t} \cdot \mu_{d,t,s}^{(6)} + T_{t,s} \cdot \mu_{t,s}^{(15)} - \mu_{d,t,s}^{(18)} + \mu_{d,t,s}^{(19)} \le 0 \qquad (y_{d,t,s})$$

$$-\mu_{l,t,s}^{(7)} + \mu_{l,t,s}^{(8)} - \mu_{s(l),t,s}^{(9)} + \mu_{r(l),t,s}^{(9)} + \mu_{l,t,s}^{(10)} - \mu_{l,t,s}^{(11)} = 0 \qquad (p_{l,t,s})$$

$$-\mu_{g,t,s,s'}^{(12)} - \mu_{g,t,s,s'}^{(20)} + \mu_{g,t,s,s'}^{(21)} \le N_{t,s,s'} \cdot C_g^{up} \qquad (su_{g,t,s,s'})$$

$$\mu_{g,t,s,s'}^{(12)} - \mu_{g,t,s,s'}^{(22)} + \mu_{g,t,s,s'}^{(23)} \le N_{t,s,s'} \cdot C_g^{dn} \qquad (sd_{g,t,s,s'})$$

$$B_l \cdot \left(-\mu_{l \in S(i),t,s}^{(10)} + \mu_{l \in S(i),t,s}^{(11)}\right) + B_l \cdot \left(\mu_{l \in R(i),t,s}^{(10)} - \mu_{l \in R(i),t,s}^{(11)}\right) - \mu_{i,t,s}^{(12)} + \mu_{i,t,s}^{(13)} = 0 \qquad (\theta_{i,t,s})$$

$$\mu_{i,t,s}^{(9)} - \mu_{i,t,s}^{(24)} \le T_{t,s} \cdot PC_t \qquad (v_{i,t,s})$$

(ii) With revealed $\boldsymbol{u}^*$ from (i) and $\boldsymbol{x}^*$ from the master problem, the inner single-level deterministic mixed-integer linear programming (MILP) problem is calculated to derive solutions $\boldsymbol{y}^*$ and $\boldsymbol{z}^*$.

(iii) Fixing binary recourse variables $\boldsymbol{y} = \boldsymbol{y}^*$, the bi-level sub-problem is converted into a max-min LP problem, which is re-computed to obtain final solutions $\boldsymbol{u^0}$ and $\tilde{V}(\boldsymbol{x}^*)$. Detailed formulations of the bi-level sub-problem with fixed $\boldsymbol{y}^*$ and its single-level equivalence are provided as follows:

$$\max_{\boldsymbol{u}\in\boldsymbol{U}} \min \left\{ \begin{array}{c} \sum_{s,g\in\boldsymbol{G}} T_{t,s} \cdot \left(VC_g \cdot p_{g,t,s}\right) + \sum_{s,d} T_{t,s} \cdot EC_{t,s} \cdot dr_{d,t,s} \\ +PC_t \cdot \sum_{s,i} T_{t,s} \cdot v_{i,t,s} \end{array} \right\}$$

s.t. $P_g^{min} \cdot \hat{y}_{g,t,s} \cdot \hat{x}_{g,t} \leq p_{g,t,s} \leq P_g^{max} \cdot \hat{y}_{g,t,s} \cdot \hat{x}_{g,t}$ $\quad \left(\eta_{g,t,s}^{(1)}, \eta_{g,t,s}^{(2)}\right)$

$0 \leq p_{w,t,s} \leq P_{w,t,s}^u$ $\quad \left(\eta_{w,t,s}^{(3)}, \eta_{w,t,s}^{(4)}\right)$

$0 \leq dr_{d,t,s} \leq DR_{d,t}^{max} \cdot \hat{x}_{d,t} \cdot \hat{y}_{d,t,s}$ $\quad \left(\eta_{d,t,s}^{(5)}, \eta_{d,t,s}^{(6)}\right)$

$-P_l^{max} \cdot \hat{x}_{l,t} \leq p_{l,t,s} \leq P_l^{max} \cdot \hat{x}_{l,t}$ $\quad \left(\eta_{l,t,s}^{(7)}, \eta_{l,t,s}^{(8)}\right)$

$$\sum_{g\in B_g(i)} p_{g,t,s} + \sum_{l\in R(i)} p_{l,t,s} - \sum_{l\in S(i)} p_{l,t,s} + \sum_{w\in B_w(i)} p_{w,t,s} + v_{i,t,s}$$
$$= \sum_{d\in B_d(i)} \left(P_{d,t,s}^u - dr_{d,t,s}\right) \quad \left(\eta_{i,t,s}^{(9)}\right)$$

$$-M \cdot \left(1 - \hat{x}_{l,t}\right) \leq B_l \cdot \left(\theta_{s(l),t,s} - \theta_{r(l),t,s}\right) - p_{l,t,s} \leq M \cdot \left(1 - \hat{x}_{l,t}\right)$$
$$\left(\eta_{l,t,s}^{(10)}, \eta_{l,t,s}^{(11)}\right)$$

$-\theta^{max} \leq \theta_{i,t,s} \leq \theta^{max}, \quad \theta_{ref,t,s} = 0$ $\quad \left(\eta_{i,t,s}^{(12)}, \eta_{i,t,s}^{(13)}\right)$

