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Investigating the effects of cooperative transmission expansion planning on grid performance during heat waves with varying spatial scales

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HIGHLIGHTS

- Institutional hurdles and lack of coordination can hinder transmission expansion.
- Considering high-value extreme weather events in power system planning is pivotal.
- This study analyzes the potential impacts of cooperation in transmission planning.
- Cooperative transmission planning helps reduce power system costs and outages.
- The extent of benefits varies with spatial coverage of extreme weather events.

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ABSTRACT

There is growing recognition of the advantages of interregional transmission capacity to decarbonize electricity grids. A less explored benefit is potential performance improvements during extreme weather events. This study examines the impacts of cooperative transmission expansion planning using an advanced modeling chain to simulate power grid operations of the United States Western Interconnection in 2019 and 2059 under different levels of collaboration between transmission planning regions. Two historical heat waves in 2019 with varying geographical coverage are replayed under future climate change in 2059 to assess the transmission cooperation benefits during grid stress. The results show that cooperative transmission planning yields the best outcomes in terms of reducing wholesale electricity prices and minimizing energy outages both for the whole interconnection and individual transmission planning regions. Compared to individual planning, cooperative planning reduces wholesale electricity prices by 64.3 % and interconnection-wide total costs (transmission investments + grid operations) by 34.6 % in 2059. It also helps decrease greenhouse gas emissions by increasing renewable energy utilization. However, the benefits of cooperation diminish during the widespread heat wave when all regions face extreme electricity demand due to higher space cooling needs. Despite this, cooperative transmission planning remains advantageous, particularly for California Independent System Operator with significant diurnal solar generation capacity. This study suggests that cooperation in transmission planning is crucial for reducing costs and increasing reliability both during normal periods and extreme weather events. It highlights the importance of optimizing the strategic investments to mitigate challenges posed by wider-scale extreme weather events of the future.

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1. Introduction

Keeping global warming under 1.5 °C or 2 °C requires reaching net-zero emissions by 2050 or 2070, respectively [1]. A global transformation of the energy sector is needed to decrease greenhouse gas (GHG)[1] emissions and achieve these climate goals [2,3]. Increasing the share of variable renewable energy resources such as solar and wind is crucial for decarbonizing electricity grids [4,5]. As intermittent and variable renewable energy capacity grows and firm thermal generation capacity shrinks, grid operators are challenged to adopt new practices to maintain balance between supply and demand. On the other hand, climate change influences electricity demand, system reliability, electricity prices, and GHG emissions in bulk power systems [6,7]. For example, the intensity and frequency of extreme weather events (e.g., heat waves and hurricanes) are increasing due to climate change. These events strain electricity grids by increasing demand and reducing the efficiency of the power grid infrastructure [8–10]. Since grid operators are facing a dual challenge of decarbonizing and maintaining the reliability of power systems during extreme weather events [11], joint consideration of these two phenomena in power system modeling is important [12].

Substantial investment in high voltage transmission capacity is now widely viewed as imperative in deep decarbonization of the power grid via variable renewable energy resources to interconnect these new generators, that are located in wind and solar resource-rich areas, with the load centers [4,5,13]. Transmission expansion planning (TEP) is the process of deciding when and where new lines should be constructed or existing lines should be upgraded [14–16]. TEP exercises attempt to meet the future electricity demand while maintaining power system resilience and minimizing the cost of long-term transmission investments [17,18]. Traditionally, transmission expansion is carried out at a regional level where each utility plans for its own infrastructure, which results in more individualized plans [19,20]. Thus, these practices do not unveil the total value of coordination between transmission planning entities [21]. However, interregional transmission capacity is crucial and can offer significant benefits to decarbonize electricity sector more efficiently [20,22].

Numerous studies have focused on TEP problems by proposing different modeling methods and/or including uncertainty with more robust planning approaches [12,19,22–33]. For instance, Ruiz et al. proposed an adaptive robust transmission optimization model to pick investment alternatives by minimizing total system costs for worst-case outcomes of uncertain parameters [23]. Choi et al. considered different types of contingencies to solve the TEP problem [24] whereas Cadini et al. introduced two objectives in a TEP problem as reliability and cost, and used a multi-objective genetic algorithm to find a solution [25]. Furthermore, Al-Saba et al. tested artificial intelligence tools like neural networks and Tabu search in solving TEP problem [27]. Lastly, Brown & Botterud provided insights on the value of interregional transmission for a decarbonized U.S. electricity grid by utilizing a co-optimized capacity planning and dispatch model [33].

However, none of these studies quantifies the value of cooperation in interregional TEP during extreme weather events under future climate projections by comparing different levels of transmission expansion cooperation. Moreover, previous studies do not consider possible reductions of potential transmission cooperation benefits under heat waves with varying spatial scales (i.e., local vs. widespread heat waves). There is a risk of understating the value of regional and interregional transmission investments if rare but important extreme conditions like heat waves are not taken into consideration [34,35]. For instance, balancing authorities (BAs) may have more opportunities to exchange electricity during more localized weather extremes if the transmission network is planned cooperatively while considering these kinds of high-value conditions. However, more widespread weather extremes in the future might deteriorate these collaboration benefits by limiting available power imports as more BAs would be under stress due to significant spikes in electricity demands within their region. Therefore, considering extreme weather events with varying geographical scale can enhance the reliability and resiliency of future power systems.

In this study, we investigate the impacts of cooperation between transmission planning entities, quantified in terms of the economic and reliability benefits under decarbonization and future climate-altered heat wave events with varying spatial scales. We make use of two western United States (U.S.) heat wave events in 2019 as base cases of local and widespread heat wave examples. Using a novel climate perturbation technique, the same two heat waves are replayed 40 years into the future (i.e., in 2059) with additional warming to reflect the average warming signal from global climate models under a specific representative concentration pathway (RCP) scenario. Grid conditions under these scenarios are simulated with a customized Grid Operations (GO) modeling framework with a production cost model (PCM) component to assess the economic and reliability impacts of individual (i.e., only intraregional) vs. cooperative (i.e., both intraregional and interregional) TEP. In order to come up with representative set of load and on-the-ground generator conditions of the U.S. electricity grid in 2059, we utilize an advanced framework that consists of several models working in sync. Those models include a transmission expansion model (TEP) [36] to optimize capacity additions to existing transmission lines, Global Change Analysis Model (GCAM) [37] to generate future annual state-level total demands, generation capacity additions, and fuel prices, Total Electricity Loads (TELL) model [38] to project hourly electricity loads in each BA, Capacity Expansion Regional Feasibility (CERF) model [39] to site the future generators to appropriate locations depending on numerous geospatial siting suitability layers [40], and Renewable Energy Potential (reV) model [41] to determine hourly solar and wind generation profiles for the future years.

2. Methods

In this section, we start with a brief explanation of the GO modeling framework as well as its PCM component. Then, we provide a description of the TEP model, which is an extension of GO model to account for transmission planning, and the other supporting models used in this study (GCAM, CERF, TELL, and reV).

2.1. Grid operations (GO) framework

Grid operations models are often customized to specific regions or applications due to higher computational intensity requirements [42]. Balancing model fidelity (i.e., accuracy) and computational burden (i.e., runtime) have become major challenges for power system researchers [43]. In this study, we utilize a customizable framework for balancing computational speed and fidelity in interconnection-wide PCMs called GO [44].

The open-source GO framework utilizes BA-level data and synthetic grid topologies [45–48] created by Texas A&M University. GO allows users to create simpler representations of U.S. interconnections to find a balance between model fidelity and runtime. Although this model is available for all three interconnections of the U.S., in this study, we utilize the U.S. Western Interconnection (WI) as a test bed with a sub-model of GO called GO WEST. The geographical scope of this model includes the 28 BAs located in the U.S. states of the WI (Arizona, California, Colorado, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington, and Wyoming).

GO WEST is a Python-based software including a PCM module that helps researchers customize the topology with respect to their research questions/needs and simulate grid operations with the resultant

[1] Although all acronyms and abbreviations used in this study are defined in the main text, readers might refer to Table S1 in the Supplementary Information to see the definitions of all acronyms and abbreviations in one place.

Table 1
Experimental setup showing the scenario parameters and scenario names.

Year	Climate Change Scenario	Transmission Expansion Type	Heat Wave Scale
2019	Historical Meteorology	Default Line Limits (Base)	Local
			Widespread
		Individual TEP	Local
			Widespread
		Intermediate TEP	Local
			Widespread
		Cooperative TEP	Local
			Widespread
2059	rcp45hotter_ssp3 (RCP4.5 representative concentration pathway, SSP3 shared socioeconomic pathway, and hotter climate model uncertainty)	Individual TEP	Local
			Widespread
		Intermediate TEP	Local
			Widespread
		Cooperative TEP	Local
			Widespread

topology. It makes use of a base 10,000-node synthetic representation of the U.S. WI [45,46]. Since running a model with this complexity would entail a significant amount of time and resources, GO WEST allows researchers to alter model complexity by creating a reduced network through four user-defined parameters which are number of nodes, mathematical formulation, transmission line capacity scaling factor, and hurdle rate scaling factor.

