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# Balancing the Energy Trilemma in energy system planning of coastal cities

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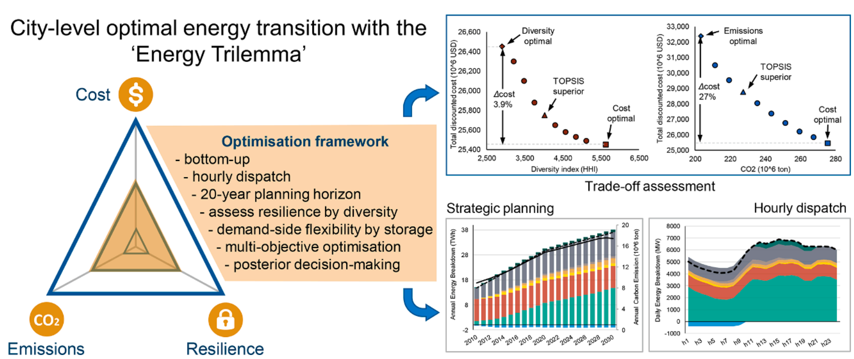
## HIGHLIGHTS

- Optimise the energy transition of coastal cities considering the Energy Trilemma.
- Develop and efficiently solve a bottom-up multi-objective non-linear model.
- Co-optimise long-term energy portfolio and short-term hourly dispatch.
- A most-diverse portfolio with demand-side storage requires 3.9% additional cost.
- A least-emission solution requires 26.8% additional cost due to limited renewables.

## GRAPHICAL ABSTRACT

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## ABSTRACT

The energy transition usually encounters challenges in balancing three competing common goals of economics costs, $CO_2$ emissions, and energy resilience (the so-called Energy Trilemma). Such trade-offs are particularly conspicuous for coastal cities, which often have more ambitious emission reduction targets and are more likely to face threats of extreme weather events such as typhoons. To tackle the Energy Trilemma of the city-level energy transition, this study develops a bottom-up multi-objective optimisation framework. The framework enables simultaneous optimising the long-term energy portfolio for a 20-year horizon and the short-term hourly dispatch strategy considering demand-side flexibility of energy storage. By setting multiple objectives, the trade-offs between three representative scenarios are evaluated via Pareto frontiers, i.e., the least-cost, the least-emissions, and the diversity-optimal scenarios. The case study in a typical coastal city, i.e., Xiamen, China, indicates that with limited local resources for solar, wind, and other renewable resources, the electricity transition would still need to rely on imported power to a large extent. Compared to the least-cost pathway, additional costs of 3.9% can help achieve a pathway with maximum energy diversity to enhance resilience, whereas 26.8% additional costs are needed to achieve the least-emissions pathway. In addition, the initial 10-year modelling results are verified by comparison with real-world actual data to further generate valuable insights into sustainable transition pathways of similar coastal cities.

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**Nomenclature**

*Abbreviations*

| | |
|---|---|
| HHI | Herfindahl–Hirschman Index |
| MOO | multi-objective optimisation |
| NLP | non-linear programming |
| PHES | pumped hydro energy storage |
| PV | photovoltaic |
| TCE | total carbon emissions |
| TDC | total discounted cost |
| TOPSIS | Technique of Order Preference Similarity to the Ideal Solution |

*Indices*

| | |
|---|---|
| $y$ | years |
| $s'$ | typical scenarios for fluctuating renewables |
| $s$ | typical seasons |
| $d$ | typical days |
| $h$ | 24 h |

*Sets*

| | |
|---|---|
| $k$ | set of all energy supply technologies |
| $ka$ | sub-set of combustion-based technologies |
| $kr$ | sub-set of renewable technologies |
| $kc$ | sub-set of technologies with zero emission |
| $kb$ | sub-set of technologies with emissions |

*Parameters*

| | |
|---|---|
| $\overline{CAP^{\text{in-st}}}$ | upper bound of PHES installed capacity |
| $E^{\text{dem}}_{y,s,s',d,h}$ | electricity demand |
| $\overline{E^{\text{cha}}_{y}}$ | upper bound of PHES charge rate |
| $\overline{E^{\text{disc}}_{y}}$ | upper bound of PHES discharge rate |
| $N$ | number of intervals in MOO |
| $P^{\text{CAP}}_{k,y}$ | unit capital price for supply technologies |
| $P^{\text{CAP}}_{\text{in-st},y}$ | unit capital price for PHES |
| $P^{\text{O\&M}}_{k,y}$ | unit O&M price for supply technologies |
| $P^{\text{O\&M}}_{\text{in-st},y}$ | unit O&M price for PHES |
| $P^{\text{fuel}}_{ka,y}$ | unit fuel price |
| $P^{\text{impt}}_{y}$ | unit price for the import power |
| $\overline{\text{Ramp}}$ | upper bound of ramping rate |
| ratio | penetration-level limit |
| $\text{RM}_{ka}$ | reserve margin |
| $\text{SRI}_{y,s,s',h}$ | solar radiation index |
| $\overline{UP^{\text{gen}}_{k,y}}$ | upper bound of power supply technology annual build rate |
| $\overline{UP^{\text{in-st}}}$ | upper bound of PHES annual build rate |
| $\text{WSF}_{y,s,s',h}$ | wind speed factor |
| $\eta^{\text{impt}}$ | import power efficiency |
| $\eta^{\text{cha}}$ | PHES charge efficiency |
| $\eta^{\text{disc}}$ | PHES discharge efficiency |
| $\lambda_{kb,y}$ | emission factors for combustion-based technologies |
| $\varepsilon$ | a parameter in MOO |
| $\mu$ | index of interval in MOO |