$v_{i,t,s} \geq 0$ $\quad \left(\eta_{i,t,s}^{(14)}\right)$

Its single level equivalent formulation is as follows.

$$\max_{\boldsymbol{u}\in\boldsymbol{U}} \sum_s \left\{ \begin{array}{c} \sum_g \hat{y}_{g,t,s} \cdot \hat{x}_{g,t} \cdot \left(-P_g^{min} \cdot \eta_{g,t,s}^{(1)} + P_g^{max} \cdot \eta_{g,t,s}^{(2)}\right) + \\ \sum_w P_{w,t,s}^u \cdot \eta_{w,t,s}^{(4)} + \sum_d DR_{d,t}^{max} \cdot \hat{x}_{d,t} \cdot \hat{y}_{d,t,s} \cdot \eta_{d,t,s}^{(6)} \\ + \sum_l \left[P_l^{max} \cdot \hat{x}_{l,t} \cdot \left(\eta_{l,t,s}^{(7)} + \eta_{l,t,s}^{(8)}\right) + M \cdot \left(1 - \hat{x}_{l,t}\right) \cdot \left(\eta_{l,t,s}^{(10)} + \eta_{l,t,s}^{(11)}\right)\right] \\ + \sum_i \left[\theta^{max} \cdot \left(\eta_{i,t,s}^{(12)} + \eta_{i,t,s}^{(13)}\right) + \left(\sum_{d\in B_d(i)} P_{d,t,s}^u\right) \cdot \eta_{i,t,s}^{(9)}\right] \end{array} \right\}$$

s.t. $-\eta_{g,t,s}^{(1)} + \eta_{g,t,s}^{(2)} + \eta_{i,t,s}^{(9)} \leq T_{t,s} \cdot VC_g,\ g \in B_g(i)$ $\quad \left(p_{g,t,s}\right)$

$-\eta_{w,t,s}^{(3)} + \eta_{w,t,s}^{(4)} + \eta_{i,t,s}^{(9)} \leq 0,\ w \in B_w(i)$ $\quad \left(p_{w,t,s}\right)$

$-\eta_{d,t,s}^{(5)} + \eta_{d,t,s}^{(6)} + \eta_{i,t,s}^{(9)} \leq T_{t,s} \cdot EC_{t,s},\ d \in B_d(i)$ $\quad \left(dr_{d,t,s}\right)$

$-\eta_{l,t,s}^{(7)} + \eta_{l,t,s}^{(8)} - \eta_{s(l),t,s}^{(9)} + \eta_{r(l),t,s}^{(9)} + \eta_{l,t,s}^{(10)} - \eta_{l,t,s}^{(11)} = 0$ $\quad \left(p_{l,t,s}\right)$

$$B_l \cdot \left(-\eta^{(10)}_{l\in S(i),t,s} + \eta^{(11)}_{l\in S(i),t,s}\right) + B_l \cdot \left(\eta^{(10)}_{l\in R(i),t,s} - \eta^{(11)}_{l\in R(i),t,s}\right) - \eta^{(12)}_{i,t,s} + \eta^{(13)}_{i,t,s} = 0 \qquad (\theta_{i,t,s})$$

$$\eta^{(9)}_{i,t,s} - \eta^{(14)}_{i,t,s} \leq T_{t,s} \cdot PC_t \qquad (v_{i,t,s})$$

The ECCG algorithm is summarized as follows.

Step 1: Initialize data, set lower bound $LB = -\infty$, upper bound $UB = +\infty$, and iteration counter $r = 1$.

Step 2: Solve the master problem and obtain the optimal solution$(\boldsymbol{x}^r, \eta^r)$, set $LB = IC(\boldsymbol{x}^r) + \eta^r$.

Step 3: Solve the sub-problem, obtain $\boldsymbol{u^0}$ and corresponding solution $\tilde{V}(\boldsymbol{x}^r)$, update $UB = min\{UB, IC(\boldsymbol{x}^r) + \tilde{V}(\boldsymbol{x}^r)\}$.

Step 4: If $(UB - LB)/LB \leq \varepsilon$, the algorithm terminates and the final solution is $\boldsymbol{x}^r$; Otherwise, set $\boldsymbol{u^{r+1}} = \boldsymbol{u^0}$ and $r = r + 1$ in the master problem, and then go to Step 2. That is, the newly identified worst scenario $\boldsymbol{u^0}$ from Step 3 is added into the master problem, for seeking new investment solutions to mitigate such worst case operation situations.

III.2. Phase II. Validation and Verification of MMCOP via Standard Testing Systems and Practical Systems

Three main activities are involved to validate and verify the MMCOP framework. First, the MMCOP is implemented through General Algebraic Modeling System (GAMS), which is a high-level modeling system with linkages to many nonlinear and mixed-integer solvers; Second, effectiveness of the developed MMCOP is verified via standard testing systems that have been widely used as benchmark in many power system studies, including the IEEE 24-bus (RTS) system, the IEEE 30-bus system, and the IEEE 118-bus system; Third, the developed MMCOP is further validated via the practical WECC Transmission Expansion Planning Dataset to illustrate its performance on practical large-scale systems in terms of the computational time and the solution optimality. Numerical case studies illustrate effectiveness of the developed MMCOP as compared to traditional generation and/or transmission planning approaches, by analyzing the impacts on annual planning and hourly operation, long-term reliability and short-term flexibility, AC power flows, as well as risk and uncertainty accommodations. Some result highlights are shown below, while the detailed testing results and the analysis can be referred to from the team's publications [18, 22-24] out of this project.