After selecting these four model parameters and creating a reduced order representation of WI via a network reduction algorithm [49], GO WEST simulates hourly grid operations with the embedded PCM module. The PCM module consists of a unit commitment/economic dispatch type model that leverages linear programming (LP) or mixed-integer linear programming (MILP) formulations depending on the user's choice. The objective function is minimizing the total operational cost of satisfying hourly electricity demand at each node subject to several constraints such as maximum generator capacities, ramp rates, and thermal capacities of transmission lines. The PCM module utilizes the

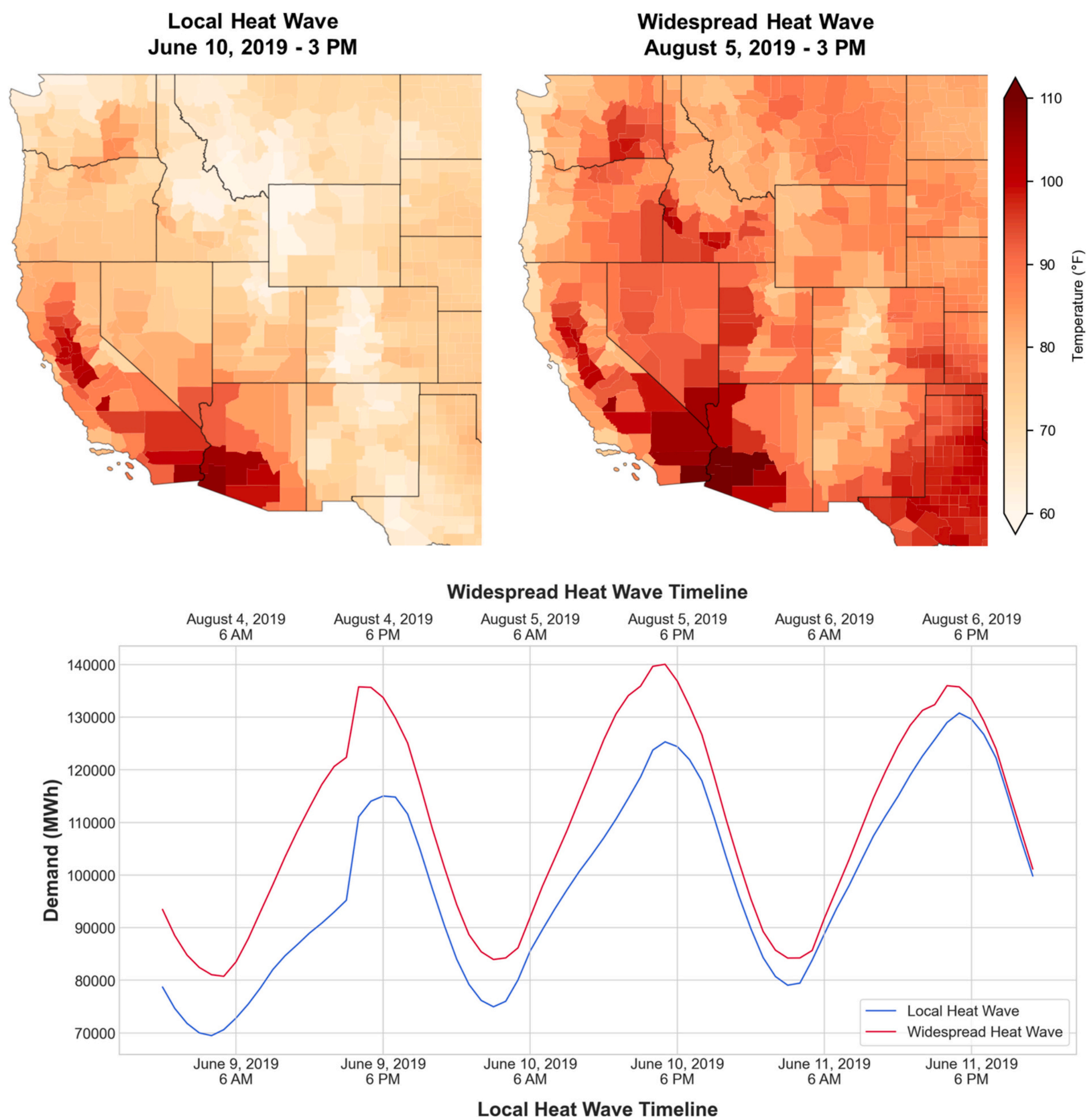

Fig. 1. (Top left) Hottest hourly temperature distribution during the 2019 local heat wave; (top right) hottest hourly temperature distribution during the 2019 widespread heat wave; (bottom) total electricity demand time series during both heat waves for the WI.

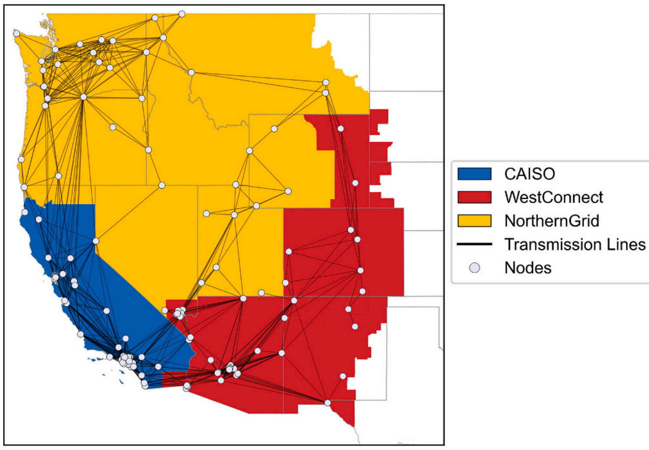

Fig. 2. 125 node topology of GO WEST and the three TPRs in the WI.

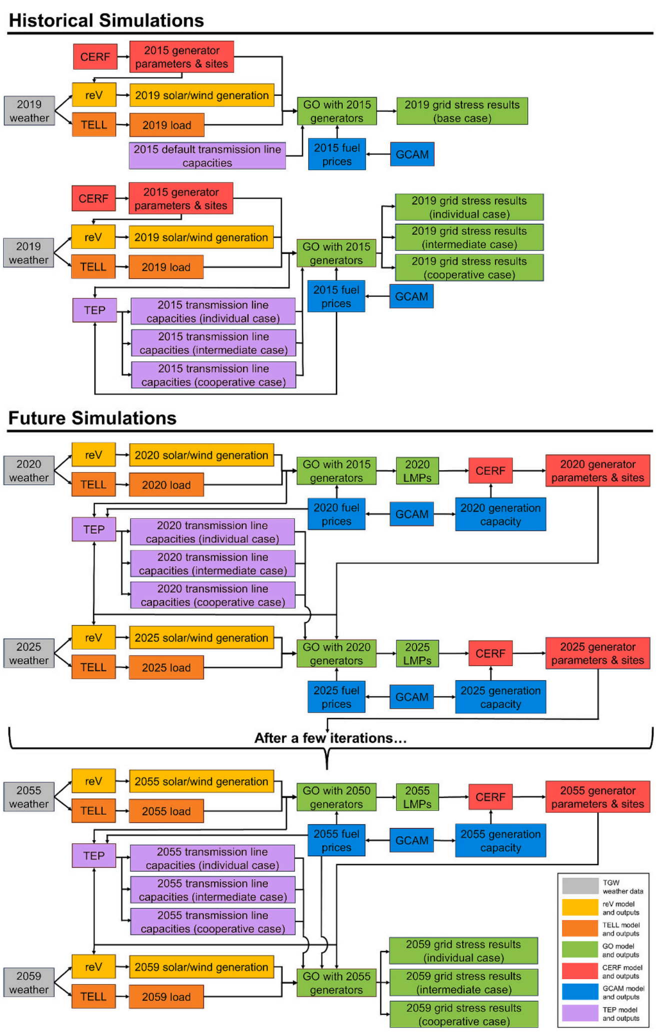

Fig. 3. Flowchart of the experimental setup to simulate grid stress during 2019 and 2059. 2015 is the baseline year of this study. Generation and transmission capacity expansion plans are made every 5 years, starting in 2020 and ending in 2055. Generation and transmission assets remain unchanged through those 5-year periods. Simulating grid stress of a year within a 5-year period is possible by using demand and solar/wind time series of that specific year.

direct current (DC) power flow approximation and has an hourly temporal resolution. The model has a user-defined planning horizon which defaults to 24-h.

