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Planning urban energy systems adapting to extreme weather

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ABSTRACT

In the context of increasing urbanization and climate change globally, urban energy systems (UES) planning needs adequate consideration of climate change, particularly to ensure energy supply during extreme weather events (EWE) such as heatwaves, floods, and typhoons. Here we propose a two-layer modeling framework for UES planning considering the impact of EWE. An application of the framework to a typical coastal city of Xiamen, China reveals that deploying energy storage (i.e., pumped hydro and battery) offers significant flexibility to ensure the critical demand is met during typhoon as a typical EWE and avoids over investment in supply technologies. This requires an extra 2.8% total cost on investment and operation of UES for 20 years. Planning energy systems with proper consideration of EWE can ensure robust urban energy services even with increasing penetration of fluctuating renewables, and we offer a flexible and computationally efficient paradigm for UES planning considering the impact of EWE.

1. Introduction

According to the latest Intergovernmental Panel on Climate Change (IPCC) assessment report [1], global climate change would lead to increasingly more frequent and intense extreme weather events (EWE), such as rainstorms, typhoons, heatwaves, droughts and wildfires (see Fig. 1), which have posed unprecedented threats to human-built infrastructures [2,3]. Failure to prepare for the impacts of EWE could lead to very costly consequences for urban areas as most of the economic activities are happening there [4]. Currently, over 3.5 billion people live in urban areas, contributing to more than 70% of energy-related greenhouse gas (GHG) emissions globally [5]. These figures are expected to increase, which makes cities standing on front lines for both human development and climate change mitigation. Facing the serious external threats from EWE as well as the internal high penetration of fluctuating renewables, designing ‘climate-resilient’ urban energy systems (UES) that are able to adapt to changing climate variables [6] is an emerging challenge. At present, the EWE induced climate risks remain insufficiently accounted among key stakeholders [7]. Without sufficient knowledge for such risks, the city administrators and energy investors can only hope the next EWE would not trigger a sudden blackout.

Understanding the impacts of EWE on UES is extremely challenging due to the multivariate and multiscale changes of climate systems as well as the complex interactions between climate systems and energy systems [8,9]. Over the last two decades, significant progress has been made in developing climate models and projecting future climate conditions. Methods are developed to generate future climate data sets based on reginal climate models [10], modified clustering approach [11], and based on historical data and simulation tools [12]. These efforts provide valuable future climate information for further impact assessments. Recently, remarkable progress has been made on understanding the impact of EWE for individual energy sector, such as solar power [13,14], wind power [15], thermal power generation [16], as well as residential energy systems [17]. Nevertheless, the impact of EWE on the supply-side, demand-side, and transition pathways of UES have not yet been adequately explored systematically.

Energy system models have been developed to address both design and dispatch uncertainties considering the integration of different sectors [18,19], which enables investigating the impact of EWE on energy systems. Stochastic programming [20,21], stochastic-robust programming [22], and a combined approach [23] have been developed for modeling energy systems with uncertainties. These modeling approaches tend to be computationally expensive. Meanwhile, quantifying the probability of EWE occurrence remains an open challenge since EWE are usually with low probability but high impact. Furthermore, EWE could be heavily fluctuating during a short period of time, typical

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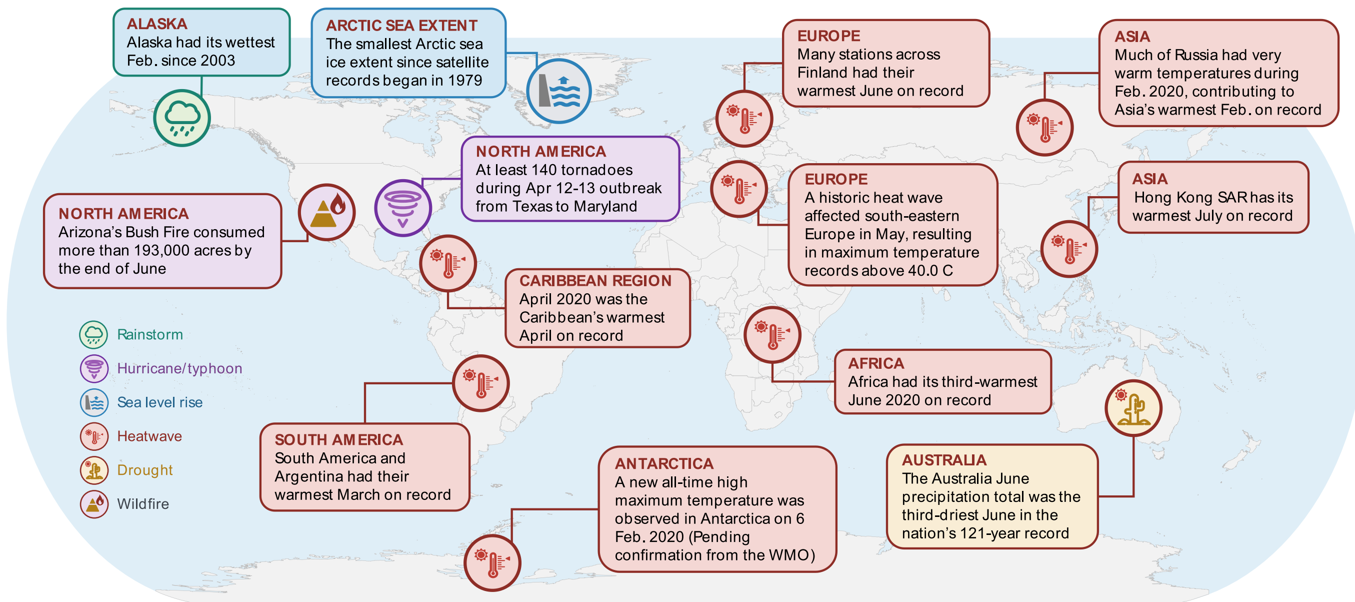

Fig. 1. The world has encountered a significant number of extreme weather events in 2020 (until July). The selected climate anomalies presented in this map is compiled from NOAA's Global Climate Reports from January to July 2020 [24].

temporal resolution in planning models may not be sufficient to capture its dynamics. More efficient and flexible approaches are therefore needed.

As an emerging concept with growing importance, understanding the impact of EWE on UES and further designing 'EWE-resilient' UES remain a research gap. Here, we propose an original two-layer modeling framework to bridge the gap of addressing EWE during UES planning. We then apply the framework to investigate the UES planning for a representative coastal city of Xiamen, China considering the typical EWE of typhoon events. The contributions of the study are:

(1) Compared to previous stochastic or robust formulation, the two-layer modeling framework splits the EWE simulation from the conventional energy planning, which offer greater flexibility on setting EWE simulation to better capture the EWE dynamics and is generally applicable for various EWE.
(2) The proposed framework enriches the methodology on designing an EWE-resilient UES, generates quantitative insights from the case study to enlighten promising strategies for the urban energy transition, and enhances the understanding for the impact of EWE on UES.