Table 1 shows the 10-year generation and transmission planning results on the modified IEEE 24-bus (RTS) system with different penetration levels of DSRs. The original RTS system contains 33 units, 40 branches, and 17 loads. 4 wind farms are added to buses 3, 10, 14, and 19 in this study. 10 candidate units from 3 different generation technologies, i.e., combustion turbine, coal steam turbine, and oil steam turbine, are considered. In addition, 8 candidate transmission lines are considered, some increase available transfer capacities of existing lines while others are planned in new corridors. DSR-0 denotes the case without DSRs, in which only generation and transmission candidates are considered, while capacities of candidate DSRs on individual buses in DSR-2 are twice of those in DSR-1. With a second subscript representing installation year of candidate assets, results of deterministic cases are shown in Table 1.

Table 1 shows that total costs are reduced when the DSR penetration level increases. Indeed, an increased deployment in DSRs could help enhance social welfare by economically reducing peak loads, which would consequently postpone expansion of expensive generation and/or transmission assets and improve economic efficiency in the operation stage. Specifically, G7 and T1 are postponed when the system faces with a higher DSR penetration level, which reflect benefits of enhanced DSR participation. In fact, as Independent System Operators (ISO) can effectively schedule DSRs in the operation stage to meet practical system needs based on system status, benefits from DSRs could be more significant when significant supply shortage occurs due to unexpected contingencies. These studies clearly show effectiveness of the proposed MMCOP model, i.e., with the technology advancement such as the integration of DSRs, more economically efficient systems can be planned by system operators. Expensive generation and transmission investments in the planning stage could be effectively postponed or even avoided, and economic efficiency in the operation stage can also be improved.

The modified IEEE 24-bus (RTS) system is further studied while considering uncertainties. Comparing with the deterministic results in Table 1, both total costs and investment costs in Table 2 are increased, because generators are invested more extensively (i.e., generators are constructed more extensively and/or earlier) and/or turned on more proactively to protect system against uncertainties.

Table 1. Deterministic planning results against different penetration levels of demand side resources

Case	Total Cost (10^{10})	Investment Cost (10^9)	Generation Investment	Transmission Investment
DSR-0	2.291	3.206	$G_{3,1}G_{4,5}\mathbf{G_{7,4}}$	$\mathbf{T_{1,4}}T_{2,1}T_{3,1}\,T_{4,1}T_{7,1}T_{8,1}$
DSR-1	2.203	3.178	$G_{3,1}G_{4,5}\mathbf{G_{7,4}}$	$\mathbf{T_{1,5}}T_{2,1}T_{3,1}\,T_{4,1}T_{7,1}T_{8,1}$
DSR-2	2.123	3.146	$G_{3,1}G_{4,5}\mathbf{G_{7,6}}$	$\mathbf{T_{1,5}}T_{2,1}T_{3,1}\,T_{4,1}T_{7,1}T_{8,1}$

Table 2. Planning results when considering uncertainties

Case	Total Cost (10^{10})	Investment Cost (10^9)	Generation Investment	Transmission Investment
DSR-0	3.080	3.426	$G_{3,1}\mathbf{G_{4,3}G_{7,3}}G_{8,10}$	$\mathbf{T_{1,2}}T_{2,1}T_{3,1}T_{4,1}\mathbf{T_{5,10}}T_{7,1}T_{8,1}$
DSR-1	2.990	3.784	$G_{3,1}\mathbf{G_{4,4}G_{7,3}}G_{8,10}$	$\mathbf{T_{1,2}}T_{2,1}T_{3,1}T_{4,1}\,\mathbf{T_{5,8}}T_{7,1}T_{8,1}$
DSR-2	2.905	3.545	$G_{3,1}\mathbf{G_{4,4}G_{7,4}}G_{8,10}$	$\mathbf{T_{1,4}}T_{2,1}T_{3,1}T_{4,1}\,\mathbf{T_{5,9}}T_{7,1}T_{8,1}$

The impacts of different load uncertainty levels on the optimal planning results are further studied. As indicated in Table 3, with an increase in the uncertainty level, the total cost increases because power system assets are constructed more extensively or much earlier for accommodating uncertainties. Specifically, deployment of G_4, G_7, G_8, T_1, T_5, D_1, and D_2 are brought forward when uncertainty level is high. However, considering that certain assets could be regarded as alternative feasible system expansion options, installation time of some assets may not follow the same trend. For instance, T_1 is constructed in year 4 with uncertainty level of 0.75 as compared to year 3 with uncertainty level of 0.5. This could be explained as that T_1 is an alternative expansion option of D_7 in year 4, whose construction in year 4 with uncertainty level of 0.5 is switched to year 1 when the uncertainty level is 0.75.