Decision variables of the model consist of on/off status (if MILP is used) and electricity generation from each generator, voltage angle at each node, power flow on each transmission line, and unserved energy (i.e., loss of load [LOL] or outages) at each node. We placed a hypothetical generator at each node with an extremely high marginal cost of generation (2000 $/MWh = value of lost load [VOLL] in the California Independent System Operator (CAISO) [50]). These hypothetical generators are only triggered when there is an energy imbalance due to a lack of generation capacity and/or transmission congestion at that node. The power generated from these hypothetical generators illustrates the amount of lost load at that node. Model outputs include hourly generation schedule of each generator, hourly locational marginal price (LMP) at each node, hourly unserved energy at each node, hourly voltage angles at each node, and hourly power flow on each transmission line. For more detailed information about GO framework and the PCM component, please refer to [44].

Table 2
LMP and unserved energy statistics for the whole WI and individual TPRs in 2019.

Region	Scenario	Average LMP ($/MWh)	Annual LOL to Demand Ratio (%)
WI	Base	94.55	0.35
	Cooperative	49.24	0
	Intermediate	53.21	0
	Individual	54.03	0
CAISO	Base	61.77	0
	Cooperative	50.29	0
	Intermediate	56.49	0
	Individual	61.62	0
WestConnect	Base	196.27	1.32
	Cooperative	45.38	0
	Intermediate	46.81	0
	Individual	45.41	0
NorthernGrid	Base	53.99	0
	Cooperative	51.03	0
	Intermediate	54.21	0
	Individual	51.39	0

2.2. *Transmission expansion planning model (TEP)*

We developed a TEP model for this study to determine the optimal thermal capacity additions to existing transmission lines, which utilize the same right of way. Our TEP model is an LP model and can be solved with both open-source and commercial solvers. Gurobi is used as the solver for both the GO and TEP models in this paper.

The objective function of the TEP model is to minimize the annualized system cost which consists of the operational cost to satisfying electricity demand (i.e., generation cost), cost of loss of load (i.e., unserved energy), and cost of new transmission capacity additions (i.e., capital/investment cost). In addition, the TEP model considers several constraints including maximum and minimum generation limits for all generators, voltage angle limits, Kirchhoff's voltage law (KVL), Kirchhoff's current law (KCL), default and new thermal capacity limits of transmission lines, and yearly transmission investment budget limits.

When making TEP decisions, the model utilizes a representative hour approach. We select 12 hourly time steps to represent the most extreme conditions in 12-months of a year. In this way, the investment decisions become more robust compared to assuming just a single highest-demand hour in a year. We assume that electricity demand is the highest total net hourly demand (i.e., demand minus solar/wind generation) within the entire WI each month. Other assumptions made by the TEP model include treating nuclear capacity as a must-run resource, using monthly average fuel prices for each generator and monthly average hydropower availability. Available solar and wind power values are gathered at the selected demand hour and paired with the hourly electricity demand in

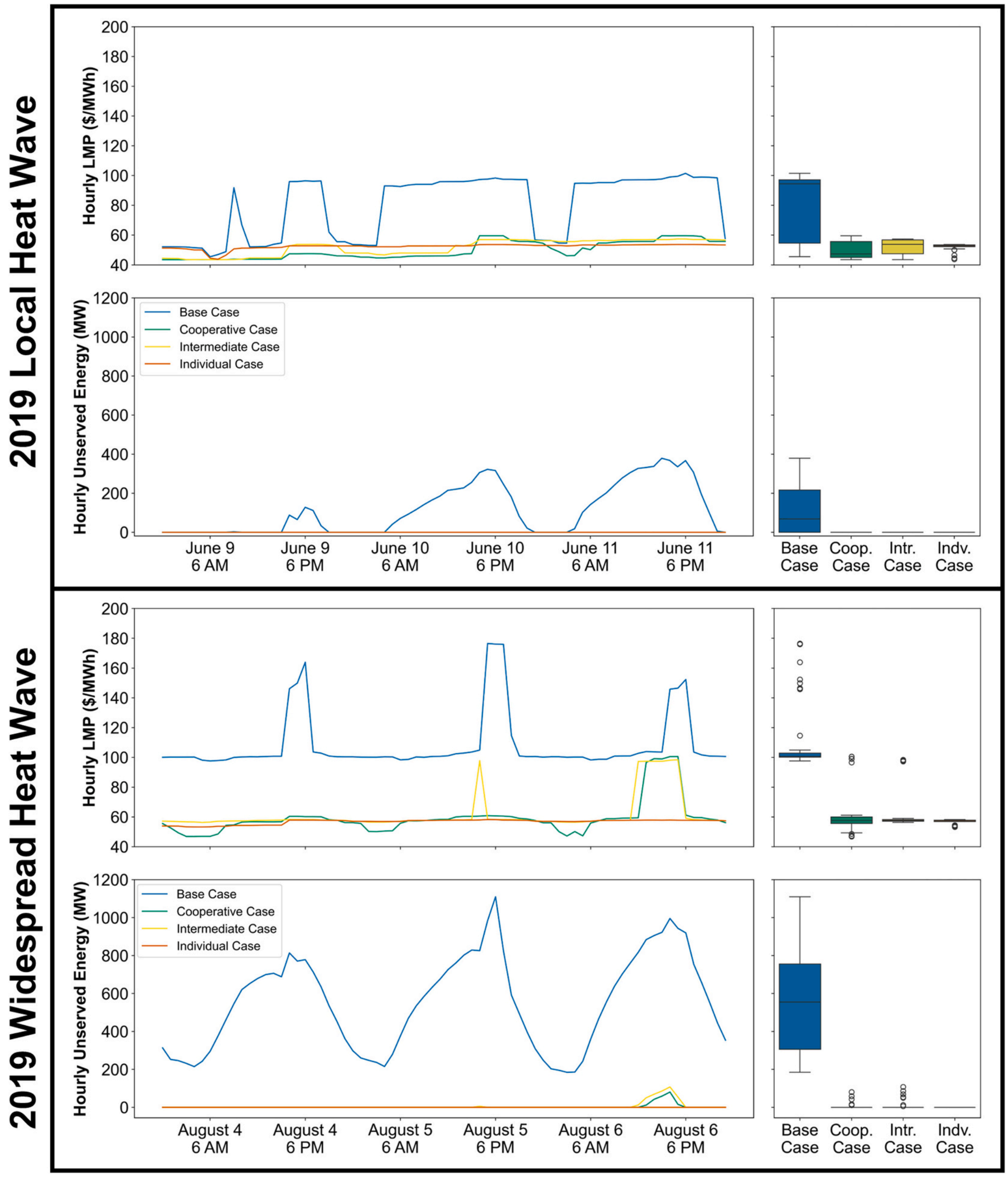

Fig. 4. Time series and distributions of hourly average LMPs and total unserved energy in the WI during the 2019 local and widespread heat waves.

each month. Lastly, we feed the model with the investment cost of new transmission capacity additions from [51], which considers length-dependent piecewise investment cost curves for alternating current (AC) and DC transmission lines.

Since investment costs are yearly but other costs are hourly, generation and unserved energy costs are scaled up to a yearly value by multiplying those costs with the number of hours in each respective month. Then, TEP model considers all these parameters in a single step to decide on the necessary transmission capacity additions. The model outputs include generation schedule of each generator, unserved energy at each node, voltage angle at each node, and power flow on each transmission line for those 12 hourly time steps, as well as incurred investment cost and new capacity addition for each transmission line. More details, including the model formulation of TEP model, are presented in Supplementary Information.

2.3. *Supporting models*

Here, we provide a brief description of supporting models, which are GCAM, TELL, CERF, and reV. More detailed information about these models can be found in Supplementary Information.

GCAM [52] is a dynamic model that captures global interactions in energy, water, land, and emissions markets, influenced by socioeconomic development, climate change, and technological advancement. It divides the world into several regions for detailed analysis. This study uses GCAM-USA v5.3 [37], which subdivides the U.S. into 51 regions, enhancing the representation of state-specific socioeconomic and energy conditions. The model balances supply and demand in each market at 5-year intervals, considering electricity trade, fuel prices and detailed end-use sectors. It distinguishes between long-term capacity expansion and short-term dispatch strategies to ensure electricity demands are met with a 15 % reserve margin at sub-annual intervals [53].