2. Methodology

2.1. Two-layer modeling framework addressing EWE impact

UES planning aims to inform the optimal decisions on UES design and dispatch, such strategies satisfying the total energy demand of a city [25,26]. Here, we propose an original two-layer modeling framework for urban energy systems (UES) planning considering the impact of extreme weather events (EWE), including the upper-layer UES optimization model that considers the conventional scenario only; and the lower-layer EWE simulation model that simulates the performance of the optimized design from upper-layer optimization model in EWE scenario.

2.1.1. Upper-layer optimization model

As outlined in Fig. 2a, we proposed a two-layer modeling framework to address the EWE impact when planning UES. The upper-layer UES optimization model is developed to optimize UES design and dispatch considering conventional scenario only [27]. We develop this model based on the bottom-up structure [28], which consists of two components: (1) characterizing the annual capacity of each energy technology from 2015 to 2035, (2) capturing the dynamic balance between demand and supply at hourly basis. The design decisions include optimal investment timing, system-level capacity, generation mix, CO_2 emissions, and total capital cost for all modeled energy technologies [29]. The dispatch decisions include optimal energy outputs, fuel consumptions, and total operational cost of all energy technologies [30]. The hourly temporal resolution of our model enables capturing the intermittent renewables and the dynamics of energy storage technologies. To reduce the computational complexity, the full hourly time sets of demand, wind speed, and solar radiation for conventional scenarios are clustered to 6 typical days by the k-means clustering approach following the method as reported in Ref. [31,32], while the EWE scenario would be simulated in the lower layer. The planning horizon is 20-year with the hourly resolution (see Fig. 2b). Daily fluctuations on demand and renewables are captured by slicing each year into three typical seasons (summer, winter, and transition seasons) and two typical days (weekday and weekend).

The outline of the upper-layer UES optimization model is presented as follows, where the objective function of the optimization model is to minimize the total discounted cost (TDC) of the energy system over the modeling horizon [33]. The constraints include energy balance (sum of supply is larger than demands), capacity expansion constraints (annual capacity expansion within limits), capacity constraints (energy output constrained by capacity), operation constraints (on/off and ramp-up/down control), conversion constraints (other energy sources such as natural gas and coal to electricity), PHES constraints (constraints on storage), grid connection constraints, and CO_2 emissions limit (annual emission reduction target). The detailed mathematical equations of the optimization model are detailed in Appendix A.2.1.

$$
\begin{aligned}
&\min \text{obj}_{\text{opt}} = \text{total discounted cost}\\
&\text{S.T. Energy balance}\\
&\quad \text{Capacity expansion constraints}\\
&\quad \text{Operation constraints}\\
&\quad \text{Conversion constraints}\\
&\quad \text{PHES constraints}\\
&\quad \text{Battery constraints}\\
&\quad \text{Grid connection constraints}\\
&\quad CO_2 \text{ emissions limit}
\end{aligned}
$$

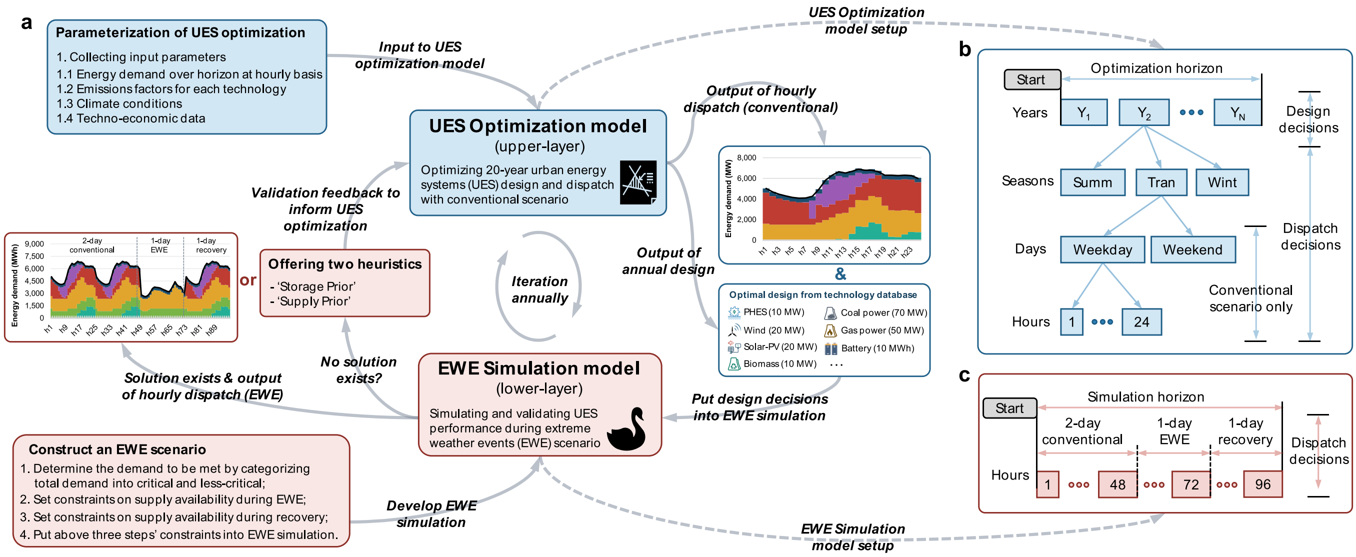

Fig. 2. Schematic of the two-layer modeling framework. a, outline of the two-layer framework. b, temporal setup for upper-layer UES optimization model. c, temporal setup for lower-layer EWE simulation model. Abbreviations: UES, urban energy systems; EWE, extreme weather events; PHES, pumped hydro energy storage; Summ, summer; Tran, transition season, Wint, winter.

2.1.2. Lower-layer simulation model

The lower-layer EWE simulation model aims to validate whether the optimized UES pre-design from the upper-layer UES optimization model can meet the critical energy demand of the city during EWE. The critical demand is extracted from the total energy demand, and the remaining demand is considered as the less-critical demand. The EWE simulation model is essentially an economic dispatch model with specific constraints on the availability of renewables during EWE. Hence, the dispatch decisions are optimized including optimal imported power, fuel consumption, and energy output for all energy technologies. The simulation horizon is set to 96 h considering 2-day before EWE (the first day is conventional, the second day preparing for EWE happens), 1-day EWE (e.g., typhoon in this case) happens, and 1-day recovery after the EWE (see Fig. 2c). So that the simulation results would iteratively inform the upper-layer optimization model to adjust UES design by either 'Storage Prior' or 'Supply Prior' heuristics when the pre-design cannot pass the EWE simulation. Therefore, the proposed two-layer modeling framework not only achieves optimal UES planning considering EWE, but also offers optimal UES dispatch decisions during EWE.

The outline of the lower-layer EWE simulation model is presented as follows, where the objective function of the simulation model is to minimize the operational cost of the energy system during the EWE, subject to the constraints including capacity constraints, energy balance, operation constraints, conversion constraints, PHES constraints, and grid connection constraints. The detailed mathematical equations of the simulation model are detailed in Appendix A.2.2.

$\min \text{obj}_{\text{sim}} = \text{operational cost}$

S.T. Energy balance
Capacity constraints
Operation constraints
Conversion constraints
PHES constraints
Battery constraints
Grid connection constraints

2.2. Logic flow of the iterative framework

Based on the setup of above mentioned two-layer modeling framework, Fig. 3 explicates how the two layers models are iterated in the proposed framework.