*Continuous Variables*

| | |
|---|---|
| $CAP^{\text{gen}}_{k,y}$ | installed capacity of supply technologies |
| $CAP^{\text{gen}}_{wind,y}$ | installed capacity of wind power |
| $CAP^{\text{gen}}_{solar,y}$ | installed capacity of solar power |
| $CAP^{\text{gen}}_{ka,y}$ | installed capacity of combustion-based technologies |
| $CAP^{\text{in-st}}_{y}$ | installed capacity of PHES |
| $C^{\text{inv}}_{y}$ | investment cost |
| $C^{\text{O\&M}}_{y}$ | operation and maintenance cost |
| $C^{\text{fuel}}_{y,s,s',d,h}$ | fuel cost |
| $C^{\text{impt}}_{y,s,s',d,h}$ | import electricity cost |
| $E^{\text{gen}}_{kr,y,s,s',d,h}$ | electricity generated by renewables |
| $E^{\text{gen}}_{solar,y,s,s',d,h}$ | electricity generated by solar power |
| $E^{\text{gen}}_{wind,y,s,s',d,h}$ | electricity generated by wind power |
| $E^{\text{gen}}_{ka,y,s,s',d,h}$ | electricity generated by combustion-based technologies |
| $E^{\text{impt}}_{y,s,s',d,h}$ | electricity imported |
| $E^{\text{cha}}_{y,s,s',d,h}$ | electricity charged into PHES |
| $E^{\text{disc}}_{y,s,s',d,h}$ | electricity discharged from PHES |
| $E^{\text{gen}}_{kb,y,s,s',d,h}$ | electricity generated by technologies with emissions |
| $E^{\text{in-st}}_{y,s,s',d,h}$ | electricity stored in PHES |
| $HHI_{y}$ | diversity index at $y$ year |
| $S^{2}_{k,y}$ | square term for the share of energy source |
| $UP^{\text{gen}}_{k,y}$ | newly build power generation capacity |
| $UP^{\text{in-st}}_{y}$ | newly build PHES capacity |
| $x_{\text{d}}$ | a dummy and free variable |

## 1. Introduction

The transition towards a low-carbon future is happening worldwide [1]. Technological improvement and rapid cost-reductions have led to many promising technologies, such as energy storage technologies and renewables, as attractive options to achieve a sustainable energy infrastructure [2]. The electricity sector is taking action by integrating a greater amount of renewable energy and shifting to a more distributed paradigm [3]. The success of this transition depends on resolving complex challenges that requires the joint efforts of academia, industries, and policy-makers from technical, economic, and environmental initiatives [4]. Energy planning is, therefore, a decision-support process to aid the energy policymaking at both national and municipal levels.

Energy planning, based on mathematical modelling, can produce future scenarios that quantifies optimal energy mix for meeting certain goals, which can generate insights on when, where, and how governments should invest in energy infrastructure [5]. Whereas, challenges such as the intermittency of renewables require specific energy planning models with more flexible temporal, spatial, and technical resolutions [6].

### 1.1. Overview of energy system modelling

Significant efforts have been spent on developing energy planning models for different purposes, and one notable effort is The Integrated MARKAL-EFOM System (TIMES) modelling framework developed by the Energy Technology Systems Analysis Programme (ETSAP) in agreement with the International Energy Agency (IEA) [7]. The TIMES model offers a technology-rich framework with great generality on various spatial scales, e.g., local, national, and multi-regional; and multi-period time horizons over a long-term. Generally, TIMES is used to analyse the entire energy sector at large scale. To make it more suitable for specific applications, many models have been further developed based the TIMES framework, including Astudillo et al. who linked the life cycle assessment with the TIMES model [8]; Salvucci et al. who enhanced the modelling of transport energy sector [9] and other TIMES applications for China [10], Denmark [11], and Iceland [12]. These models tend to simulate the energy system at a large spatial scale for a long temporal horizon, while the temporal resolution is relatively simplified with less consideration of demand-side flexibility and operational constraints.

Another important type of model is the Integrated Assessment Model (IAM), which generally includes both physical and social science models to analyse climate change, one of the most complicated global environmental problem. The IAM is usually based on regional to global spatial resolution and with up to 100 years of modelling time horizon. Several representative IAM include GCAM [13], DICE/RICE [14], IMAGE [15], MESSAGE [16], REMIND [17]. Considering the different purpose of the IAM and the present study, the IAM is not detailed here.

Considering the intermittency and growing penetration of variable renewables sources in the power system, more technical constraints such as ramp-rate and minimum operation point that are usually in the unit commitment (UC) model, need to be represented in the long-term planning models. Concerns over the high penetration levels of renewables and flexibility of power systems have spurred several studies to integrate demand-side flexibility constraints into long-term planning models. Koltsaklis et al. integrated the short-term unit commitment constraints into an investment planning model, using an hourly time resolution and with each year represented by 12 typical months [18]. Pereira et al. developed a generation expansion planning model by using mixed-integer non-linear programming with UC constraints to model the Portuguese system with variable renewable sources [19]. The typical weeks or days approach is also applied to represent the whole year to maintain computational tractability. Chen et al. [20] proposed a multi-region power generation expansion model with unit commitment constraints. Each year is divided into four seasons, and a representative day is selected for each season. Emissions are specifically modelled, and the model presents a solution to the policy challenge of imbalanced regional emission reductions. Poncelet et al. [21] considered the alternative sources of flexibility offered by pumped hydro and battery storage technologies by proposing a generation expansion model with unit commitment constraints at the hourly time resolution. A comprehensive review is conducted by Collins et al. [22] categorising the features of models at different scales and indicating the potential of developing bi-directional soft-linking methods for integration models from different scales. All these studies lay a solid foundation for modelling demand-side flexibilities and long-term strategic investments.

Based on the above literature, energy system models can be classified into three categories as illustrated in Fig. 1. The temporal, spatial, and technical resolutions vary significantly for different categories of models with different purposes. The model proposed in the present study is a hybrid of the unit commitment model and the long-term planning model.

### 1.2. Motivation and contribution

Balancing the Energy Trilemma when planning energy systems remains an open challenge. This issue is particularly prominent for coastal cities' energy systems as they are more susceptible to extreme weather events such as typhoons and usually have more ambitious $CO_2$ emission reduction targets than many other cities. However, to the best of our knowledge, few studies have evaluated the city-level energy transition (particularly coastal cities) considering multiple competing objectives at a detailed hourly temporal resolution. Thus, a knowledge gap exists in understanding the optimal transition pathway for coastal cities that considers the possible trade-offs among the Energy Trilemma of cost, emissions, and resilience goals.