In order to further illustrate the impact of solution robustness against different uncertainty levels and facilitate system planners with a better choice, Monte Carlo simulation with 1,000 scenarios is conducted to compare the expected total costs (i.e., investment cost and expected operation cost of the 1,000 scenarios) of individual investment solutions in Table 3. Scenarios are generated from normal distributions with mean values of $P_{d,t,s}$ and $P_{w,t,s}$ and standard deviations of $\tilde{P}^{+}_{d,t,s}/1.95$ and $\tilde{P}^{+}_{w,t,s}/1.95$. Results in Table 4 show a trade-off between investment cost and expected operation cost. That is, a higher uncertainty level would derive a more expensive expansion plan to immunize against more significant worst cases, which would lead to a lower expected operation cost of scenarios. Indeed, uncertainty level of around 0.75 would be the best choice in this case, which achieves the smallest expected total cost.

Table 3. Planning results against different uncertainty levels

Uncertainty level	Total cost ($\$10^{10}$)	Increase in total cost (%)	Generation investment	Transmission investment
0	2.203	0	$G_{3,1}G_{4,5}G_{7,4}$	$T_{1,5}T_{2,1}T_{3,1}T_{4,1}T_{7,1}T_{8,1}$
0.25	2.642	19.9	$G_{3,1}G_{4,4}G_{7,4}$	$T_{1,4}T_{2,1}T_{3,1}T_{4,1}T_{7,1}T_{8,1}$
0.5	2.800	27.1	$G_{3,1}G_{4,4}G_{7,4}G_{8,10}$	$T_{1,3}T_{2,1}T_{3,1}T_{4,1}T_{5,10}T_{7,1}T_{8,1}$
0.75	2.933	33.1	$G_{3,1}G_{4,4}G_{7,3}G_{8,10}$	$T_{1,4}T_{2,1}T_{3,1}T_{4,1}T_{5,8}T_{7,1}T_{8,1}$
1	2.990	35.7	$G_{3,1}G_{4,4}G_{7,3}G_{8,10}$	$T_{1,2}T_{2,1}T_{3,1}T_{4,1}T_{5,8}T_{7,1}T_{8,1}$

Table 4. Monte Carlo simulation results

Budget	0	0.25	0.5	0.75	1
Investment cost ($\$10^{9}$)	3.178	3.294	3.496	3.547	3.784
Expected operation cost ($\$10^{10}$)	1.909	1.894	1.868	1.861	1.840
Expected total cost ($\$10^{10}$)	2.227	2.223	2.218	2.216	2.218

Computational effort of the MMCOP could be quite expensive due to a large number of binary variables related to unit commitment status in the operation model, as well as time coupling constraints of investment decisions throughout the long-term planning horizon. Indeed, significant computational effort comes mainly from the master problem of the proposed ECCG based decomposition approach, while the well-recognized computational burden from the mixed-integer recourse problem has been successfully handled by the proposed ECCG approach. Figure 3 shows computational time on the modified IEEE 24-bus (RTS) system study. It clearly shows that computational effort from the sub-problem only takes a small portion of total calculation time, which greatly relieves computational burden of the traditional CCG decomposition algorithm for solving mixed-integer recourse sub-problems.

Computational performance of the proposed ECCG is further compared with the traditional CCG approach, as shown in Table 5. In Table 5, "***" indicates that the computational time limit is reached while no solution satisfying the predefined mixed-integer programming (MIP) gap threshold is found, and "OOM" represents that the test is out of memory before reaching the time limit while no solution satisfying the predefined MIP gap threshold is found. As shown in Table 5, the proposed ECCG algorithm takes less time than the traditional CCG approach algorithm to derive final solutions. Specifically, compared with the proposed ECCG algorithm, traditional CCG approach algorithm could not find feasible solutions for most cases within time or memory limit, showing that traditional CCG approach algorithm might be poor to handle certain practical instances. While for the instances that can be solved by traditional CCG approach, solutions derived by the proposed ECCG are the same as those of traditional CCG approach, which verifies the exactness of solutions derived by the proposed ECCG algorithm. As all the instances are solved within the required MIP gap via the proposed ECCG, optimality of the solution is indeed guaranteed and solution quality is not sacrificed for the studied instances. Therefore, these studies clearly demonstrate the effectiveness and practicality of the proposed ECCG algorithm, as well as its superiority over the traditional CCG approach algorithm.

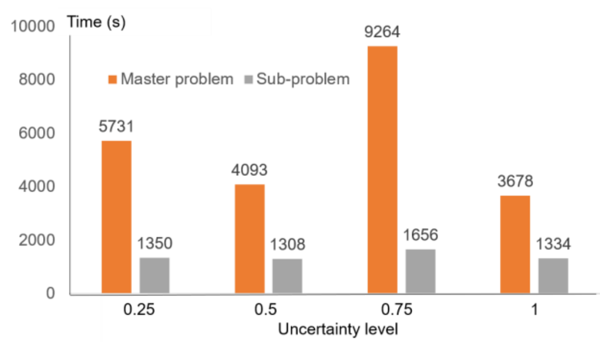


Figure 3. Computational time of master and sub-problem

Table 5. Results comparison between the proposed ECCG and traditional CCG approaches