- Step 1: Run the upper-layer UES optimization model with conventional scenario only.
- Step 2: Record all optimized design and dispatch decisions.
- Step 3: Put design decisions (i.e., optimal capacity expansion) of year i into the lower-layer EWE simulation model and run the simulation as the validation.
- Step 4: If a solution exists from the Step 3 simulation (i.e., validation passed), retain the design and dispatch decisions from year 1 to i, then set $i + 1$, and redo the Step 3 for next run of the EWE simulation.
- Step 5: If no solution exists from the Step 3 simulation (i.e., validation failed), indicating that either increase supply or energy storage is necessary to ensure the critical demand to be met during the EWE scenario. We, therefore, offer two strategies for model-users to select one, namely, 'Storage Prior' and 'Supply Prior' heuristics.

As displayed in Fig. 3b, in the 'Storage Prior' heuristics (from Step 5.1 to 5.6), PHES has the priority to incrementally increase its capacity, retaining other design decision fixed, and iteratively running the EWE simulation model (Step 5.1 and 5.2). If the capacity increase of PHES reaches the upper limit on the annual built rate but a feasible solution still cannot be found for the EWE simulation, then incrementally increase the capacity of battery storage (Step 5.3 and 5.4). If no solution can be found for the EWE simulation until battery storage reaches its annual built rate limit, then incrementally increase the capacity of gas power. The reason why putting PHES prior to battery storage lies in the fact that PHES has both lower investment and operational cost than that of battery storage, which makes PHES more likely to be implemented. Note that PHES may not always available in other cities, so model-users could skip Step 5.1 and 5.2 and start from Step 5.3 for cities without PHES development potential. As shown by Fig. 3c, the logic of the 'Supply Prior' heuristics (Step 5.7 to 5.11) is similar to the 'Storage Prior' but in a reverse order, i.e., the capacity of gas power is incrementally increased first (Step 5.7 and 5.8), followed by PHES (Step 5.9 and 5.10), then battery storage (Step 5.11 and 5.12).

- Step 6: By either the 'Storage Prior' or 'Supply Prior' heuristics in Step 5, the updated design decisions (i.e., values of capacities) for gas power, PHES, and battery storage are set as lower bounds for corresponding capacity variables. Then, re-run the UES optimization model with these lower bounds. So far, the EWE simulation

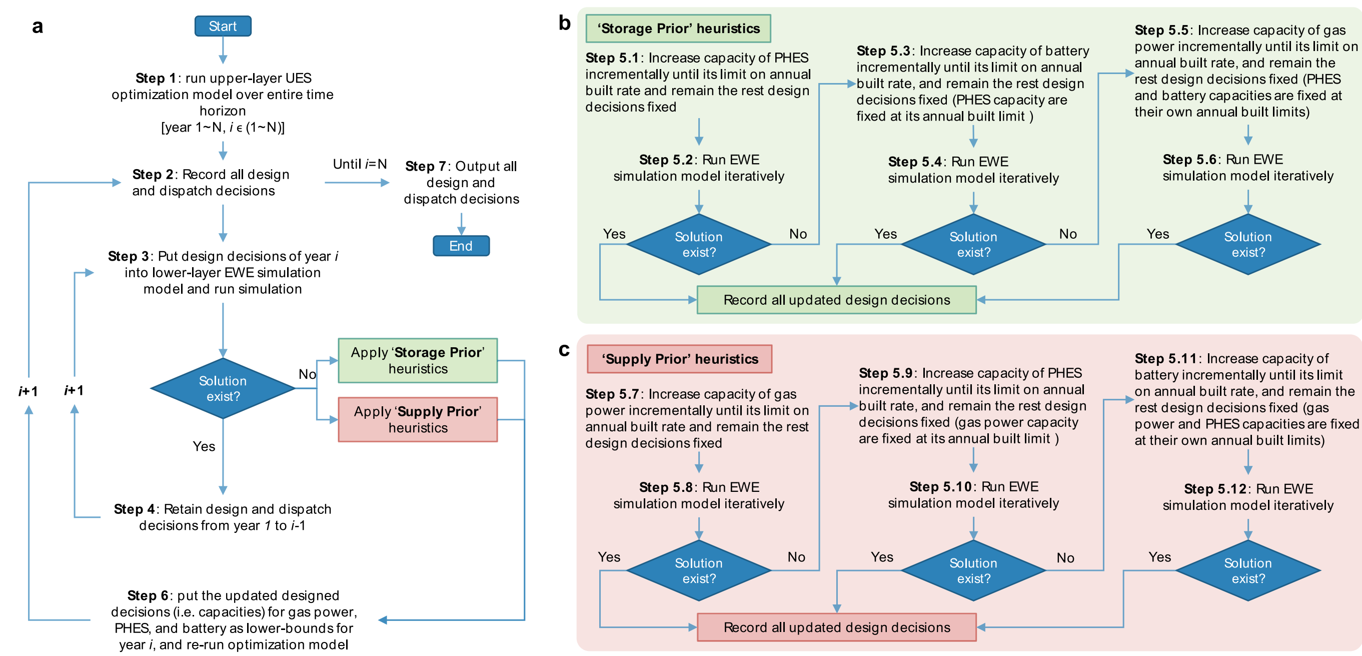

Fig. 3. Logic flow of the two-layer modeling framework to achieve UES planning with EWE. (a) Major steps of the logic flow. (b) The procedure of implementing 'Storage Prior' heuristics. (c) The procedure of implementing 'Supply Prior' heuristics.

of year i is completed and the impact of EWE has been considered during the UES optimization for year i. By setting $i+1$ and redo Step 2 to 6, the EWE simulation for year $i+1$ can be done and iteratively inform the UES optimization model to adjust its design and dispatch decisions if needed.

- Step 7: When $i = N$, the UES design for all years over the planning horizon has been validated by the EWE simulation. Corresponding optimal UES design can ensure the critical demand to be met when EWE happens.

2.3. Categorizing energy demand

When the EWE happens, the energy system has to ensure at least the critical demand is fulfilled. The critical demand is categorized as one type of demand from the total energy demand (hourly-basis) and the rest demand belongs to the less-critical demand. To do the categorization, the total electricity demand of a city is firstly breakdown by different sectors, including the industry, service, residential, transport & agriculture sectors. This breakdown is based on the typical demand profile (hourly) for each sector [34] and the amount of annual electricity consumption for each sector, which could be found in the statistical yearbook of the city [35]. Then, for each sector, the demand is further categorized into the two types based on the priority, i.e., critical demand and less-critical demand. The priority is based on the rules of power supply coordination by consulting to the local utility company. For the industry sector, the demands of uninterruptible process and conditioned workshops are categorized to the critical demand, while the demand for other industry usage belongs to the less-critical demand. For the service sector, the demands of utility infrastructure, government essential, and critical public services belong to the critical demand, while the demands for other public service and general business are categorized to the less-critical demand. All residential demand is considered as critical demand. As for the transport & agriculture sector, the demands of railways, seaports, and airports belong to critical demand, while the demands for other transport and agriculture activity are considered as less-critical demand. The typical demand profile (hourly) for each sector and the energy demand categorizing results for Xiamen city are presented in Appendix Fig. A2.