To fill this knowledge gap, we develop a bottom-up and multi-objective optimisation framework, which is structured with the short-term hourly temporal resolution considering demand-side flexibility, and able to assess the impacts on long-term investment decisions over 20-year transition horizon. Notably, we consider the demand-side electricity storage and the objective function of technological diversity in our model to enhance system resilience. Multiple scenarios considering various criteria of least cost, least emission, and maximised diversity are evaluated. The modelling results are further validated with real-world conditions to generate valuable insights from both political and methodological perspectives.

The contribution of this study are as follows.

(1) From a political perspective, this study highlights the important role that municipal policymakers can play in guiding future energy planning investments towards sustainable energy infrastructure, and provides timely findings just as several pilot projects are being launched in China [23]. As a representative coastal city in China, the policy insights generated from Xiamen's

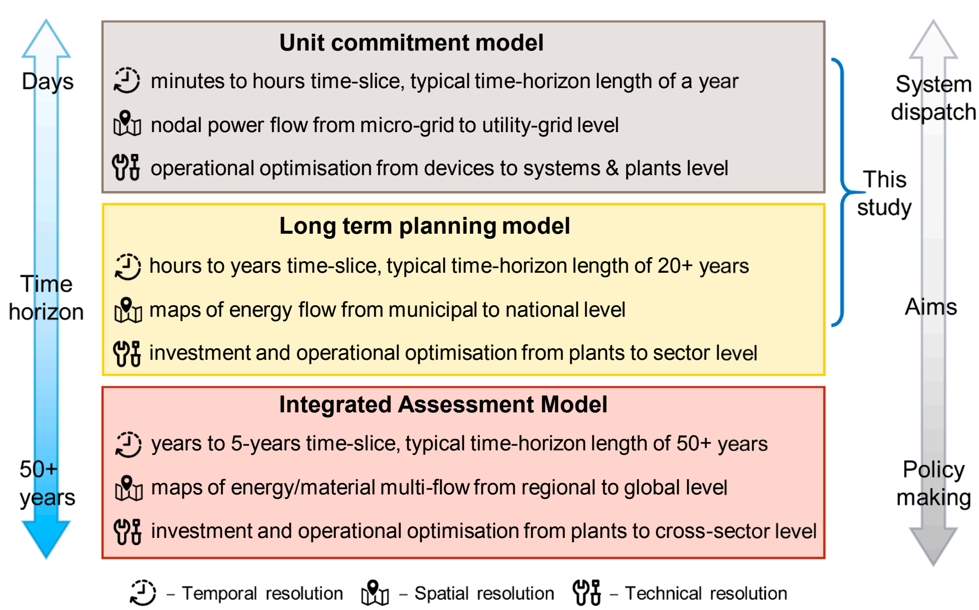


**Fig. 1.** Three principal categories of energy planning models and corresponding temporal-spatial-technical features.

energy transition also serve as a valuable reference for other similar cities. Moreover, the first 10-year modelled results are validated with actual data to ensure the model's validity and quality of generated insights.

(2) From a scientific methodological perspective, we develop a multi-objective bottom-up optimisation model that enables assessing different transition pathways considering the Energy Trilemma goals of cost, emissions, and resilience. The proposed model also differs from other long-term energy transition models by the setup of hourly temporal resolution to capture the flexibility of demand-side technologies such as energy storage. Additionally, an efficient model-solving strategy is proposed to tackle the non-linear multi-objective computationally-costly issue when modelling the resilience by energy diversity.

The rest of the paper is organised as follows: section 2 describes the modelling methodology in detail, proposes a modeling framework for energy planning, and introduces the multi-objective optimisation and decision-making functions. Section 3 presents detailed a case study of Xiamen City, China. Section 4 analyses the modelling results and discusses the policymaking implications and methodological contributions. Section 5 summarises the key findings and highlights future research directions.

## 2. Method

This study addresses city-level energy planning challenges by proposing a bottom-up optimisation model, which optimises energy portfolio and hourly operation strategy under specific constraints. Fig. 2 shows the schematic of the proposed model for evaluating different transition pathways to meet energy demand based on three competing objectives. Inputs of the model include energy demand, energy resource, and technology details; subject to constraints of demand–supply balance, emissions control, and technology operations. The whole model is developed based on non-linear programming (NLP), and solved by the NLP engine. Several specific features of the proposed model are described as follows:

(1) Various supply and demand-side technologies are considered and classified into sets for the ease of model development and further model extension.
(2) Hourly dispatch resolution capturing demand-side flexibility and the energy transition pathway over the 20-year horizon are optimised simultaneously.
(3) Multi-objective optimisation and posterior decision-making based assessment of the trade-offs of the Energy Trilemma.

### 2.1. Model assumptions

To tackle the research question and minimise the computational efforts, the following assumptions are included in the model formulation:

(1) The model assumes perfect foresight over the entire planning horizon;
(2) Each year during the planning horizon is sliced into certain representative slots;
(3) We model the targeted system as one node and can purchase electricity from the wider national grid but do not consider feeding power back to the national grid; surplus can be stored in pumped hydro energy storage (PHES) if available;
(4) We model the installed capacity of each technology as a continuous variable considering the computational expense caused by the nonlinearity for modelling the diversity;
(5) We take the high-level master planning perspective, where policy-makers can make overall decisions on investment timing, capacity expansion, and operational strategy for each energy technology.