Uncertainty level	ECCG		NCCG	
	Obj ($\$10^{10}$)	Time (h)	Obj ($\$10^{10}$)	Time (h)
0.25	2.687	1.87	2.687	22.74
0.5	2.805	2.35	***	***
0.75	2.941	7.88	OOM	OOM
1	3.000	2.70	3.000	10.49

For real-world tests and scalability validations, the MMCOP is further tested on the modify WECC 243-bus system for a 5-year planning study. The WECC 243-bus system is a real-world test case originally designed for unit commitment (UC) problems, which includes 451 existing transmission lines. 58 potential locations are considered to install new coal-fired generators, combustion generators, as well as wind and solar farms. As for the transmission network, we consider that no new corridors are allowed, while new lines can be built following existing corridors to enhance transmission capabilities. Notably, we simulate a case with the annual capacity phasing-out rate of 25% for conventional generations, and evaluate whether it is feasible to reach a 100% renewable penetration environment in a 5-year planning process. Both regional N-1 contingencies and hourly operation characteristics are considered within the long-term planning horizon. Figure 4 depicts the scheduled installed capacity for each generation technology and transmission line, which shows that the investment on solar and wind generators grows sharply in the first year and keeps increasing. Particularly, aiming at investigating the 100% renewable penetration scenario, the test results show that the investment in solar and wind generators grows sharply in the first year and keeps increasing, due to the 25% annual phasing-out rate of conventional generators. The computational time of the WECC simulation is 27 hours, which is comparably reasonable concerning the scale of the multi-year stochastic and robust planning problem.

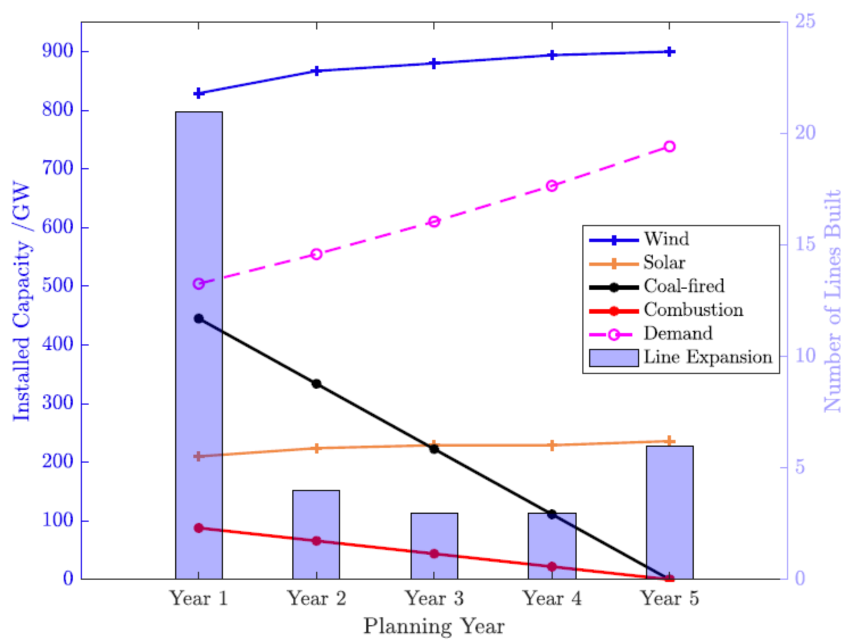


Figure 4. Planning results of the WECC system

III.3. Phase III. Dissemination of The Results and The Final Reporting

The research findings of this project have been disseminated to the community via 8 journal publications and 4 technical conference presentations. APPENDIX A: Product or Technology Production provides the full list of these publications and presentations out of this project.

The project team has also interacted with multiple industry partners, seeking potential opportunities to customize the MMCOP models and computational tools according to their specifications and needs and to provide technical support for promoting co-optimization in their system expansion planning practice. Specifically, (i) PI Wu presented the proposed MMCOP framework as well as the preliminary results to New York Independent System Operator (NYISO) on September 2017; (ii) PI Wu visited MISO in April 2018, discussing about the potential applicability of the MMCOP framework to address their challenges of integrating a high penetration of distributed resources and utility-scale energy storage assets in the MISO market. As MISO currently uses PLEXOS for its planning studies, the team conducted a preliminary survey on PLEXOS about how heterogeneous assets of the MISO system are modelled in PLEXOS and the long-term planning is calculated via PLEXOS, and evaluated the potential possibility in incorporating some of the proposed approaches to solve the MISO system planning problem.

Multiple undergraduate and graduate students at Clarkson University, University of Pittsburgh, and Southern Methodist University have participated in this project, receiving training and professional development on areas of power and energy systems, mathematical optimization, and algorithms. Specifically, (i) The Ph.D. thesis "Multiple Timescale Power Systems Operation and Planning with Renewable Energy, Demand Side Resource, and Energy Storage" was completed in August 2018 at Clarkson University; (ii) One undergraduate student of Industrial Engineering at University of Pittsburgh, graduated in December 2018, was motivated by this research project and worked on an undergraduate research project about capacity expansion considering both wind and nuclear generations in a stochastic environment; (iii) Some of the developed mathematical models and computational algorithms, i.e., stochastic programming and robust optimization models as well as ECCG based decomposition approach for energy system planning, have been supplemented and presented in multiple undergraduate and graduate courses offered at Clarkson University and University of Pittsburgh. For instance, the development of computational algorithms, i.e., the bilinear Benders decomposition for chance constrained system planning, has been supplemented and presented in Dr. Zeng's graduate course, "computational optimization" in Fall 2017, as a demonstration for large-scale system optimization. Moreover, in Dr. Wu’s course, EE452/552 “Optimization Techniques in Engineering” in Spring 2018, these developed mathematical models and computational algorithms were used as a demonstration for large-scale system optimization. In Spring 2018, 5 undergraduate students and 11 graduate students enrolled in this class, from both engineering and business schools.