TELL [38] is a machine learning model that predicts hourly load profiles for each BA. It trains a unique multilayered perceptron model

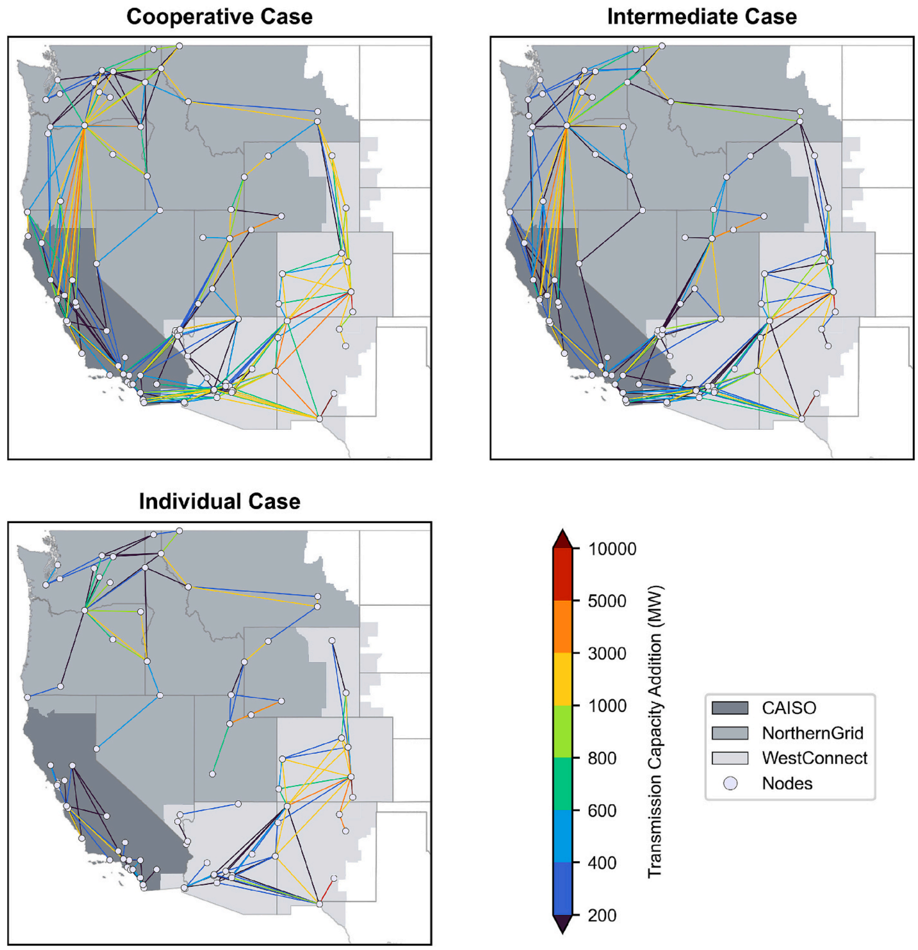

Fig. 5. Transmission investment paths under cooperative, intermediate, and individual TEP scenarios. The color bar represents the additional transmission capacity investment at each existing line between 2015 and 2055.

for each BA, using historical load data from 2016 to 2018 and meteorological variables like temperature, humidity, shortwave radiation, longwave radiation, and wind speed. It also considers time of day, day of the week, and federal holidays. The unique meteorology forcing in this experiment is described in [54,55], which was processed to the county and then BA-scale as documented in [56,57]. TELL's output is scaled to match state-level annual loads simulated by GCAM-USA to account for population and socioeconomic impacts.

CERF [39] is a geospatial power plant siting tool that downscales regional capacity expansion plans to assess the power plant landscape over time. It identifies feasible sites for renewable and non-renewable technologies by integrating geospatial suitability data with an economic algorithm [40]. CERF selects optimal plant locations based on factors like grid interconnection costs and locational marginal value of new generation. Operating at a 1 km^2 resolution, it considers factors such as protected lands, population density, and water availability to ensure viable and accurate expansion planning by siting the new generators coming from GCAM-USA to appropriate locations.

reV [41,58] is a tool that models renewable energy systems, covering generation, capacity, and economics aspects. It is used to project solar and wind generation for future years. reV utilizes numerous meteorological inputs such as temperature, solar irradiance, pressure, wind direction and wind speed. These inputs were derived from Thermodynamic Global Warming (TGW) dataset, a dynamically downscaled meteorological dataset available at 1/8th degree over the continental U.S. [50], which were preprocessed to produce all the necessary wind and solar input variables for future hourly solar and wind generation projections.

3. Experimental design

In this section, we describe our experimental design, including the different modeling scenarios used to quantify differences between the effects of individual, intermediate, and cooperative TEP (Table 1).

We selected two heat waves between 2015 and 2019 by analyzing the 2-m temperatures and electricity demands between 1980 and 2019 of WI BAs [54,56,57,59]. For selecting the heat waves, we calculated three different metrics: (1) hourly BA temperature anomalies with respect to average temperature between 1980 and 2014, (2) hourly WI temperature anomalies (by calculating BA area weighted temperature anomalies) with respect to average temperature between 1980 and 2014 to assess the geographical coverage of the heat waves, and (3) hourly cooling degree days (CDD) for each BA to assess the severity of the heat waves. We have analyzed these metrics to make sure the selected heat waves led to extreme temperatures for at least three consecutive days. Furthermore, we made sure that the interconnection-wide hourly demands during the widespread heat wave were higher than hourly demands during local heat wave to understand the unique resource adequacy implications of this type of event. Considering all these together, we selected one local and one widespread heat wave. The hottest temperatures and demand profiles throughout these heat waves are shown in Fig. 1. The local heat wave occurred between June 9–11, 2019 [60] and the widespread heat wave occurred between August 4–6, 2019 [61].

Using the GO framework, we selected a PCM version with 125 nodes, an LP formulation, +500 MW transmission line limit scaling factor, and a − 100 % hurdle rate scaling factor, since these parameters led to the

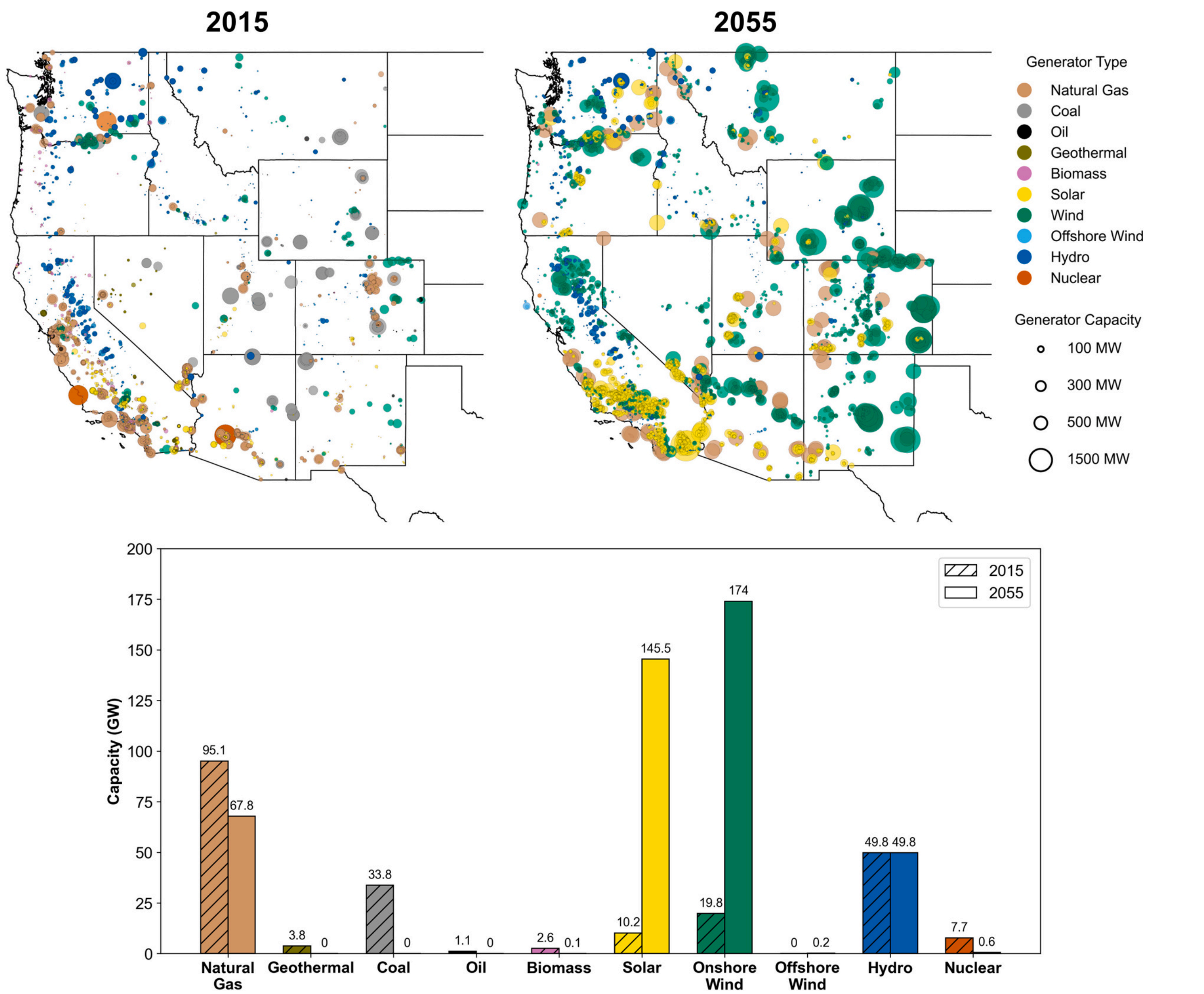

Fig. 6. (Top) Individual generator locations and capacity by type in 2015 and 2055; (bottom) total generator capacity by type in 2015 and 2055.