2.4. Constructing an EWE scenario

We construct the EWE scenario and develop the EWE simulation model to validate the performance of the optimized UES design when EWE happens. Before that, it is noteworthy that the global climate & weather data can be obtained from the NASA MERRA-2 database [36]. In particular, the historical data for hurricane (also known as typhoon in specific regions) can be obtained from the associated visualized tool [37]. Meanwhile, it is helpful to consult local power suppliers for the demand to be met during EWE, the supply technologies' availability, and possible damage recovery after EWE.

Since an EWE simulation model is essentially an economic dispatch model with specific constraints on both demand and supply, there are four major steps to generate an EWE scenario. (Step 1) Determine the demand to be met. For the disruptive EWE that seriously affects the energy supply, e.g., typhoons, the critical demand (part of total demand) needs to be met at least; while the demand of all-day could rise rapidly during heatwaves. Model-users are flexible to self-define the demand to be met in their cases. (Step 2) Set specific constraints on supply. During an EWE, the availability of different energy supplies could be affected to different degrees. In this study, the solar, wind, and import power are considered completely not available when encountering typhoons. Another good example is that the availability of coal and gas power would drop when encountering heatwaves as the cooling water temperature may rise and affect the power output of combustion-based power technologies. (Step 3) Set specific constraints on technology availability during the recovery stage. After the EWE, a certain portion of each energy supply might still be unavailable due to the damage during EWE. Hence, specific constraints can be set on the availability of each energy supply technology if needed in the recovery stage. In this case, we assume all technologies could be fully recovered after the EWE (i.e., in Day-4), in other word, no specific constraints are set. (Step 4) Construct the economic dispatch model with the demand settings (Step 1), the sup-

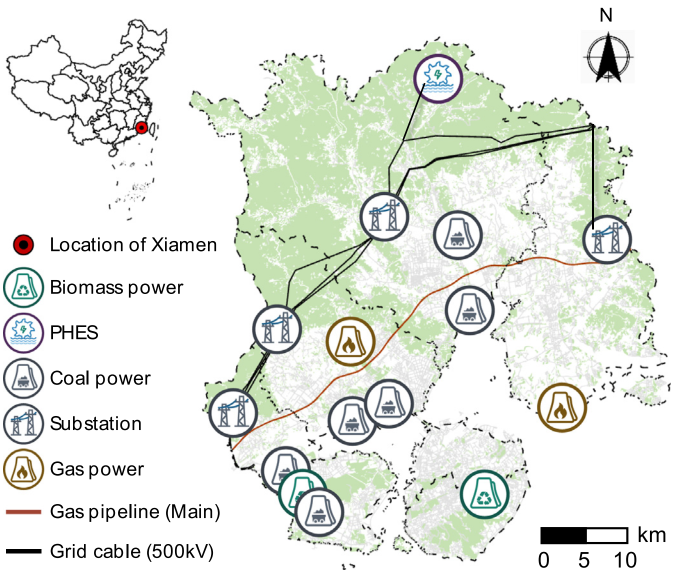

Fig 4. Map of the studied region (Xiamen) with existing energy infrastructures.

ply availability settings from (Step 2), and the recovery settings (Step 3), so as to generate an EWE simulation model.

2.5. Model assumptions for the optimization and the simulation

A set of assumptions are made to enable computational tractability of both optimization and simulation models as following. (1) The frequency and voltage control relate to a sub-hourly temporal resolution; we approximate these options by the hourly resolution with sufficient access to ancillary services. (2) The modeled power plants would not be decommissioned during the planning horizon. Battery storage replacement is considered due to its relatively short service time. (3) The whole UES is represented as a single-node network; and the electricity transmission losses are considered. (4) Electricity demand and electricity import prices are inelastic; uncertainty of input parameters is not considered; the model is deterministic with perfect foresight.

Both the upper-layer UES optimization model and lower-layer EWE simulation model are developed based on Mixed Integer Linear Programming (MILP) approach. The upper-layer UES optimization model typically has 5.8×10^5 variables, of which 2.2×10^5 are discrete, resulting in approximately 15 min solution time per run by an Intel Core i7, 1.8 GHz, 8GB RAM personal computer with CPLEX 28.2 solver [38]. The lower-layer EWE simulation model has 2500 variables with a solution time less than 1 second on the same machine.

3. Results

3.1. Case setup for urban energy planning

We apply the proposed framework to investigate the impact of EWE on UES planning for Xiamen City, China, as Xiamen is a representative coastal city on the southeast coast of China (see Fig. 4) encountering EWE of typhoons occasionally. Typhoons (or Hurricanes) are one kind of the most destructive and expensive EWE – for example, hurricanes lead to 9 of the top 10 U.S. EWE disasters by cost since 2000 [39]. Xiamen is one of China's first special economic zones with over 4.3 million residents in 2019 and it is one of the first batch of low-carbon pilot cities [40]. In general, the critical demand and less-critical demand account for 52% and 48% of the total electrical demand, respectively in Xiamen. In this use case, the planning temporal horizon is intended from 2015 to 2035 instead of starting from 2020 for the convenience of model validation with historical recorded data (i.e., 2015∼2019).

Table 1
Situation definitions and TDC cost difference compared to Situ-1.

Situation	Planning with EWE	EWE simulation	EWE handling heuristics	TDC higher than Situ-1
Situ-1	No	No	No	0%
Situ-2	Yes	Yes	Storage Prior	2.8%
Situ-3	Yes	Yes	Supply Prior	5.4%

Note: TDC, total discounted cost, is the objective function for the UES optimization model to be minimized.

The local power supply of Xiamen relies on coal-fired power plants at present. Due to the emissions peaking mission, no new coal-fired power plants are planned, and the CO_2 emissions should peak no later than 2030. The natural gas supply is sufficient, whereas the unit cost of natural gas is relatively high. Biomass power (waste incineration based) is promising but the maximum potential is relatively small. The imported power from the provincial grid of Fujian province is another important energy source of Xiamen. Detailed inputs including total demand, existing energy technology and deployment potential, energy tariffs, as well as other techno-economic parameters, are provided in Appendix A.3.

3.2. Adapt urban energy to extreme weather with affordable extra cost

We investigate three situations for UES planning with EWE in Xiamen (see Table 1). Situ-1 refers to the 'baseline' situation without considering EWE impact, and therefore, EWE simulation is not implemented; and the TDC is the lowest. Situ-2 and Situ-3 consider EWE impacts by the 'Storage Prior' and 'Supply Prior' heuristics, respectively. The 'Storage Prior' refers to the heuristics that expand storage capacity prior when the pre-design from upper-layer UES optimization cannot pass the lower-layer EWE simulation, while 'Supply Prior' refers to the heuristics that expand gas power capacity prior when the same issue occurs.

The results indicate that both heuristics can help to achieve an EWE-resilient UES for Xiamen, among which an extra 2.8% cost is required when implementing the 'Storage Prior' heuristics, whereas 5.4% more cost is needed when implementing the 'Supply Prior' heuristics.