IV. Accomplishments and Conclusions

IV.1. Major Accomplishments

During the project period, the team has developed the MMCOP prototype, which integrates the modeling and algorithm features as detailed in Section III of this report. The MMCOP prototype has been tested via several IEEE benchmark systems and the practical WECC system to illustrate its effectiveness and efficiency. The detailed modeling and solution techniques, as well as research findings of this project have been disseminated to the community via 8 journal publications and 4 technical conference presentations. APPENDIX A: Product or Technology Production provides the full list of publications and presentations out of this project.

Table 6 lists the milestones of the project and the related completion information.

Table 6. List of milestones of the project

Milestone	Completion Date		Detailed Completion Information
	Planned	Actual	
1. Presentation, Year 1	9/30/2017	9/30/2017	Invited presentation in the 2017 INFORMs Meeting. L. Wu and B. Zeng, "Integrating Demand Side Resources into Multi-Stage and Multi-Timescale Robust Generation and Transmission Expansion Planning," INFORMS Annual Meeting, Houston, TX, Oct. 2017.
2. Publication, Year 1	9/30/2017	9/30/2017	By 9/30/2017, two journal papers related to this project have been published. Z. Bao, Q. Zhou, L. Wu, Z. Yang, and J. Zhang, "Optimal Capacity Planning of MG with Multi-energy Coordinated Scheduling under Uncertainties Considered," IET Generation, Transmission & Distribution, vol. 11, no. 17, pp. 4146-4157, Jan. 2017. A. Bagheri, J. Wang, and C. Zhao, "Data-Driven Stochastic Transmission Expansion Planning," IEEE Transactions on Power Systems, vol. 32, no. 5, pp. 3461-3470, Sept. 2017.
3. Completion of MMCOP prototype	3/31/2018	3/31/2018	A MMCOP prototype has been built. The documentation that describes the basic functionalities of the MMCOP prototype has been submitted to DOE.

4. Validate MMCOP via standard IEEE testing systems	9/30/2018	9/30/2018	Test results of MMCOP via standard IEEE testing systems (including a modified IEEE 24-bus system and a modified IEEE 118-bus system) have been reported in a Ph.D. Thesis and a journal paper. Ph.D. Thesis, C. Dai, Multiple Timescale Power Systems Operation and Planning with Renewable Energy, Demand Side Resource, and Energy Storage, Clarkson University, August 2018. A paper "A System State Model Based Multi-Period Robust Generation, Transmission, and Demand Side Resource Co-Optimization Planning" has been submitted to IET Generation, Transmission & Distribution for review.
5. Presentation, Year 2	9/30/2018	9/30/2018	B. Zeng, "A Study on Generalized Security Games in Power Systems," in 2018 INFORMS Optimization Conference, Denver, CO, March 23-25, 2018.
6. Publication, Year 2	9/30/2018	9/30/2018	By 9/30/2018, one journal paper related to this project has been published. Y. Wang, L. Wu, and J. Li, "A Fully-Distributed Asynchronous Approach for Multi-Area Coordinated Network-Constrained Unit Commitment," Optimization and Engineering, pp. 1-34, DOI: https://doi.org/10.1007/s11081-018-9375-8, February 2018.
7. Test MMCOP via practical systems	6/30/2020	6/30/2020	Due to the change of PI and the delay on renewing of subawards with the two subcontracts, the project progress falls behind what was originally proposed. On June 13, 2019, the PI of this project was officially changed to Jie Li. On June 29, 2020, Clarkson updated the PO for the Southern Methodist University subaward to reflect the new end date 9/30/2020 after non-cost extension. The team was planning to include Stevens Institute of Technology as a new subaward of this project (where the original PI Lei Wu moved to). However, Clarkson was unable to complete this in time. As the current team members had no active data usage agreement with the targeted industry partners (Lei Wu has an active agreement with MISO, but cannot

			use that to conduct this project as he is not part of the project team without the subaward being set up), additional testing on practical system has stalled.
8. Presentation, Year 3	9/30/2019	9/30/2019	S. Yin and J. Wang, "Generation and Transmission Expansion Planning Towards a 100% Renewable Future," ECE Seminar, Southern Methodist University, March 2019.
9. Publication, Year 3	9/30/2019	9/30/2019	By 9/30/2019, three journal papers related to this project have been published. C. Dai, L. Wu, B. Zeng, and C. Liu, "A System State Model Based Multi-Period Robust Generation, Transmission, and Demand Side Resource Co-Optimization Planning," IET Generation, Transmission & Distribution, DOI:10.1049/iet-gtd.2018.5936, November 2018. X. Cao, J. Wang, and B. Zeng, "Networked Microgrids Planning Through Chance Constrained Stochastic Conic Programming," IEEE Transactions on Smart Grid, vol. 10, no. 6, pp. 6619-6628, April 2019. X. Cao, J. Wang, J. Wang, and B. Zeng, "A Risk-Averse Conic Model for Networked Microgrids Planning with Reconfiguration and Reorgani-zations," DOI:10.1109/TSG.2019.2927833, IEEE Transactions on Smart Grid, July 2019
10. Ph.D. Award	9/30/2020	8/30/2018	Ph.D. Thesis, Chenxi Dai, Multiple Timescale Power Systems Operation and Planning with Renewable Energy, Demand Side Resource, and Energy Storage, Clarkson University, August 2018.