### 2.2. Model temporal resolution

The temporal resolution of the proposed model is shown in Fig. 3, where the modelling horizon is 2010 ~ 2030 and the model has finer season-day-scenario-hour resolutions to model the demand-side flexibility and engagement of storage technologies. Three representative seasons of summer (Apr. 15th to Oct. 15th), winter (Dec. 15th to Feb. 15th), and the transition season (the rest of days) are considered; and further represented by two typical days, including a weekday and a weekend day. For each kind of typical day, four scenarios representing the fluctuation of solar and wind profiles are considered with hourly resolution. Hence, each year is sliced into 576 temporal slots (i.e. 3 seasons × 2 days × 4 scenarios × 24 h = 576 temporal slots). Investment decisions are made annually; whereas operation decisions are made at hourly resolution.

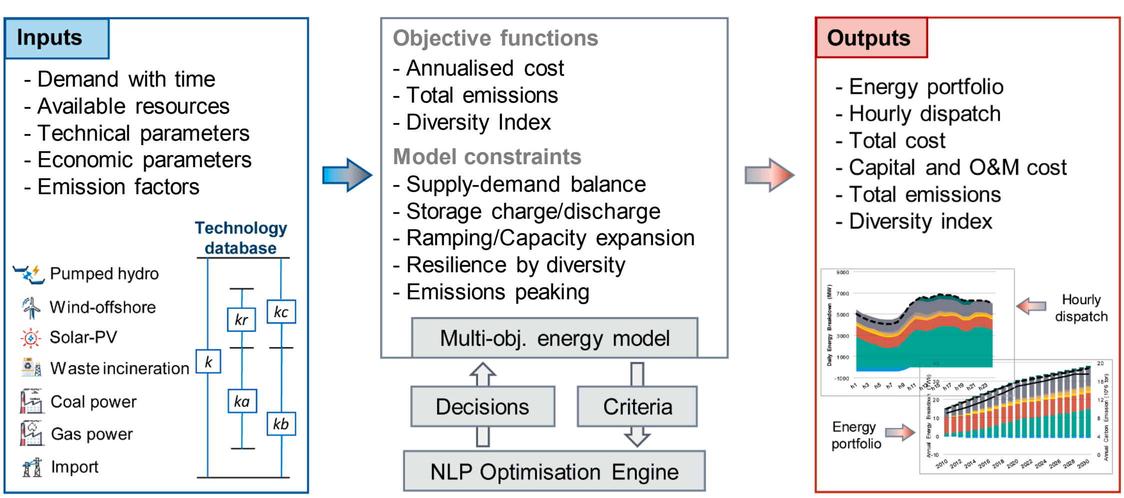


**Fig. 2.** Outline of proposed energy planning framework.

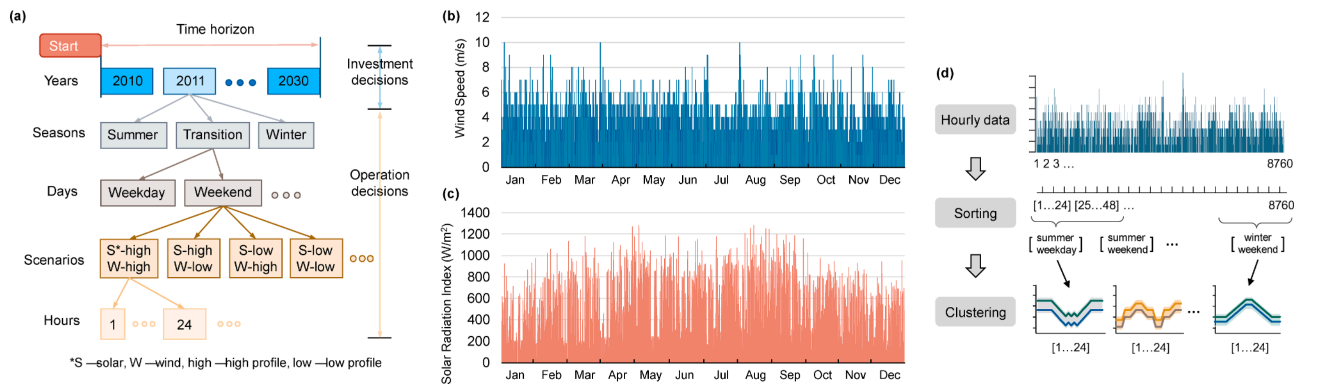


**Fig. 3.** Model temporal resolution (a), wind fluctuating profile (b), solar fluctuating profile (c), and process of generating representative profile (d). (b) and (c) show the hourly distributions and variation of wind and solar radiation based on three-year (2013–2015) historical data obtained from online sources [25]. (d) shows the k-means clustering approach for generating representative profiles for solar and wind.

The solar and wind profiles fluctuate daily over the time horizon as shown in Fig. 3(b and c). The k-means clustering approach is applied to generate representative profiles for wind and solar as shown in Fig. 3(d). The whole set of hourly weather data is sorted first by representative days. Then, for each type of typical day, the array of data points is clustered into the pre-defined number of clusters (i.e., 2 in this case), such that the Euclidean distance between the data points and the corresponding cluster centroid is minimised. For each cluster, a representative profile can be chosen by collecting the cluster centroids of that cluster and is further weighted by the frequency of occurrence for the data points in that cluster. Hence, for each kind of typical day, two representative profiles (i.e., high profile and low profile) are chosen for wind and solar, respectively. The detailed procedure of k-means clustering is explained in Ref. [24].