Table 3
LMP and unserved energy statistics for the whole WI and individual TPRs in 2059.

Region	Scenario	Average LMP ($/MWh)	Annual LOL to Demand Ratio (%)
WI	Cooperative	135.82	0.15
	Intermediate	178.44	0.28
	Individual	380.19	3.06
CAISO	Cooperative	142.31	0.21
	Intermediate	193.18	0.27
	Individual	724.48	6.98
WestConnect	Cooperative	112.18	0.11
	Intermediate	125.53	0.26
	Individual	118.13	0.04
NorthernGrid	Cooperative	146.67	0.11
	Intermediate	202.49	0.32
	Individual	155.65	0.01

best results in terms of matching historical LMPs and generation mix throughout the WI in the original GO parameter sweep experiment [44]. The GO WEST topology we utilized including 125 nodes and three transmission planning regions (TPRs) in the WI (CAISO, WestConnect and NorthernGrid [62]) are shown in Fig. 2.

For the historical runs (i.e., the actual heat waves in 2019), we assumed 2015 installed power system infrastructure (i.e., generators and transmission lines) and 2015 fuel prices, but used 2019 demand and solar/wind generation profiles. We first simulated the model under a historical base case using current transmission line capacities (i.e., default 2015 values from GO framework). Then, we ran the TEP model to get three different 2019 transmission networks, assuming three different levels of coordination.

To represent the cooperative TEP scenario, we ran the TEP model to minimize the cost of grid operations and capital costs of transmission capacity additions throughout the WI. For the individual TEP scenario, we enforced an extremely high interregional transmission line investment cost penalty to completely prohibit increasing transmission line capacities between any two TPRs. For the intermediate TEP scenario, we applied a + 200 % penalty (i.e., increased cost of building interregional transmission capacity) to the lines crossing boundaries of TPRs. In this way, the TEP model is discouraged (but not prohibited) from increasing transmission line capacities of the lines between any two TPRs, emulating institutional hurdles.

A + 200 % cost penalty for the intermediate TEP scenario provided a middle point for the interregional transmission expansion. We conducted a sensitivity analysis around different interregional cost penalties on transmission line buildouts (see Figs. S1-S5 in Supplementary Information). When investments are analyzed between 2015 and 2020, ~34 % of all transmission investments are interregional in the cooperative TEP scenario (i.e., 0 % interregional cost penalty). On the other hand, 0

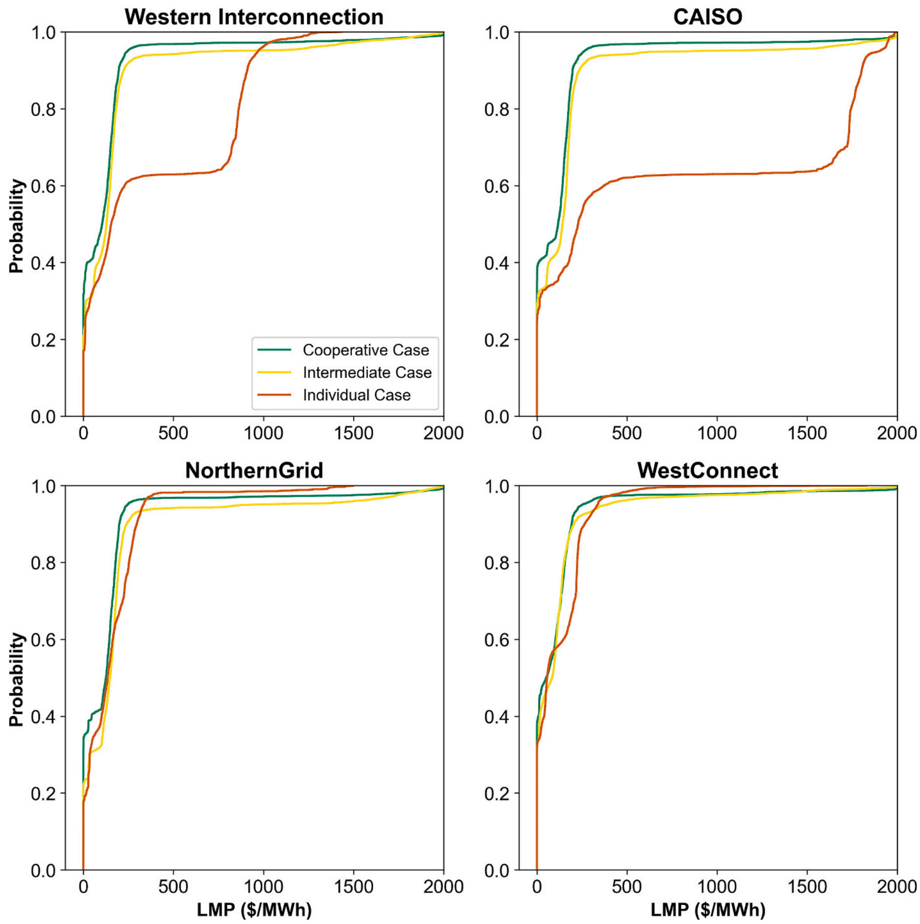

Fig. 7. Hourly average LMP distributions for the whole WI and individual TPRs in 2059.

% of all transmission investments are interregional in the individual TEP scenario. When we enforce a + 200 % cost penalty, the share of interregional transmission expansion is ~16 %, which is close to the middle point of interregional investment shares from the individual and cooperative TEP scenarios.

These three TEP scenarios (individual, intermediate, cooperative) are proxies for different possible cooperation levels. Current transmission practices are likely to be somewhere between individual and intermediate scenarios, due to complex permitting and siting processes, cost allocation disagreements, and lack of comprehensive and consistent benefit analysis methods to capture full range of scenarios. Finding solutions to these challenges through new policies, incentives, and mechanisms can lead to a more cooperative transmission expansion scenario.

For the future runs, we run the model toolchain in an iterative fashion (i.e., GCAM-TELL-GO-CERF-reV-TEP iteration) in 5-year timesteps to create a projection of the power system as it might develop between 2015 and 2055. This iterative simulation process is an effort to mimic the actual decision-making on generator investments by considering grid conditions (e.g., demand, LMPs) and determining where to site new generators in each timestep. Electricity demand and wind/solar generation profiles are modeled with TELL and reV, respectively. GCAM-USA is key in providing capacity expansion plans for each state in the WI as well as generator costs and fuel prices. CERF sites the new generators coming from GCAM-USA within each state. LMPs from the GO model are a key input into CERF's economic algorithm and are dynamic over the course of the experiment as new infrastructure is tested in GO. The specific scenario we used, a combination of RCP 4.5 climate and emissions projections and SSP3 populations (i.e., rcp45hotter_ssp3), results in a significant buildout of renewables in the WI to keep the global GHG emissions below the 4.5 Wm^{-2} forcing threshold. The origin of this scenario is the TGW datasets [54] and projections of hourly meteorology by BA based on TGW datasets [57]. For more information about how TGW data is created, please refer to [55].

To explore the future heat waves (i.e., heat waves in 2059), we assume the 2055 power system infrastructure (i.e., generators and transmission lines) and fuel prices created by the iterative process described above, but 2059 demand and solar/wind values. Since transmission infrastructure will have changed by 2055, we make use of TEP model to come up with individual, intermediate, and cooperative transmission line capacities at every 5-year time step. A case with no TEP in the future (i.e., keeping transmission capacities constant through 2055) is not considered because it would not be realistic as significant transmission investments are expected for the future due to decarbonization efforts [63–66]. In this study, future individual, intermediate, and cooperative TEP approaches persist throughout the experiment (up until 2055) and do not affect each other. Therefore, there are three independent branches to represent individual vs. intermediate vs. cooperative TEP scenarios.

In order to provide equal grounds for each TEP scenario, a yearly transmission investment budget is enforced as a constraint in TEP model. Between 2015 and 2020, the transmission budget is determined as $4 billion/year, informed by historical investments within WI [67,68]. This budget is raised by 20 % (i.e., to $4.8 billion/year) and by 50 % (i.e., to $6 billion/year) between 2020 and 2030 and 2030–2055, respectively to prevent possible underinvestment issues. Transmission budget outlooks are gathered from the base electrification case in [69]. Fig. 3 provides an overall representation of the experimental setup, which resembles an integrated, iterative and multiscale framework as discussed in [70].