3.3. Impacts of extreme weather on capacity expansion

Planning UES considering the impacts of EWE could lead to significantly different capacity expansion plans as shown in Fig. 5a-c. Generally, the differences in capacity expansion are comprehensively caused by the supply-demand balance for increasing demand, physical constraints of system operation particularly during EWE, and the investment cost of each technology that may vary over the planning horizon.

When EWE is not considered, i.e., Situ-1 (see Fig. 5a), there is no plan for implementing energy storage technologies, and capacity expansion plans on energy supply technologies could be completed before 2030. In Situ-2, since the 'Storage Prior' heuristics is applied, PHES is deployed during 2020 to 2030, and Lithium battery is further deployed from 2030 t0 2035 (see Fig. 5b). The PHES is deployed ahead of battery storage due to its lower investment and operational cost compared to that of battery storage. When the capacity expansion of PHES reaches its upper limit in 2030, battery storage is further deployed to ensure critical demand is met during EWE. As for Situ-3, in light of the 'Supply Prior' heuristics, energy storage technologies are not deployed, but instead, a 300MW capacity expansion of gas power is planned at 2016 to handle the EWE from 2016 to 2022 (see Fig. 5c). The capacity of gas power is further expanded from 2023 to 2035 to ensure energy supply during EWE thereafter.

Taking an overview of Fig. 5a-c, renewable energy (e.g., biomass power, solar power, and wind power) could be deployed as soon as possible within the built rate limits annually no matter considering EWE or not. Even for the places with limited renewable potential, the 'Enclaves Economy' mode that enables a renewable-resource-poor area to invest in

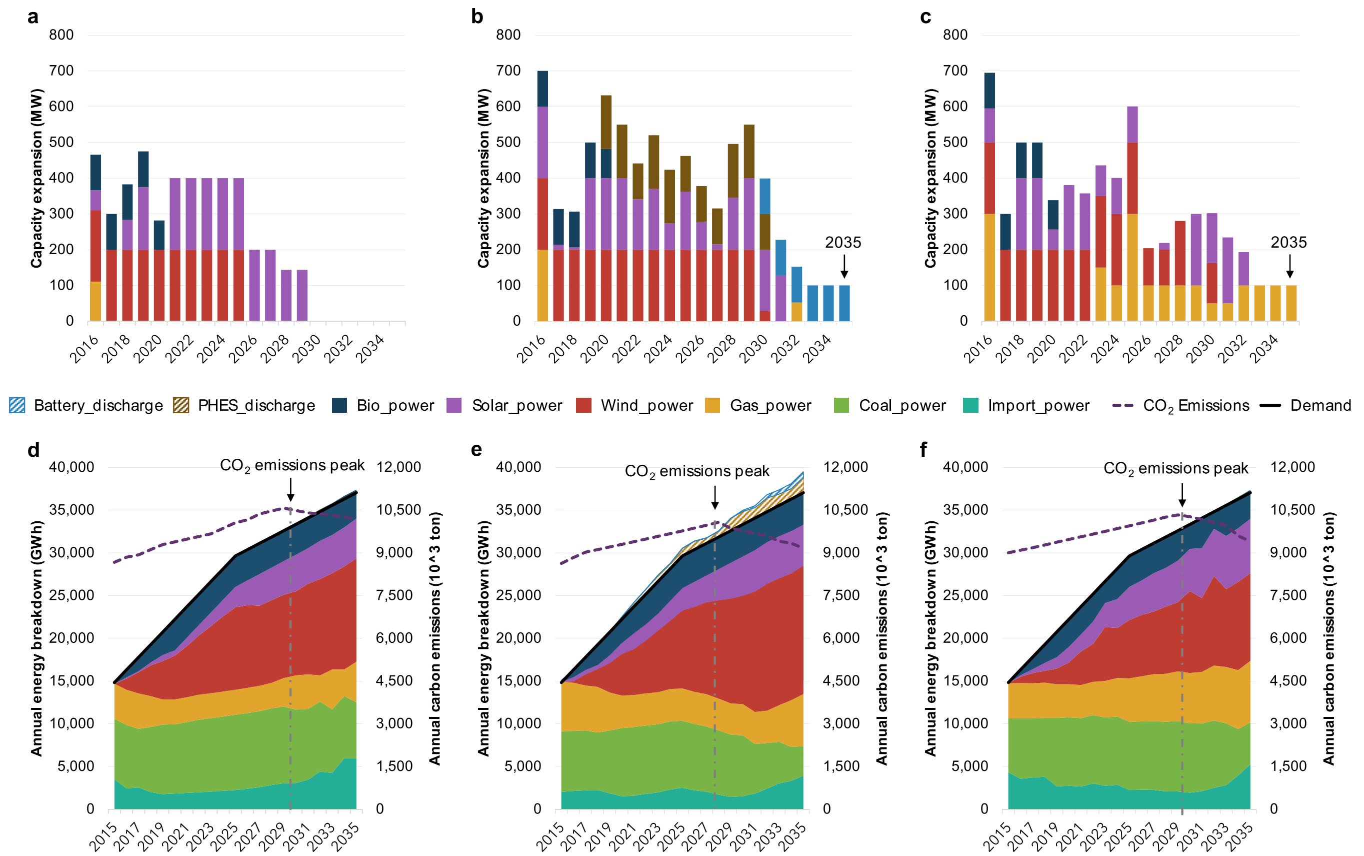

Fig. 5. Three situations lead to different solutions for annual capacity expansion, energy output by technology types, and carbon emissions from 2016 to 2035. a, Capacity expansion without considering EWE, referring to as Situ-1. b, Capacity expansion considering EWE by the 'Storage Prior' heuristics, Situ-2. c, Capacity expansion considering EWE by the 'Supply Prior' heuristics, Situ-3. d~f, Annual energy output by technology types and annual carbon emissions for Situ-1, Situ-2, and Situ-3, respectively.

a renewable-resource-rich area would help the sustainable development of both areas. In general, a larger total expanded capacity of either storage technologies or energy supply is needed by Situ-2 and 3 compared to the Situ-1 (not considering EWE) as the weather-dependent renewables might not function properly during the EWE. Both the 'Storage Prior' heuristics (i.e., Situ-2) and 'Supply Prior heuristics' (i.e., Situ-3) could generate their optimal UES plans considering the impact of EWE, while the differences on capacity expansion plans are due to the priority settings on technology deployment for two heuristics.

3.4. Energy breakdown under carbon mitigation target

Fig. 5d-f shows the annual energy output breakdown by technology types from 2015 to 2035 for different situations under the constraint of the carbon mitigation target. We set the carbon mitigation target as the CO_2 emissions should peak no later than 2030, which is modeled as a constraint in the UES optimization model and is consistent with the commitments of China on the Paris Agreement. Throughout Fig. 5d-f, three situations could all achieve the target of CO_2 emissions peak before 2030; and the output of biomass power, solar power, and wind power continue to rise in all three situations.