This project is highly in line with the objective of DE-FOA-0001493 "Addressing Risk and Uncertainty in the Future Power System". Specifically,

- The MMCOP prototype co-optimizes generation and transmission planning, which adequately addresses "*uncertainty in the location and type of future generation*";
- The MMCOP prototype optimizes spatial transmission network based on the raster map in GIS while considering physical nonlinear AC power flow characteristics, which effectively accounts for "*environmental and other public policies simultaneously with electrical engineering considerations*";

- The MMCOP prototype adopts tighter convex formulations of non-linear AC power flows, which presents an effective approach "*for dealing realistically with alternating current (AC) networks*";
- The MMCOP prototype integrates long-term reliability, short-term flexibility, and hourly operation details in a single analytical framework, which effectively addresses "*both engineering considerations and economic realities of perhaps integrated system planning and operations*";
- The MMCOP prototype adopts the hybrid robust and stochastic optimization model to systematically evaluate the impacts of spatial and temporal variability as well as uncertainty correlations on planning and operation decisions, which effectively quantifies "*the uncertainty that has become ubiquitous in electric power systems planning and operation" and provides good "tradeoffs between economics and reliability*".

The MMCOP prototype presents fundamental and transformative changes beyond existing generation and transmission planning practices. A clear comparison between the existing planning approaches and the MMCOP prototype is conducted in Table 7, which shows the innovative and significant contribution of the MMCOP prototype in a number of areas.

Table 7. Comparison between existing planning approaches and the MMCOP prototype

Existing Planning Approaches [9-17]	The Proposed MMCOP Prototype
Modeling Capability	**Modeling Capability**
- Generation and transmission planning in a queue;	+ Generation and transmission co-optimization;
- A set of predefined generation and configurations;	+ Network topology, line routing, topology control capacity, and generation sizing and sitting are co-optimized;
- Static or dynamic expansion plan that only considers the most stressful hours while neglecting operation details or the production cost minimization;	+ Multi-stage and multi-timescale planning, while accurately evaluating broader reliability, sustainability, and economic benefits;
- Deterministic derated generation capacity, without possibilities of generator or line outages;	+ Robust optimization model to fully consider N-1, N-2, and N-1-1 reliability criteria;
- Uncertainties and risks in future economic, policy, and technology	+ Hybrid robust and stochastic optimization model to systematically

conditions are either neglected or evaluated by a limited number of independent scenarios;	evaluate spatial and temporal variability and correlations on planning and operation decisions, and to ensure resilience under different disruptions;
- (Successive) Linear approximations of AC transmission network;	+ Full non-linear AC power flow via tight convex formulation using SOCP and cutting planes;
- System aggregation based on static similarity of loads and/or generations.	+ Dynamic system aggregation based on actual system operation status.
Solution Methodology	**Solution Methodology**
- Weak approximation (e.g., LP, or rule-based approximations) and computationally heavy decomposition methods (e.g., successive LP and traditional Benders decomposition);	+ Integrated decomposition techniques, e.g., Benders decomposition and ECCG generation integration;
- Centralized computational approaches without considering distributed implementation.	+ Distributed computational methods, e.g., ADMM, to handle complexities and multi-area coordination.

IV.2. Major Conclusions

By comparing with existing long-term generation and/or transmission planning approaches in literature, the following conclusions are observed via extensive studies on standard IEEE testing systems and the practical WECC Transmission Expansion Planning Dataset:

(i) By considering flexible resources, especially those non-wire technologies on the demand side, and capturing short-term operation status of the power systems, more economically efficient and reliable systems can be planned.

(ii) The hybrid stochastic and robust model used in the MMCOP prototype can accurately capture various discrete and continuous uncertainties in modern power grid, thus facilitating the long-term planning with significant renewables while ensuring cost effectiveness, reliability, and sustainability.

(iii) Extensive studies also show that the proposed advanced solution approaches have the potential to enhance computational efficiency for solving real-world large-scale long-term planning problems.