### 2.3. Model formulation

This section presents the mathematical formulation of the proposed model as outlined below. All parameters and variables have been defined in Nomenclature.

| | |
|---|---|
| min | $obj_1$ = Total Discounted Cost (TDC) by Eq. 5 |
| min | $obj_2$ = Total $CO_2$ Emissions (TCE) by Eq. 6 |
| min | $obj_3$ = Diversity Index (HHI) by Eq. 7 |
| S.T. | Energy balance by Eq. 1 |
| | Capacity expansion constraints by Eq. 2 |
| | Operation constraints by Eq. 3 |
| | Pumped hydro energy storage constraints by Eq. 4 |

#### 2.3.1. Energy balance

The main constraint is the matching of electricity supply and demand for every interval as shown in Eq. 1. For each hour, the total electricity generation, the electricity import, and the electricity discharge from PHES cover the demand and the electricity charge into PHES. The stochastic scenarios of solar and wind would affect all these terms in Eq. 1.

$$E^{dem}_{y,s,s',d,h} + E^{cha}_{y,s,s',d,h} = E^{disc}_{y,s,s',d,h} + E^{impt}_{y,s,s',d,h} \times \left(1-\eta^{impt}\right) + \sum_{kr} E^{gen}_{kr,y,s,s',d,h} + \sum_{ka} E^{gen}_{ka,y,s,s',d,h} \tag{1}$$

where $E^{dem}$ denotes electricity demand, $E^{cha}$ and $E^{disc}$ are electricity charge and discharge, respectively; $E^{impt}$ represents electricity import considering transmission efficiency of $\eta^{impt}$; $E^{gen}_{kr}$ and $E^{gen}_{ka}$ are electricity generated by renewable and combustion-based technologies, respectively.

#### 2.3.2. Capacity expansion

The investment decisions are made annually in that the energy portfolio could change each year; and the electricity generated is constrained by the available capacity of each technology as shown in Eq. 2a. The reserve margin is considered for combustion-based technologies in Eq. 2b; while solar power relies on both the annual installed capacity and the hourly variation in solar radiation as constrained by Eq. 2c; wind power depends on the installed capacity and the hourly variations in wind speeds as constrained by Eq. 2d. In addition, upper bounds are set on the annual capacity increase in Eq. 2e and total maximum potential of each technology in Eq. 2f.

$$CAP^{gen}_{k,y} \leqslant CAP^{gen}_{k,y-1} + UP^{gen}_{k,y} \tag{2a}$$

$$E^{gen}_{ka,y,s,s',d,h} \leqslant CAP^{gen}_{ka,y} \times \left(1 + RM_{ka}\right) \tag{2b}$$

$$E^{gen}_{solar,y,s,s',d,h} \leqslant CAP^{gen}_{solar,y} \times \mathrm{SRI}_{y,s,s',h} \tag{2c}$$

$$E^{gen}_{wind,y,s,s',d,h} \leqslant CAP^{gen}_{wind,y} \times \mathrm{WSF}_{y,s,s',h} \tag{2d}$$

$$UP^{gen}_{k,y} \leqslant \overline{UP^{gen}_{k,y}} \tag{2e}$$

$$\sum_{y} UP^{gen}_{k,y} \leqslant \overline{\sum_{y} UP^{gen}_{k,y}} \tag{2f}$$

where $CAP^{gen}$ denotes available capacity for each technology, $UP^{gen}$ represents newly installed capacity, RM is a parameter of reserve margin, SRI is a parameter of Solar Radiation Index factor (ranges between $0 \sim 1$, 0 is no solar radiation, 1 is maximum solar radiation), WSF is a parameter of wind speed factor.

#### 2.3.3. Operation constraints

The variations on electricity generation output are constrained by ramping limits ($\overline{\mathrm{Ramp}}$) as derived in Eq. 3a. Other realistic operational constraints are also included, such as limits on the penetration levels (by setting a ratio of 20%) for variable renewables in Eq. 3b.

$$\left| E^{gen}_{ka,y,s,s',d,h} - E^{gen}_{ka,y,s,s',d,h-1} \right| \leqslant \overline{\mathrm{Ramp}} \tag{3a}$$

$$\sum_{kr} E^{gen}_{kr,y,s,s',d,h} \leqslant \mathrm{ratio} \times E^{dem}_{y,s,s',d,h} \tag{3b}$$

#### 2.3.4. Pumped hydro energy storage (PHES)

The model incorporates the PHES technology, which offers flexibility with the increasing penetration of solar and wind renewables. As an established utility-scale electricity storage technology, a typical PHES involves reversible pumps/generators, and two reservoirs at low/high elevations, respectively [26]. During low-demand and surplus supply period, water is pumped up to the upper reservoir for storing electricity, i.e., charging; and the stored energy is released to the lower reservoir during the high-demand and low-supply periods, i.e., discharging [27]. In this study, the flexible operation of PHES is modelled by Eq. 4. In Eq. 4a, the energy stored ($E^{in\text{-}st}_{y,s,s',d,h}$) at $h$ time-slot (i.e. hour) is equal to the energy stored ($E^{in\text{-}st}_{y,s,s',d,h-1}$) at previous hour $h$-1 plus the energy being charged into the high reservoir ($E^{cha}_{y,s,s',d,h}$) at hour $h$ minus the energy being discharged ($E^{disc}_{y,s,s',d,h}$) to the lower reservoir at hour $h$ considering the charging and discharging efficiency ($\eta^{\text{cha}}$ and $\eta^{\text{disc}}$) for a certain scenario (*s'*), a typical day (*d*), a selected season (*s*), and a year (*y*). The energy stored ($E^{\text{in-st}}_{y,s,s',d,h}$) cannot be larger than the installed capacity ($CAP^{\text{in-st}}_{y}$) or less than 15% of the installed capacity as shown in Eq. 4b. The installed capacity ($CAP^{\text{in-st}}_{y}$) at *y* time-slot is equal to the installed capacity ($CAP^{\text{in-st}}_{y-1}$) at *y*-1 time-slot plus the newly installed capacity ($UP^{\text{in-st}}_{y}$) as defined by Eq. 4c. The installed capacity ($CAP^{\text{in-st}}_{y}$) cannot be greater than the maximum potential in practice; the newly installed capacity ($UP^{\text{in-st}}_{y}$) is limited by annual build-rate ($\overline{UP^{\text{in-st}}}$) as shown in Eq. 4d. Meanwhile, both charge and discharge rates have the upper bounds ($\overline{E^{\text{cha}}_{y}}$and $\overline{E^{\text{disc}}_{y}}$) as derived in Eq. 4e.