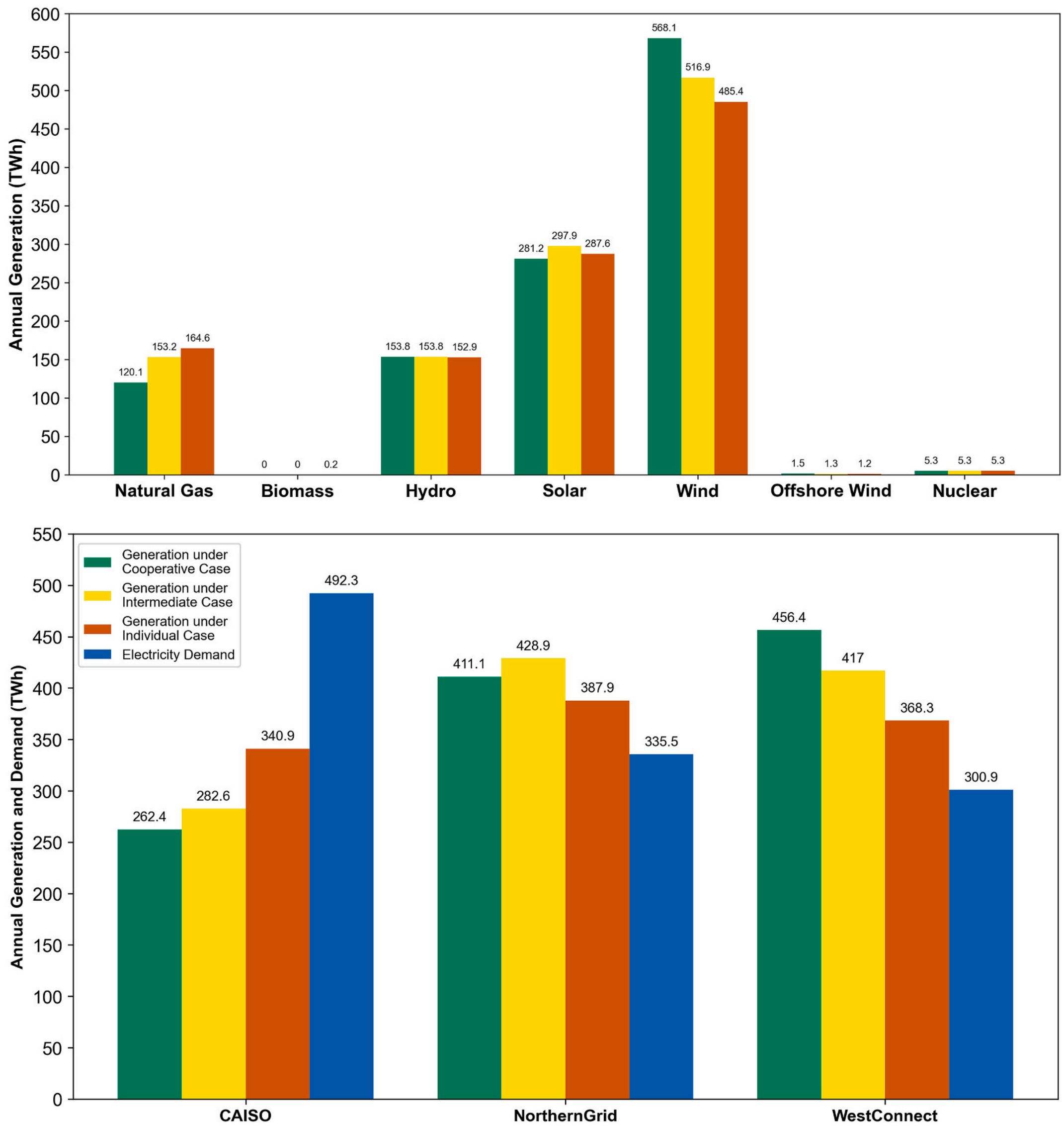

Fig. 8. (Top) Annual generation by type in the WI in 2059; (bottom) total annual generation and demand in three TPRs in 2059. Colors designate the three TEP scenarios and electricity demand.

The 2019 and 2059 heat waves capture the highest temperature anomalies in the western U.S. and serve as a representative cases in this study. In order to capture the worst-case conditions (i.e., highest CDDs), years 2017 and 2057 including a local and widespread heat wave are also simulated with the same experimental setup. The outcomes of these additional simulations can be found in the Supplementary Information. The results of these additional simulations fully support the results and conclusions reached in this study.

4. Results and discussion

In this section, annual and heat wave-specific results from the historical simulations are discussed first. Then, we outline how the WI evolved under the rcp45hotter_ssp3 scenario. Lastly, we present more in-depth results on the LMPs, unserved energy, generation mix, and power flow from the future simulations.

All hourly average LMPs reported in this section are demand-weighted so that nodes with higher demand contribute more to regional (i.e., hub) LMPs. Moreover, although no TEP were required in 2019, we included the historical results briefly to show how historical grid operations could have been affected by different transmission planning approaches and to lay the foundation for the future results which is our main focus.

4.1. General results in 2019

LMPs and unserved energy are two useful metrics to understand the impact of different TEP approaches on the electricity grid. LMP and unserved energy results in 2019 are presented in Table 2. Any type of transmission expansion in 2019 reduces the LMPs compared to the base case, especially for WestConnect. Because new transmission capacity relieves congestion on the lines and make it possible to utilize cheaper generators such as solar and wind more, which is a part of LMP calculation. However, the impact of individual TEP on CAISO LMPs is negligible compared to the base case, which shows that CAISO needs new interregional transmission capacity more than intraregional transmission capacity.

In general, LMPs are reduced most with cooperative TEP, followed by the intermediate TEP and then individual TEP scenarios. Compared to base case, throughout the WI, average LMPs are reduced by 45.31, 41.34, and 40.52 \$/MWh under cooperative, intermediate, and individual TEP cases, respectively. Cooperative TEP benefits CAISO the most

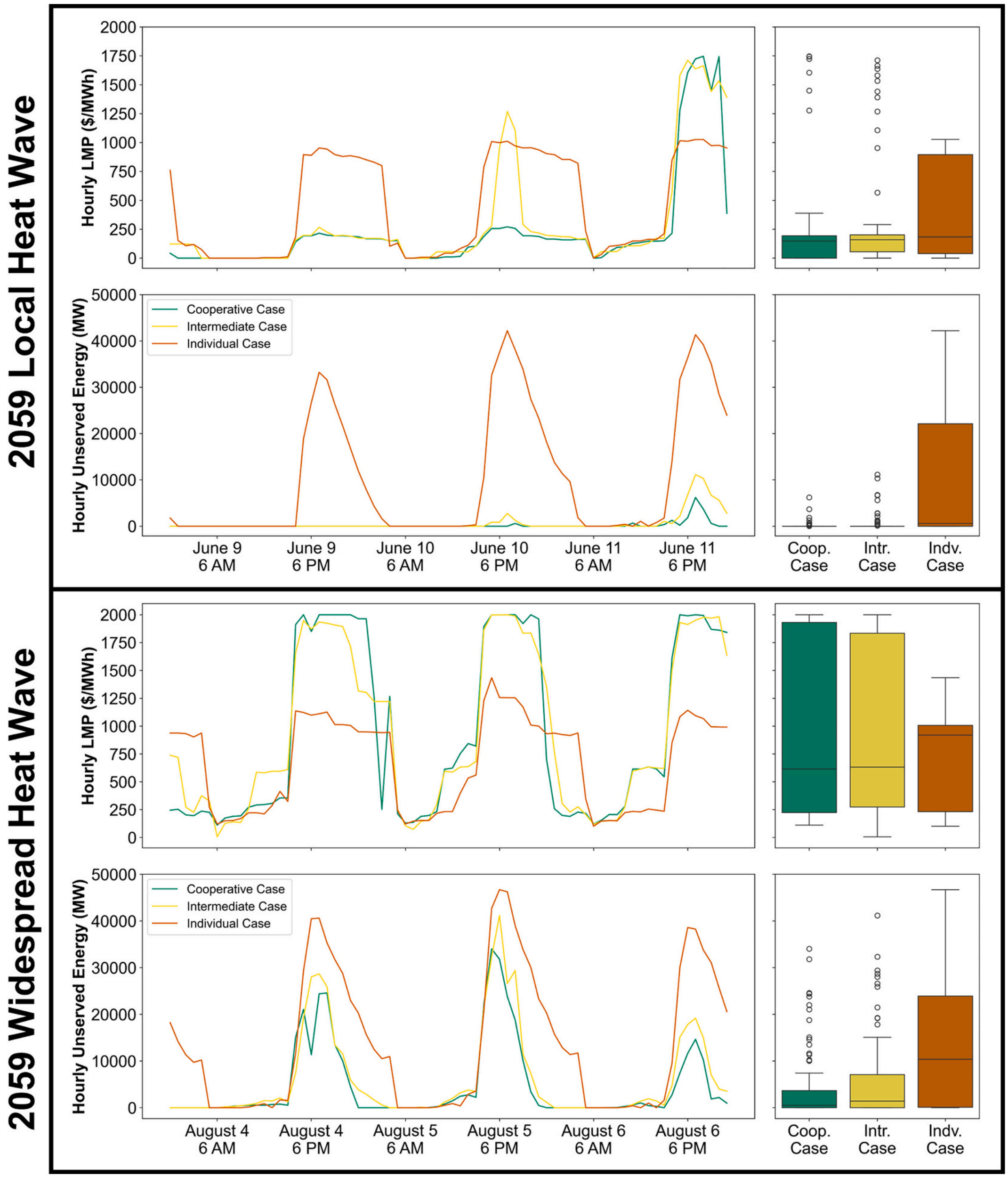

Fig. 9. Time series and distribution of hourly average LMPs and total unserved energy in the WI during 2059 local and widespread heat waves.

in terms of LMP reduction as CAISO relies on imports the most among all TPRs (see Fig. S7 in Supplementary Information). In comparison to individual TEP, the marginal LMP benefit of cooperative TEP is 11.33, 0.03, and 0.36 $/MWh for CAISO, WestConnect, and NorthernGrid, respectively. Lastly, any type of TEP substantially enhances power system reliability by zeroing out the annual LOL to demand ratio (a metric for reliability in which lower values indicate better reliability) in 2019. This is because additional transmission capacity made it possible to exchange more electricity to prevent outages in some nodes.