Specifically, in Situ-1, the TDC of Situ-1 is the lowest among the three situations because the output from low-cost coal power remains stable over the planning horizon of 2015~2035, accounting for 17.8% of the total energy output at 2035 (see Fig. 5d). The output of gas power remains stable as well. Hence, the CO_2 emissions peak in 2030 is slightly higher than the other two situations, and the carbon mitigation target is mainly achieved by implementing biomass, solar, and wind power technologies. Starting from 2031, the lower carbon electricity generated from biomass, solar, and wind power would be fully utilized. To further reducing CO_2 emissions while meeting the increasing demand, an increased amount of lower carbon electricity from the provincial grid is imported. This increase of power import from 2031 to 2035 is also observed in Situ-2 and 3 for a similar reason. Fig. 5e shows the annual energy output breakdown of Situ 2, where the CO_2 emissions will peak in 2028. After that, the share of coal power gradually declines, leading to the decrease of CO_2 emissions, and the increasing demand is then met by expanding output share from energy storage technologies (i.e., PHES and battery), gas power, and renewables (i.e., solar and wind). Due to the deployment of PHES and battery storage, 7% of the total energy demand is met by PHES and battery storage in 2035, and more wind power (usually abundant during the off-peak period) could be utilized compared to other situations. Fig. 5f displays the annual energy output breakdown for Situ 3. Instead of deploying energy storage technologies, the capacity of gas power expands gradually from 2015 to 2035 along with solar and wind power. The CO_2 emissions will peak in 2030 and then decrease along with the decline of coal power's share as well as the rise of import power's share.

3.5. Dispatch during extreme weather events

Fig. 6 presents a representative optimized UES dispatch during the EWE Simulation in 2035, showing that the critical demand can be successfully met by either the 'Storage Prior' or 'Supply Prior' heuristics during the EWE scenario. Fig. 6a shows the 96-hour EWE-simulation results for Situ-2 by applying the 'Storage Prior' heuristics. During the first 48-hour (i.e., Day-1 and 2), the outputs from biomass, gas, coal, and wind power keep stable, and solar power only contributes during

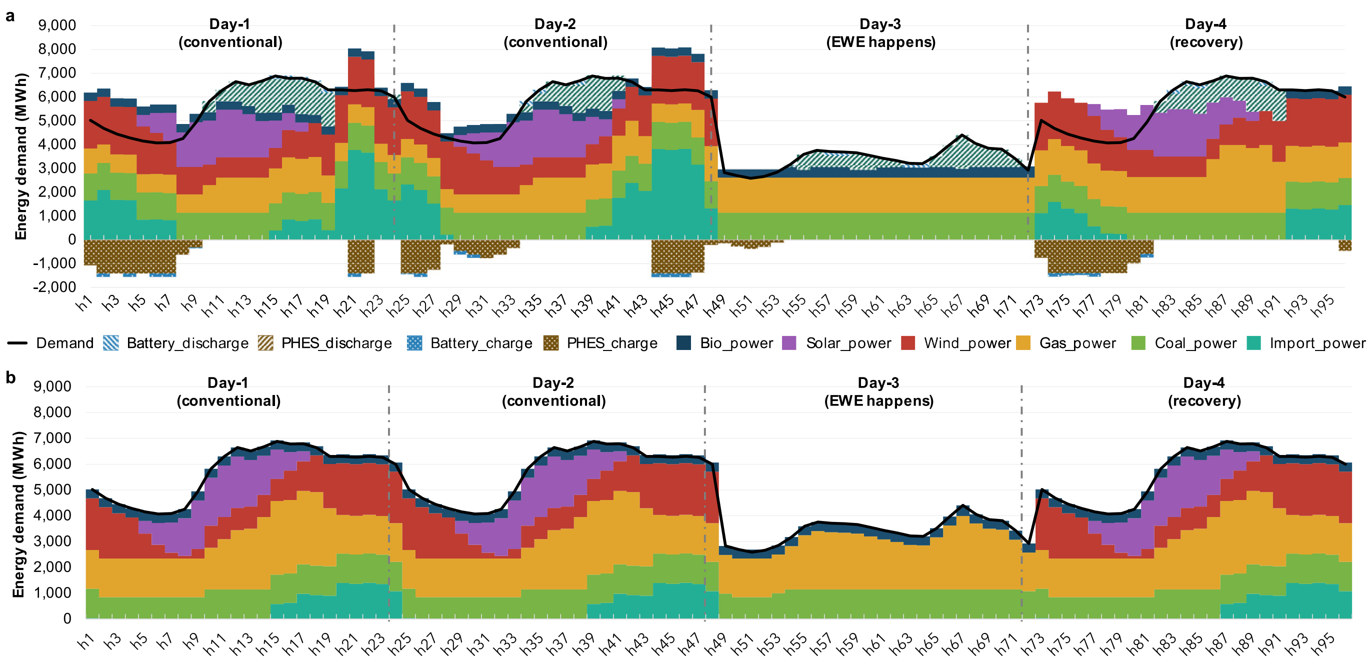

Fig. 6. EWE Simulation results of the optimized UES in 2035 under different heuristics. a, 96-hour UES dispatch during EWE simulation with 'Storage Prior' heuristics in Situ-2. b, 96-hour UES dispatch during EWE simulation with 'Storage Prior' heuristics in Situ-3.

the day-time (i.e., 6 a.m. to 5 p.m.). Import power is greatly utilized during the off-peak period (i.e., 1 a.m. to 8 a.m. and 9 p.m. to 12 p.m.) based on the time-of-use tariff. The cheap import power and surplus renewable power are charged into storage technologies, and the stored power is then discharged for peak shaving during 11 a.m. to 7 p.m. It is noteworthy that, compared to Day-1, more power is charged into storage technologies (mainly in PHES) at the end of Day-2 (i.e., before EWE happens). This part of energy will be discharged to cover the peak of critical demand when EWE happens in Day-3. The rest of critical demand is met by the stable outputs from biomass, gas, and coal power. When it comes to the recovery stage (i.e., Day-4), since most of stored energy (in both PHES and battery) are discharged in Day-3, a significant amount of energy would be charged into the storage at the beginning 7 h in Day-4. Gas and coal power remain stable operation, solar and wind power recover to the conventional operation immediately, and biomass power returns to use until 8 p.m. of Day-4.

Fig. 6b presents the system dispatch during EWE simulation for Situ-3 by implementing the 'Supply Prior' heuristics. Day-1 and Day-2 have a similar dispatch decision, i.e., biomass and coal power remain stable, and solar power only contributes during the daytime. Compared to Situ-2, since a larger capacity of gas power is installed in Situ-3, an increasing amount of gas power will be generated as expected. Due to no deployment of energy storage technology, the wind power will be partially curtailed during the solar power abundant period (i.e., daytime), and the amount of import power is significantly less than that in Situ-2. When the EWE happens in Day-3, biomass and coal power outputs remain stable, and the fluctuation of critical demand is met by the output from gas power. In the recovery stage (i.e., Day-4), all technologies recover to conventional dispatch strategies immediately, which are identical to those in Day-1 and 2.