$$E^{\text{in-st}}_{y,s,s',d,h} = E^{\text{in-st}}_{y,s,s',d,h-1} + \eta^{\text{cha}} \times E^{\text{cha}}_{y,s,s',d,h} - E^{\text{disc}}_{y,s,s',d,h}/\eta^{\text{disc}} \tag{4a}$$

$$15\% \times CAP^{\text{in-st}}_{y} \leqslant E^{\text{in-st}}_{y,s,s',d,h} \leqslant CAP^{\text{in-st}}_{y} \tag{4b}$$

$$CAP^{\text{in-st}}_{y} = CAP^{\text{in-st}}_{y-1} + UP^{\text{in-st}}_{y} \tag{4c}$$

$$CAP^{\text{in-st}}_{y} \leqslant \overline{CAP^{\text{in-st}}},\ UP^{\text{in-st}}_{y} \leqslant \overline{UP^{\text{in-st}}} \tag{4d}$$

$$E^{\text{cha}}_{y,s,s',d,h} \leqslant \overline{E^{\text{cha}}_{y}},\ E^{\text{disc}}_{y,s,s',d,h} \leqslant \overline{E^{\text{disc}}_{y}} \tag{4e}$$

### 2.4. Objective function

The energy system model considers three objective functions from economic, environmental, and energy resilience perspectives, namely, the total discounted cost (*TDC*) including energy system investment and operation cost, the total $CO_2$ emissions, and the Herfindahl–Hirschman Index (*HHI*) for diversity.

#### 2.4.1. Economic objective

The *TDC* accounts for the investment cost ($C^{\text{inv}}$), the fuel cost ($C^{\text{fuel}}$), imported electricity cost ($C^{\text{impt}}$), and the operation and maintenance (O&M) cost ($C^{\text{O\&M}}$) over the modelling horizon. The investment decisions are made annually; while other cost terms need to sum over representative seasons, days, stochastic weather scenarios, and hours. The O&M cost is proportional to the available capacity; while different operation scenarios would affect the fuel cost and electricity import cost.

$$obj_1 = min\ TDC \tag{5a}$$

$$TDC = \sum_{y=1}^{20} \frac{1}{(1+r)^{y-y_0}} \left( C^{\text{inv}}_{y} + \sum_{s,d,h} C^{\text{O\&M}}_{y} + \sum_{s,s',d,h} C^{\text{fuel}}_{y,s,s',d,h} + \sum_{s,s',d,h} C^{\text{impt}}_{y,s,s',d,h} \right) \tag{5b}$$

$$C^{\text{inv}}_{y} = \sum_{k} CAP^{\text{gen}}_{k,y} \times P^{\text{CAP}}_{k,y} + CAP^{\text{in-st}}_{y} \times P^{\text{CAP}}_{\text{in-st},y} \tag{5c}$$

$$C^{\text{O\&M}}_{y} = \sum_{k} CAP^{\text{gen}}_{k,y} \times P^{\text{O\&M}}_{k,y} + CAP^{\text{in-st}}_{y} \times P^{\text{O\&M}}_{\text{in-st},y} \tag{5d}$$

$$C^{\text{fuel}}_{y,s,s',d,h} = \sum_{ka} \frac{E^{\text{gen}}_{ka,y,s,s',d,h}}{\eta_{ka}} \times P^{\text{fuel}}_{ka,y} \tag{5e}$$

$$C^{\text{impt}}_{y,s,s',d,h} = E^{\text{impt}}_{y,s,s',d,h} \times P^{\text{impt}}_{y} \tag{5f}$$

where r is discount rate, *y* is each year, $y_0$ is the reference year that all costs are discounted to, $P^{\text{CAP}}$ denotes unit capital price, $P^{\text{O\&M}}$ is unit O&M price, $P^{\text{fuel}}$ is unit fuel price, $P^{\text{impt}}$ is unit price for the import power.

#### 2.4.2. Environmental objective

The total $CO_2$ emissions (*TCE*) over the modelling horizon can be calculated as Eq. 6(a and b). The Chinese government commitment on emission peaking before 2030 is modeled by Eq. 6c

$$obj_2 = min\ TCE \tag{6a}$$

$$TCE = \sum_{y=1}^{20} \left( \sum_{kb,s,s',d,h} E^{\text{gen}}_{kb,y,s,s',d,h} \times \lambda_{kb,y} + \sum_{s,s',d,h} E^{\text{impt}}_{y,s,s',d,h} \times \lambda_{\text{impt},y} \right) \tag{6b}$$

$$\left( \sum_{kb,s,s',d,h} E^{\text{gen}}_{kb,y<20,s,s',d,h} \times \lambda_{kb,y<20} + \sum_{s,s',d,h} E^{\text{impt}}_{y<20,s,s',d,h} \times \lambda_{\text{impt},y<20} \right) > \left( \sum_{kb,s,s',d,h} E^{\text{gen}}_{kb,y=20,s,s',d,h} \times \lambda_{kb,y=20} + \sum_{s,s',d,h} E^{\text{impt}}_{y=20,s,s',d,h} \times \lambda_{\text{impt},y=20} \right) \tag{6c}$$

where $\lambda_{kb}$ and $\lambda_{\text{impt}}$ denote the emissions factor for combustion-based technologies and imported power, and varies annually.

#### 2.4.3. Diversity objective

Energy planning with diversity could enhance the resilience of energy systems by preventing over-dependence on single energy source, as the basic idea of diversity is to avoid "putting all eggs in one basket" [28]. Energy diversity is the relative contribution of various energy sources to the energy mix. In this study, we apply the Herfindahl–Hirschman Index (HHI) as displayed in Eq. 7 because it can provide sufficient insights with fewer complex expressions. In order to maximise the diversity at the end of the planning horizon, the HHI should be minimised as defined in Eq. (7a).

$$obj_3 = min\ HHI_{y=20} \tag{7a}$$

$$HHI_y = \sum_{k=1}^{K} S^2_{k,y} \tag{7b}$$

where $S_{k,y}$ is the share of energy source *k* in total energy supply for each year *y*, expressed as a whole number.