In terms of generation mix, there are no significant changes across the different TEP scenarios. More cooperative TEP approaches lead to slightly lower utilization of coal and higher utilization of natural gas generators, but this is mostly due to increased connectivity and locational fuel price differences. In this sense, cheaper electricity was able to move via new transmission capacity to supply the load. On the other hand, more individualized TEP approaches cause CAISO to utilize its local generators more, limiting the amount of electricity imports from NorthernGrid and WestConnect (see Fig. S7 in Supplementary Information).

4.2. Heat wave results in 2019

Every TEP scenario helped reduce the LMPs and zeroed out unserved energy during 2019 local heat wave. However, the extent of the benefits changes among different scenarios. Throughout the local heat wave, average LMPs were 79.83, 49.8, 51.69, and 52.39 $/MWh for base case, cooperative TEP, intermediate TEP, and individual TEP, respectively. During 2019 widespread heat wave, average LMPs were 108.19, 59.09, 61.38, and 56.73 $/MWh for the base case, cooperative TEP, intermediate TEP, and individual TEP, respectively. In addition, minor unserved energy events persist in the cooperative and intermediate TEP cases whereas they are zeroed out in the individual case (see Fig. 4). This is because as individual TEP approach is prohibited from building interregional transmission lines, the model allocates the available funds to strengthen intraregional lines, which increases nodal connectivity within TPRs that helps amidst widespread heat wave during which the

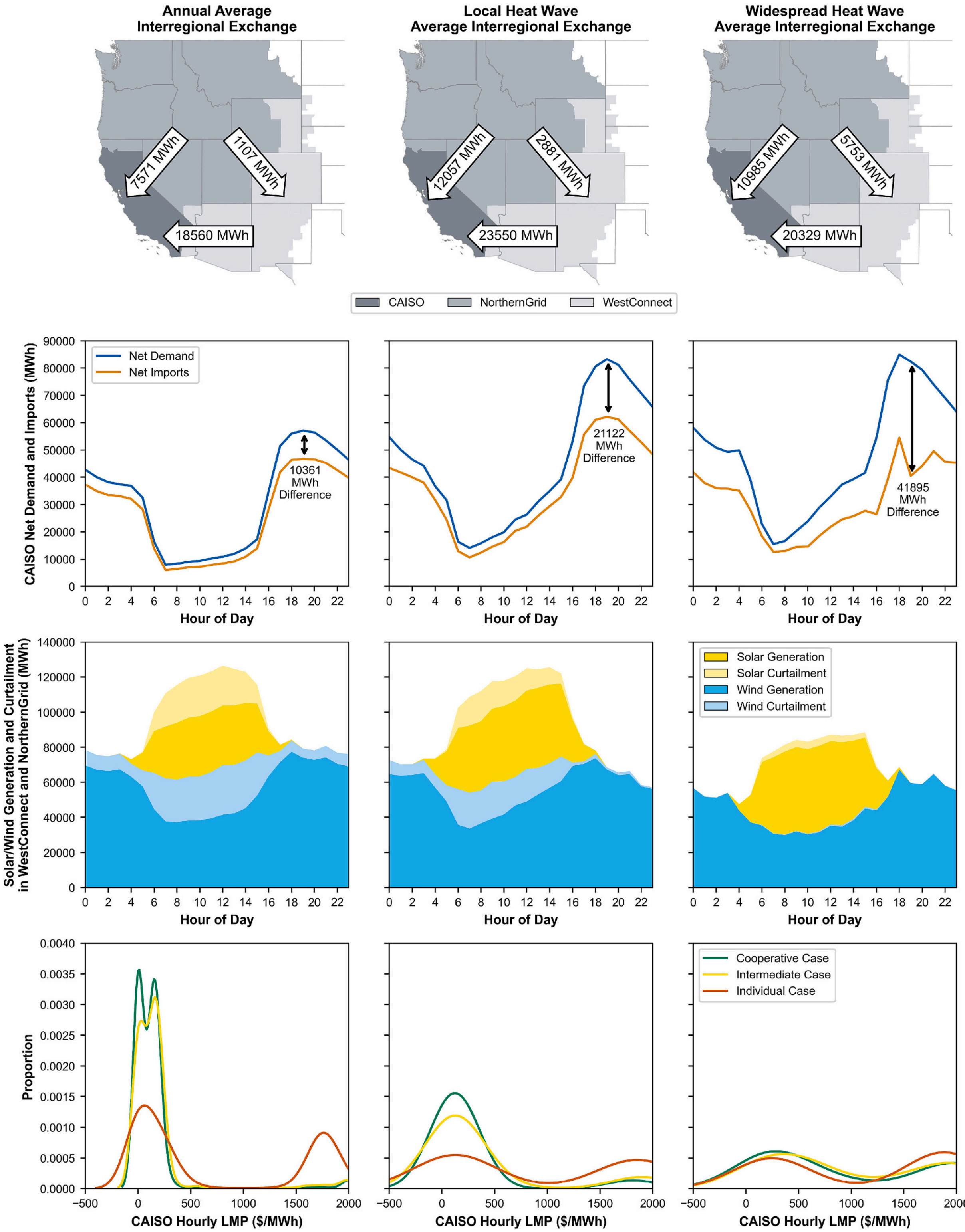

Fig. 10. (Top row) Average interregional power exchanges between TPRs; (second row) daily profile of net demand (i.e., demand - solar and wind generation) and net imports to CAISO; (third row) daily profile of solar/wind generation/curtailment in WestConnect and NorthernGrid; (bottom row) kernel density distribution of LMPs in CAISO under the three TEP cases. The left, middle, and right columns illustrate the annual average conditions, conditions during the local heat wave, and conditions during the widespread heat wave, respectively.

available imports are very low. These results suggest that although cooperative TEP is the most advantageous approach in terms of LMPs both annually and during a local heat wave, the positive impacts are not large enough to avoid possible LOL during the widespread heat wave.

4.3. Grid transformation between 2015 and 2055

The transmission network in 2055 varies substantially depending on TEP scenarios, even though all three have the same annual investment budget (Fig. 5). This divergence stems from distinct interregional transmission line investment cost penalties, which lead to better utilization of the budget in the cooperative TEP compared to intermediate and individual TEP. The individual TEP scenario allowed only intraregional transmission development, which lead to underutilization of the available budget in some years. This behavior might undermine system reliability and resiliency during high-value times such as contingency and extreme weather events. Another interesting outcome from Fig. 5 is that new transmission capacity between NorthernGrid and WestConnect is considerably low under cooperative case. Most of the new interregional transmission lines are built to connect CAISO with other two TPRs, which illustrates the high electricity import demands in CAISO.

Next, we present generation mix changes between 2015 and 2055 simulated by GCAM-USA in Fig. 6. There is significant investment in installed solar and wind capacity by 2055. Furthermore, all coal and oil capacity are retired, and natural gas and nuclear capacity are reduced. As in 2015, solar and hydropower generators are mostly located in CAISO and NorthernGrid (mostly in the Pacific Northwest), respectively. Most of the new wind generators are installed in WestConnect.

4.4. General results in 2059

Similar to our historical (i.e., 2019) results, outputs from the GO model in the 2059 simulation year indicate that the lowest average LMPs are observed in the cooperative TEP case in WI and all three TPRs. Again, CAISO may benefit the most from cooperative TEP. Contrasted with the individual TEP scenario, cooperative TEP leads to 244.37 \$/MWh (64.3 %), 582.17 \$/MWh (80.4 %), 5.95 \$/MWh (5 %), and 8.98 \$/MWh (5.8 %) drops in average LMPs in the WI, CAISO, WestConnect, and NorthernGrid, respectively (Table 3).