4. Discussion

4.1. Multiple measures adapting urban energy to extreme weather

Climate change brings about more frequent and intense EWE, which has posed serious challenges to urban energy security. Due to record-breaking heatwaves, wildfires, and possibly inadequate planning, the power supply has to be cut off for thousands of residences in California (US) [41,42]. The power cut worsens as the fluctuating renewables account for a significant share in the local energy mix (up to 67.5%) and could not secure energy supply during peak hours. Such types of extraordinary events are becoming increasingly common in a world rapidly being impacted by climate change, and careful planning to ensure adequate power supplies is therefore becoming more important globally [43].

Our research shows that both the 'Storage Prior' and 'Supply Prior' heuristics turn out effective to inform the upper-layer UES optimization model and eventually address EWE impacts on UES planning in the case of Xiamen (China). Storage technologies could play key roles to ensure energy supply reliability during EWE when solar, wind, and import power are not available [44]. An acceptable 2.8% extra cost is needed when applying the 'Storage Prior' heuristics, which avoids over-investment in installing too large supply capacity. Hence, the 'Storage Prior' heuristics could be preferable.

However, utility-scale battery storage is still not economically attractive so far [45]. For a city that does not have local PHES potential, applying 'Supply Prior' heuristics could also ensure energy supply during EWE with an extra 5.4% cost. Meanwhile, alternative strategies such as (1) enhancing the connection with neighboring grids as 'virtual energy storage' [46], (2) implementing coal power flexibility retrofit [47], and (3) developing demand-side management, especially coordinating with the growing penetration of electric vehicle charging, can offer flexibility during EWE and significantly save capital investment in the battery storage.

4.2. Flexibility of the framework

The proposed two-layer modeling framework captures the system dispatch for the whole 'before-in-after' process of EWE and the impacts on investment decisions of UES. The framework also has the advantages of high flexibility compared to earlier studies, described as follows.

(1) The framework has the generality for investigating various kinds of EWE, such as heatwaves, drought, etc. We take the typhoon as a representative example of EWE in this study considering it is one major EWE threatening an enormous number of coastal

cities, as well as the data availability from local authorities. While the framework is widely applicable for investigating other kinds of EWE, future model-users could construct their own EWE scenario following a similar procedure as detailed in Section 2.4.

(2) The frequency of implementing the simulation is user-defined. We implement the lower-layer EWE simulation annually in this study, which is consistent with the frequency of the design decision-making in the upper-layer UES optimization model. Future model-users can self-define the EWE simulation frequency such as annually, per 5-year, per 10-year or referring to the frequency of the design decision-making in the UES optimization model as we did in this study. In addition, the probability of EWE is highly unpredictable, but it is one essential element in generating a scenario tree by a stochastic or stochastic-robust approach. The probability assignment of an EWE scenario could affect the UES planning results for those approaches. In contrast, high-accuracy prediction for the probability of EWE is not necessary for our framework.

(3) The temporal setup in EWE simulation is flexible. This temporal setup flexibility is reflected in two aspects: (a) the EWE simulation's temporal horizon, (b) the EWE simulation's temporal resolution. In terms of the EWE simulation's temporal horizon, it could be set to more than one day so as to leave sufficient time for each technology to act, e.g., let the PHES alter its reserve; and consider the EWE may last more than one day; and (c) able to simulate days before EWE, EWE happens, and recovery after EWE. Hence, the EWE simulation horizon (e.g., four-day) in our framework is not necessarily to be the same as that of the UES optimization model (e.g., usually by typical day). In this case, we chose four consecutive days including two days of before EWE happens, one day when EWE happens, and one day after EWE for the recovery. As for the EWE simulation's temporal resolution, we chose the hourly resolution considering the data availability of the case study. Nevertheless, the EWE simulation's temporal resolution could be even finer than that of the UES optimization model. Such features on temporal setup offer greater accuracy and flexibility to capture a variety of EWE compared to the typical stochastic, robust, or combined approaches.

(4) Compared to previous optimization model developed by stochastic programming, robust programming, or combined approaches for investigating the impact of EWE on UES planning, the proposed two-layer modeling framework in this study does not need to directly model the EWE scenario in the upper-layer optimization model, which greatly reduces the complexity and computational burden of the optimization model. Instead, we validate the optimized UES design during EWE by developing the simulation model and iteratively inform the optimization model to adjust the design if needed. Although the iterative runs of the optimization model (informed by the simulation model) would take some time, the framework is still computationally efficient for handling EWE in UES planning. In this case, the total computational time by the framework is 1/3 for that of a stochastic model (for comparison purpose), but the computational savings could case specific. The computational complexity could be a key factor particularly when the conventional optimization model itself is already time-consuming even without the EWE scenario. With that in mind, the proposed framework offers an efficient paradigm by modeling the EWE scenario and the conventional scenario separately.

4.3. Insights on simulating extreme weather events

Here we provide general insights on establishing an EWE simulation model for common types of EWE. Similar to the case study of typhoon EWE simulation, suggested settings of EWE simulation model are provided from four perspectives (see Table 2), i.e., temporal resolution, temporal horizon, demand-side, and supply-side. When setting the temporal resolution of an EWE simulation, the dynamic characteristics of an EWE needs to be considered. In terms of temporal horizon, the duration time of an EWE is the most important concern. As for demand-side settings, some EWE could lead to drastic demand increase, and at least critical demand needs to be met during other destructive EWE. For supply-side settings, the impact of an EWE on each energy technology needs to be evaluated considering the sites of energy infrastructure and EWE. Note that the impact levels of an EWE on both supply and demand sides could be case-specific; meanwhile, constructing a sequential or joint EWE simulation model could also originated from the four aspects of settings, i.e., temporal resolution, temporal horizon, demand-side, and supply-side.

In addition, 'EWE includes unexpected, unusual, severe, or unseasonal weather; weather at the extremes of the historical distribution' [48]. Definitions of 'unexpected' or 'unusual' could vary, but most lists of EWE would include hurricanes (or typhoons), heatwaves, cold waves (or blizzards), wildfires, rainstorms (or downpours), and droughts.

4.4. Uncertainty handling

Energy system modeling is always with uncertainties induced by energy demand, fuel cost, weather data, etc. In this study, since we aim to investigate the impact of EWE, we set the situation without considering EWE (Situ-1) as the benchmark and other situations (i.e., Situ-2 and Situ-3) are compared to Situ-1. Hence, all situations are in the same uncertain circumstance, and then by calculating the cost difference of Situ-2 and Situ-3 from Situ-1, the uncertainty could be potentially offset to achieve a relatively robust cost differences, e.g., 2.8% and 5.4% for the 'Storage Prior' and the 'Supply Prior' heuristics, respectively, as reported in Section 3.2.

Note that uncertain factors could still be modeled by a stochastic formulation in the upper-layer UES optimization model. As the focus of this study is the impact of EWE, we only apply a deterministic UES optimization model here. Note that modeling uncertainty by a stochastic approach could already lead to a computationally complex UES optimization model even without considering EWE (just as we discussed in Section 4.2). This further highlights the necessity for our two-layer framework to address the impact of EWE without adding too much computational burden.