Indeed, extensive studies show that the developed MMCOP prototype could help enhance the energy reliability and sustainability of the existing grid with the most economic integration of additional generation and transmission assets. Specifically, it can help electricity grid planners and operators better plan additional resources, manage available resources, achieve higher reliability standards, and increase renewable energy penetration, which otherwise may not have been explored due to the lack of analytical tools for simultaneously addressing co-optimization of generation and transmission assets under uncertain environments. The developed MMCOP prototype can also assist market participants including generation and transmission companies, renewable energy developers, independent system operators, power system planners and operators in vertically integrated utilities, and regulatory agencies to analyze economics, reliability, and sustainability of various options for transmission upgrades and the planning of new generation and transmission facilities. The developed MMCOP prototype can also be conveniently customized to regulatory requirements such as RPS standards and other state mandates. It can also be used by industry for teaching and training next-generation power system planners and operators for analyzing renewable energy integration uncertainties, identifying critical spots in power system operation, analyzing power system vulnerabilities, and providing credible decisions for examining operation and planning options.

IV.3. Recommendations for Future Work

The framework and algorithms of the MMCOP prototype are applicable to most of the organized wholesale electricity markets in the North American grid, as the underlying modeling assumptions and principles are generic to the industry practice regardless of the differences in regional resource and transmission topology. Although the industry participants of this project (e.g., MISO, Pennsylvania-New Jersey-Maryland Interconnection (PJM), and ISO New England (ISO-NE)) provided technical advice and assistance on industry power system expansion planning practice, the MMCOP prototype was not tested via real data of Regional Transmission Organization (RTO) systems. The MMCOP prototype could be further tested on RTO systems using their actual data, and comparing the performance with their existing planning tools. For instance, MISO currently uses PLEXOS for their long-term planning studies. The team did a preliminary study on PLEXOS about how different types of assets in the MISO system are modelled and how the long-term planning is calculated in PLEXOS. It would be interesting to compare the developed MMCOP prototype and PLEXOS against multiple MISO instances, evaluating their performance in terms of computational performance and solution quality (i.e., cost effectiveness, reliability, and sustainability). It would also be interesting to explore if certain models and solutions approaches developed under the MMCOP prototype could be integrated in the PLEXOS to potentially improve its modeling and computational performance.

APPENDIX A: Product or Technology Production

The project team has delivered 9 peer-reviewed journal papers and 4 technical presentations to disseminate research findings during the period of performance.

Peer-reviewed Publications

[J1] Z. Bao, Q. Zhou, L. Wu, Z. Yang, and J. Zhang, "Optimal Capacity Planning of MG with Multi-energy Coordinated Scheduling under Uncertainties Considered," IET Generation, Transmission & Distribution, vol. 11, no. 17, pp. 4146-4157, January 2017.

[J2] A. Bagheri, J. Wang, and C. Zhao, "Data-Driven Stochastic Transmission Expansion Planning," IEEE Transactions on Power Systems, vol. 32, no. 5, pp. 3461-3470, September 2017.

[J3] Y. Wang, L. Wu, and J. Li, "A Fully-Distributed Asynchronous Approach for Multi-Area Coordinated Network-Constrained Unit Commitment," Optimization and Engineering, pp. 1-34, DOI: https://doi.org/10.1007/s11081-018-9375-8, February 2018.

[J4] C. He, L. Wu, T. Liu, and Z. Bie, "Robust Co-Optimization Planning of Interdependent Electricity and Natural Gas Systems With a Joint N-1 and Probabilistic Reliability Criterion," IEEE Transactions on Power Systems, vol. 33, no. 2, pp. 2140-2154, March 2018.

[J5] X. Cao, J. Wang, and B. Zeng. "A Chance Constrained Information-Gap Decision Model for Multi-Period Microgrid Planning." IEEE Transactions on Power Systems, vo. 33, no. 3, pp. 2684-2695, May 2018.

[J6] C. Dai, L. Wu, B. Zeng, and C. Liu, "System State Model Based Multi-Period Robust Generation, Transmission, and Demand Side Resource Co-Optimization Planning," IET Generation, Transmission & Distribution, vol. 13, no. 3, pp. 345-354, February 2019.

[J7] X. Cao, J. Wang, and B. Zeng, "Networked Microgrids Planning Through Chance Constrained Stochastic Conic Programming," IEEE Transactions on Smart Grid, vol. 10, no. 6, pp. 6619-6628, April 2019.

[J8] X. Cao, J. Wang, J. Wang, and B. Zeng, "A Risk-Averse Conic Model for Networked Microgrids Planning with Reconfiguration and Reorganizations," IEEE Transactions on Smart Grid, vol. 11, no. 1, pp. 696-709, January 2020.

[J9] S. Yin and J. Wang, "Generation and Transmission Expansion Planning Towards a 100% Renewable Future," IEEE Transactions on Power Systems, accepted, September 2020.

Invited Presentations

[P1] L. Wu and B. Zeng, “Integrating Demand Side Resources into Multi-Stage and Multi-Timescale Robust Generation and Transmission Expansion Planning,” INFORMS Annual Meeting, Houston, TX, October 2017.

[P2] C. He, T. Liu, and L. Wu, “Robust Co-optimization Planning of Electricity and Natural Gas Systems,” in the 1st IEEE Conference on Energy Internet and Energy System Integration, Beijing China, November 2017.

[P3] B. Zeng, “A Study on Generalized Security Games in Power Systems,” in 2018 INFORMS Optimization Conference, Denver, CO, March 23-25, 2018.

[P4] S. Yin and J. Wang, “Generation and Transmission Expansion Planning Towards a 100% Renewable Future,” ECE Seminar, Southern Methodist University, March 2019.

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