Even when transmission investment costs under different scenarios are considered, the cooperative TEP still provides significant overall cost reductions. Between 2015 and 2055 and for the whole WI, incurred transmission investment costs are 64.4 % lower in individual TEP compared to cooperative TEP. However, grid operations costs are 152.1 % higher in individual TEP than in cooperative TEP in 2059. Compared to individual TEP, every additional \$1 billion spent on transmission infrastructure between 2015 and 2055 under cooperative TEP led to a corresponding grid operations cost reduction of \$2.79 billion in 2059 only. Consequently, overall interconnection-wide cost (i.e., total transmission investment + yearly grid operations cost) is 34.6 % lower in cooperative TEP than individual TEP in 2059 (see Table S2 in Supplementary Information).

Also, cooperative TEP mitigates electricity outages (i.e., unserved energy) throughout the whole interconnection in general but primarily in CAISO. The potential benefits of cooperation in transmission expansion are much smaller in WestConnect and NorthernGrid in terms of LMP reduction and reliability improvements (Table 3 and Fig. 7). This is because CAISO requires substantial imports in early mornings and late evenings due to diurnal cycle of available solar generation.

Other than LMP and outage reduction, cooperative TEP induces lower electricity generation from fossil fuel sources like natural gas and higher generation from renewable sources like wind (Fig. 8). Higher utilization of wind power is mainly because CAISO can import more wind power from WestConnect (see Figs. S8-S13 in Supplementary Information for separate generation mixes of the three TPRs). In this sense, a more cooperative TEP approach might aid in lowering electricity related GHG emissions to achieve climate goals. For instance, total renewable curtailments are 23.9 %, 27.7 %, and 30.9 % under cooperative, intermediate, and individual TEP scenarios. Thus, cooperatively planning transmission investment supports minimizing renewable curtailments which in turn draw down LMPs and GHG emissions.

4.5. Heat wave results in 2059

The negative impacts of the same local and widespread heat waves are more noticeable in 2059 than in 2019 (see Fig. 9). Since the variable renewable energy sources dominate the power supply of the electricity grid in 2059, the grid becomes more volatile in terms of LMPs and unserved energy in the absence of electricity storage. Average interconnection wide LMPs during the 2059 local heat wave event are 231.72, 300.76, and 459.26 \$/MWh under the cooperative, intermediate, and individual TEP scenarios, respectively. Moreover, we see significantly lower average outages in the cooperative TEP (214.66 MW) compared to the intermediate TEP (739.23 MW) and individual TEP scenarios (10,527.72 MW).

On the other hand, during the 2059 widespread heat wave, average LMPs are 942.62, 954.07, and 671.42 \$/MWh for the cooperative, intermediate, and individual TEP scenarios, respectively. Even though the lowest average LMPs are observed in the individual TEP scenario, median LMPs under the cooperative TEP are lower. Furthermore, the lowest average unserved energy is observed under the cooperative TEP (4690.92 MW) compared to the intermediate TEP (6078.53 MW) and individual TEP (13,512.89 MW).

The fact that CAISO reaps the most benefits of cooperative TEP can be explained by the generation mix and power exchange characteristics. As shown in Fig. 6, CAISO has significant solar power penetration in 2059, which necessitates importing electricity from the other two TPRs at night. Since the GO model does not currently have a representation of electricity storage, these imports occur especially in late evening hours when available solar generation is minimal. CAISO imports a significant amount of electricity from the other two TPRs throughout the year (Fig. 10). During both heat waves, electricity imports to CAISO are higher than the yearly average, but the other two TPRs have less excess electricity to transmit during the widespread heat wave compared to the local heat wave (which affected only CAISO and the desert southwest). Electricity imports to CAISO follow the net demand trend (i.e., the "duck curve" [71]) throughout the day, but the difference between net demand and net imports increases as we go from annual timeframe to local and widespread heat wave timeframes. Net demand is defined as total demand minus total generation from solar and wind generators. There is substantial renewable curtailment on an average day, but the curtailment decreases during the local heat wave and approaches zero during the widespread heat wave due to very high demands. As CAISO can import less electricity during those less curtailment times, difference between net demand and net imports peaks, and the potential benefit of cooperative TEP drops. We can conclude that cooperative TEP is helpful on average, but the marginal LMP benefit of cooperative TEP significantly decreases as we go from annual timeframe to local and widespread heat wave timeframes.

5. Limitations and future work

Though this study offers useful insights on different transmission planning approaches, it comes with some limitations that are also directions for future work. First, GO model has perfect foresight, meaning that it models only day-ahead electricity market operations with no forecast errors. Incorporating real-time markets with demand/renewable forecast errors would enhance the scope of questions that could be answered using the tool. Moreover, there is no electricity storage representation in the GO and TEP models. Integrating energy storage investment decisions and operations into the modeling chain would provide further insight into the value of interregional cooperation. This point would also require increasing the number of investment decision periods represented in the TEP model. Furthermore, robust and/or stochastic methods can be incorporated into our modeling chain to represent a broader range of probabilities/scenarios, which would be useful to come up with a method to allocate transmission costs by expected benefits among different TPRs. Lastly, the GO model assumes only a central operator with one objective function for the whole interconnection. Finding a way to mimic a cost-minimizing approach within each BA/TPR would help simulate individual decision-making within these zones.

6. Conclusion

Electricity grids are undergoing serious transformations due to decarbonization and electrification efforts. Interregional transmission planning is needed for decarbonization, but the benefits for reliability (especially during extreme weather events) are less clear. In this paper, we examine the benefits of cooperative transmission planning for grid performance during heat waves. We utilized 2019 as a base year and selected two heat waves of different spatial scales (one local and one widespread). Then, we replayed the same heatwaves in 2059 with a future representation of the WI (i.e., generators, fuel prices, demand, etc.) that reflects a high renewable energy penetration scenario with climate/socioeconomic changes (i.e., rcp45hotter_ssp3). We developed and used a TEP model to try different transmission planning approaches including a full cooperation scenario, intermediate cooperation scenario, and no cooperation scenario by imposing varied investment costs of interregional transmission lines between three transmission planning regions in the WI.

The results suggest that cooperative TEP yields the best results in terms of average LMPs and unserved energy (i.e., outages). From a yearly perspective, the lowest hourly average LMPs are observed under the cooperative TEP compared to the intermediate TEP and individual TEP for the whole interconnection and for all three planning regions. Total interconnection-wide cost including transmission investments and grid operations is 34.6 % lower in cooperative TEP compared to individual TEP in 2059. Moreover, cooperative TEP helps substantially with minimizing unserved energy and decreasing GHG emissions through decreasing reliance on natural gas while reducing renewable energy curtailment and increasing wind power utilization.

When results are analyzed specifically for the local and widespread heat wave events, we see that cooperative TEP turns out to be advantageous during a localized heat wave. However, since all regions are under stress to meet extreme demand due to increased cooling needs, the marginal benefit of cooperative TEP becomes small during the widespread heat wave. Although similar trends are observed in both 2019 and 2059, the overall distinction between cooperative vs. individual TEP is more apparent in 2059. Furthermore, cooperative TEP turned out to be most favorable for CAISO as a significant number of solar installations caused the region to import a substantial amount of electricity (mostly from wind power) from other regions to balance supply and demand, especially during the late evening hours when available solar power is minimal. Building on top of this experiment, more detailed probabilistic assessments that utilize robust/stochastic methods can be used to allocate the investment cost of interregional lines depending on the prospective regional benefits in terms of expected grid operation cost reductions and reliability improvements.

All in all, cooperation during transmission expansion planning is extremely useful in terms of reducing LMPs and increasing reliability by minimizing outages during extreme weather events. Since wider-scale extreme weather events like widespread heat waves can undermine the potential benefits of cooperation, strategic power system infrastructure investments are essential. Consequently, robust optimization techniques that consider high-value periods like heat waves should be used while making decisions about the capacity and location of power system infrastructure including energy storage, which would enable full utilization of these investments.

Software and data availability

The model is open-source and publicly available. All codes of the model and data used are available under [36,72]. All model outputs utilized in this study are available under [73]. Also, a meta-repository with the workflow and visualization scripts for the whole experiment is available under [74].

CRediT authorship contribution statement

Kerem Ziya Akdemir: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Kendall Mongird:** Writing – original draft, Software, Methodology, Investigation, Data curation, Conceptualization. **Jordan D. Kern:** Writing – review & editing, Software, Resources, Methodology, Conceptualization. **Konstantinos Oikonomou:** Writing – review & editing, Software, Methodology, Data curation, Conceptualization. **Nathalie Voisin:** Writing – review & editing, Software, Methodology, Conceptualization. **Casey D. Burleyson:** Writing – original draft, Software, Methodology, Data curation, Conceptualization. **Jennie S. Rice:** Writing – review & editing, Software, Methodology, Funding acquisition, Conceptualization. **Mengqi Zhao:** Writing – original draft, Software, Methodology. **Cameron Bracken:** Writing – original draft, Software, Methodology. **Chris Vernon:** Writing – review & editing, Software, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The models and data are open-source and publicly available. All codes of the model and data used are available under Software and Data Availability section of this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2024.124825.

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