4.5. The way forward

4.5.1. Quantify extreme weather resilience

We preliminary explore the urban energy planning adapting to EWE in this study and the framework is developed based on the resilience principles as illustrated in Fig. 7. It embodies the four major attributes of system resilience (i.e., diversity, adaptability, flexibility, and no free lunch) and covers the four major stages of evaluating resilience (i.e., plan/prepare, absorb, recover, and adapt).

Based on the existing study, a promising direction forward is to better quantify the EWE-resilience of UES. Though there might be no generalized form to do so, the tiered resilience assessment approach [49] or creating an evaluation matrix with multi-criteria assessment combined [50] deserves an investigation.

4.5.2. Reduce unsatisfied demand

In this case, the less-critical demand could be unsatisfied during EWE. In order to minimize that unsatisfied demand, one alternative is put the unsatisfied demand as a penalty term into the objective function, so that the model would balance the trade-off between investment more on supply capacity and leaving a certain amount of demand unsatisfied. To do so, it is noticed that quantifying the unit penalty cost of unsatisfied demand could be a challenge and vary case by case .

Table 2
Suggested settings of establishing an EWE simulation model for typical EWE.

EWE type	Temporal resolution	Temporal horizon	Demand-side settings	Supply-side settings
Typhoon (Hurricane)	- hourly or finer	- 4 days or longer (e.g., 2-day before EWE, 1-day EWE happens, and 1-day recovery)	- critical demand to be met all-day - less-critical demand to be met as much as possible	- PV and wind power may not be available- combustion based power sources remain stable- import power could be affected- possible damage to transmission lines
Heatwave	- hourly or finer	- 4 days or longer (e.g., 2-day before EWE, 1-day EWE happens, and 1-day recovery)	- air conditioning induced rapid rise of energy demand all-day	- combustion-based power output may drop due to cooling water temperature rise - PV output may drop due to extreme high temperature
Cold wave (blizzard)	- hourly or finer	- 4 days or longer (e.g., 2-day before EWE, 1-day EWE happens, and 1-day recovery)	- space heating induced rapid rise of energy demand all-day	- combustion-based power output may drop due to frozen cooling water intakes - PV output may drop due to snow accumulation- possible damage to transmission lines
Drought	- daily or coarser	- days to months	- critical demand to be met all-day- less-critical demand to be met as much as possible	- combustion-based power output may drop due to lack of cooling water- PV output may drop due to poor cleaning
Wildfire	- hourly or coarser	- 5 days or longer (e.g., 2-day before EWE, 2-day EWE happens, and 1-day recovery)	- critical demand to be met all-day- less-critical demand to be met as much as possible - specific to fire sites and energy-user sites	- PV output may drop due to dust accumulation - specific to fire sites and energy infrastructure sites - possible damage to transmission lines
Rainstorm (downpour)	- hourly or finer	- 4 days or longer (e.g., 2-day before EWE, 1-day EWE happens, and 1-day recovery)	- critical demand to be met all-day- less-critical demand to be met as much as possible	- PV may not be available- specific to possible waterlogging sites and energy infrastructure sites - possible damage to transmission lines

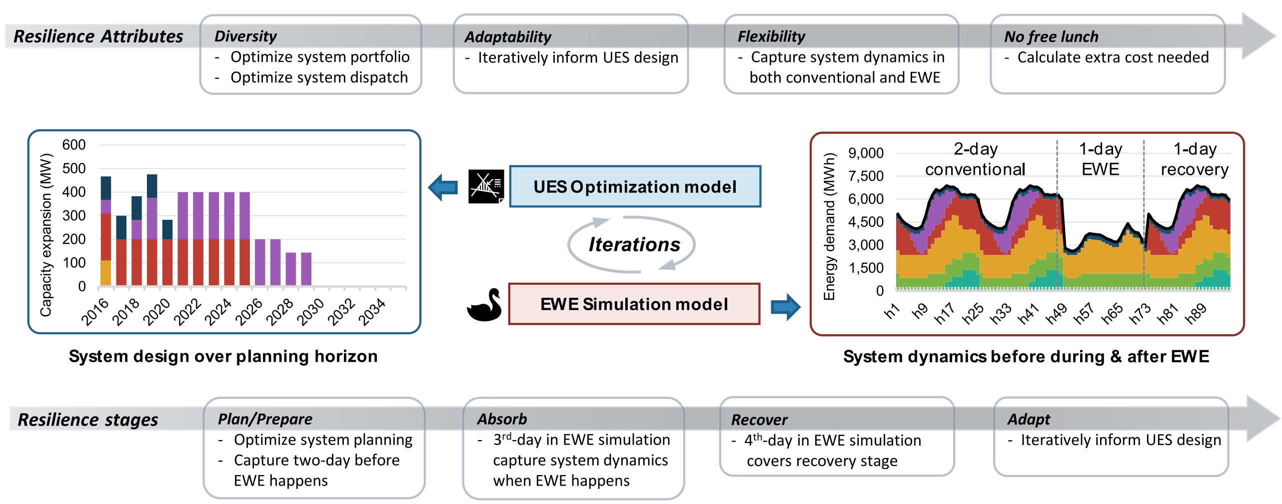

Fig. 7. The developed EWE-resilient urban energy planning framework following resilience concept.

5. Conclusions

To prepare for the global urbanization and climate change, it is critical to developing urban energy systems (UES) that are affordable, sustainable, and reliable. These requirements are particularly emergent considering the intense extreme weather events (EWE), tightening emissions constraint, and increasing penetration of fluctuating renewables. To advance the understanding of the impacts of EWE on UES, here we propose an original two-layer modeling framework for 'EWE-resilient' UES planning. By splitting the EWE scenario into lower-layer, constructing an EWE simulation model, and iteratively informing the upper-layer UES optimization model (which only considers conventional scenario) to adjust the design with specific-designed heuristics, the developed framework not only achieves 'EWE-resilient' UES design and dispatch but also optimizes dispatch decisions during EWE.

The investigation in UES planning for a typical coastal city, i.e., Xiamen, China (encountering typhoon EWE frequently), reveals that deploying energy storage including pumped hydro and batteries (i.e., 'Storage Prior' heuristics) offers great flexibility to ensure the critical energy demand is met when EWE happen. Compared to not considering EWE, an affordable 2.8% extra cost can achieve the least-cost and EWE-resilient UES optimally, which may potentially reduce the losses during EWE (usually counted by billons of money). It is noteworthy that the observations from the Xiamen case could vary with different applications, but future UES would surely need both stability by reliable sources and flexibility by energy storage technologies.

Overall, by providing the forward-looking perspectives into the 'EWE-resilient' UES planning, our research offers a flexible and computationally efficient modeling framework to address the impacts of EWE on UES planning. The proposed framework is generic and extensible, following the procedure of how to construct an EWE scenario, how to categorize energy demand, and how to develop the heuristics as we explicated. Future model-users could further develop more EWE scenarios, e.g., heatwaves, drought, sequential and joint EWE, and further planning 'EWE-resilient' UES for other cities. The energy network topology will be further considered in future research.

Data and code availability

The model formulation and data that support the findings of this study are available by reasonable request to authors.

Declaration of Competing Interest

There are no conflicts to declare.

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Supplementary materials

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