### 2.5. Multi-objective optimisation and decision-making

Multi-objective optimisation is an efficient tool used to assess the trade-offs among competing objectives. We apply the eps-constraint based multi-objective optimisation approach for the convenience of reformulating the model [29]. Eq. 8a presents the general formulation of a bi-objective minimisation problem, where the eps-constraint approach converts one objective function $f_2(x)$ to a constraint by introducing a parameter epsilon (ε), then optimises the other objective function $f_1(x)$ satifying both the original model constraints and the $f_2(x)$ converted constraint [30]. The value of ε is determined by Eq. 8b, where the maximum $f_2^{\max}(x)$ can be obtained by minimising $f_1(x)$ and collecting the $f_2(x)$ value in that minimisation of $f_1(x)$; the minimum $f_2^{\min}(x)$ values can be obtained by directly minimising $f_2(x)$. *N* is a user-defined number of intervals, $\mu = 0,\ldots,N$. By updating the value of ε and running the optimisation model as illustrated in Eq. 8a iteratively, a set of optimal solutions can be obtained. Note that the larger the value of *N*, the finer the interval of the obtained optimal results, while the computational expense increase accordingly [31].

$$\begin{aligned} & min\ f_1(x) \\ & \text{S.T. } f_2(x) \leqslant \varepsilon \\ & \text{and constraints from original model} \end{aligned} \tag{8a}$$

$$\varepsilon = f_2^{max}(x) - \frac{f_2^{max}(x) - f_2^{min}(x)}{N}\mu \tag{8b}$$

The set of optimal results from the multi-objective optimisation is usually presented as a Pareto frontier [32]. As all of the solutions presented on the Pareto frontier are non-dominant and all solutions on the Pareto frontier are considered optimal solutions, it is a challenge to specify one "superior" solution among them. Several posterior decision-making approaches can be used to assist the decision-maker in ultimately selecting one superior solution with maximised rationality [33]. In this case, we introduce one Euclidean distance-based approach, i.e., Technique of Order Preference Similarity to the Ideal Solution (TOPSIS). Firstly, all solutions on the Pareto frontier are normalised ($f_{ij}^{\text{norm}}$). Then a "Ideal" point located in the theoretical best but not achievable place is defined ($f_j^{\text{ideal}}$), so that the Euclidian distance ($ED_{i+}$) between each solution on the Pareto frontier and the "Ideal" point can be calculated by

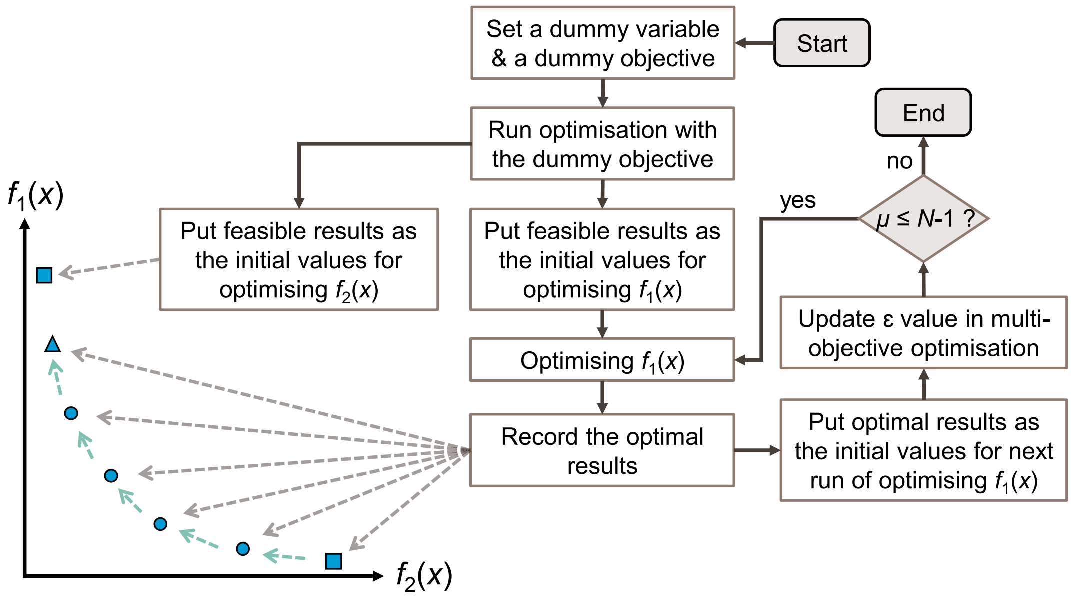


**Fig. 4.** Model solving strategy combined the pre-solving technique and eps-constraint multi-objective optimisation. The definitions of $\mu$, $N$, $f_1(x)$ and $f_2(x)$ are in accordance with Section 5.2

Eq. 9a. Next, a "Nadir" point located in the opposite side of the Pareto frontier (compared to the "Ideal" point) is defined, and the Euclidian distance ($ED_{i-}$) between each solution on the Pareto frontier and the "Nadir" point can be calculated by Eq. 9b. Finally, the solution with the largest relative distance ($Y_i$) to the "Nadir" point is considered as the superior solution, as derived in Eq. 9c [34]. In this posterior decision-making approach, all objectives are assumed equally important by the normalisation, then the identification of a "superior" solution merely depends on the distribution of all solutions on the Pareto frontier.

$$ED_{i+} = \sqrt{\sum_{j=1}^{n} \left(f_{ij}^{\text{norm}} - f_j^{\text{ideal}}\right)^2} \tag{9a}$$

$$ED_{i-} = \sqrt{\sum_{j=1}^{n} \left(f_{ij}^{\text{norm}} - f_j^{\text{nadir}}\right)^2} \tag{9b}$$

$$Y_i = \frac{ED_{i-}}{ED_{i-} + ED_{i+}} \tag{9c}$$

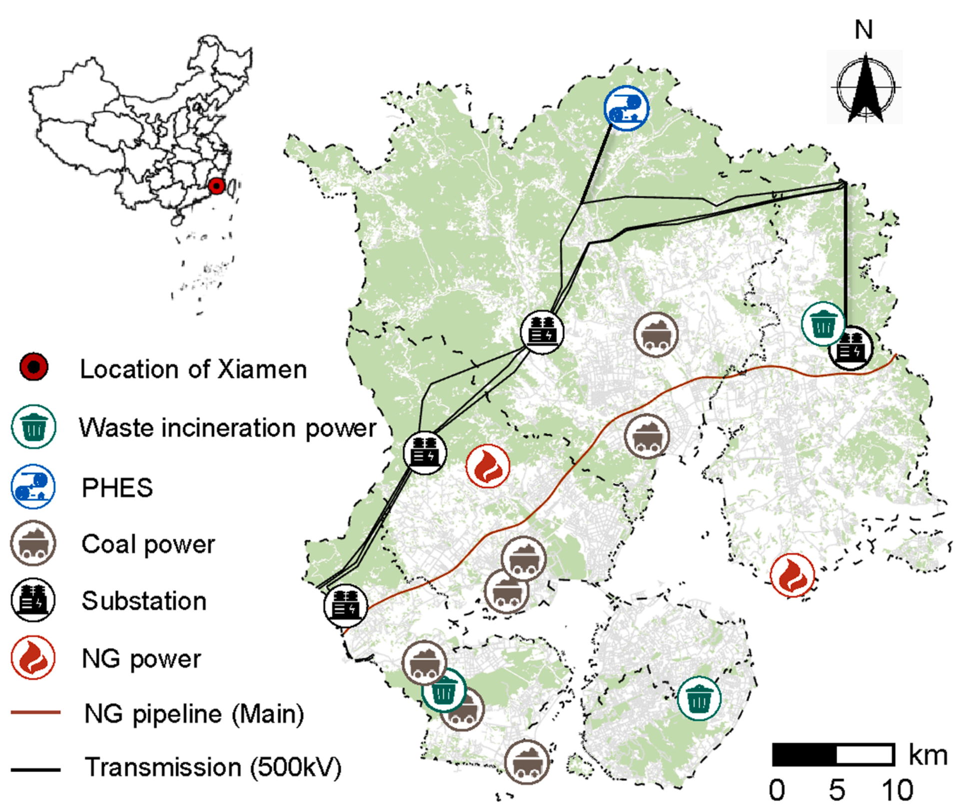


**Fig. 5.** Map of Xiamen and its existing energy infrastructure in Fujian Province, China

**Table 1**
Existing capacities, build rate limit, and maximal developing potential of each energy technology.

| Technology | Existing capacity (MW) | Build rate limit (MW/year) | Maximum potential (MW) |
|---|---|---|---|
| Coal | 1200 | 100 | 1200 |
| Gas | 1000 | 0 | – |
| Solar | 0 | 20 | 500 |
| Wind | 0 | 40 | 160 |
| Waste Incineration | 18 | 15 | – |
| PHES | 0 | 300 | 1400 |

### 2.6. Model solving strategy

Because the non-linearity induced by the diversity formulation leads to much greater computational efforts than a linear model, we introduce a pre-solving technique, i.e., the initial value assignment, to reduce the computational requirements. The concept of the initial value assignment is to assign proper initial values for variables during the optimisation process. Combined with the eps-constraint multi-objective optimisation approach, the outline of the pre-solving is depicted in Fig. 4. First, we define a dummy and free variable $x_d$, and a dummy objective $f_d(x)$. Let $f_d(x)$ equals to $x_d = 1$. Since the $x_d$ is a free variable, the objective function of $x_d = 1$ is always true. By running the optimisation model with the dummy objective, the solver would instantly generate a feasible solution and assign feasible values for all variables satisfying the model's constraints. These feasible values (not optimal) could be valuable initial values for the running of optimising $f_1(x)$ and $f_2(x)$, by which the two endpoints on the Pareto frontier can be obtained (illustrated as square points). After that, the optimal results for optimising $f_1(x)$ could be the initial values for the next run of optimising $f_1(x)$ align with the iteratively update of ε value in the multi-objective optimisation. The iteration will end when $\mu = N$-1, where the point next (the triangle point) to the endpoint (by optimising $f_2(x)$) is obtained.

By implementing the pre-solving technique, the computational time will be reduced by roughly 20% for different runs of optimisation, with case-specific variations on computation time savings.

## 3. Case specifications in Xiamen

Xiamen is a typical coastal city located in Fujian Province on the southeast coast of the People's Republic of China (see Fig. 5). With a population of over 3.5 million residents in 2010, Xiamen is one of China's first special economic zones and one of the first batches of low-carbon pilot cities [35]. Due to its geographic location, extreme weather events of typhoons occur occasionally.

The energy system of Xiamen city has the following features. Due to emission concerns, there are no new plans for building coal-fired power plants; the natural gas supply is sufficient; and waste incineration power generation is a promising solution considering the growing amount of municipal waste produced. Nuclear power is not considered due to land limit. Building-integrated photovoltaic (BiPV) pilot projects have been initiated as one of China's demonstration cities for energy-efficient urban retrofit with annual availability of 2200 ~ 3000 solar hours but face relatively limited available rooftop space. The average wind speed is 2.7 m/s [36]; but there are relatively limited potential sites available for both off-shore and on-shore due to the city's land-use patterns and landscape constraints [37]. Other than local power generation, Xiamen's electricity supply relies heavily on imported electricity from the provincial grid of Fujian province, where the proportion of nuclear and wind power is gradually increasing, and is sufficient to meet Xiamen's needs. In addition, Xiamen has a geographical advantage for developing PHES with a potential of 1,400 MW. Table 1 lists the existing capacity, annual expansion limit, and maximal potential of different energy supply alternatives for Xiamen, based on open literature [38,39] and consultation with local authorities.

The trends of some key input parameters for Xiamen are presented in Fig. 6, which is obtained from open literature and calibrated with national and local situations. The annual electricity demand for 2010 ~ 2019 is obtained from the local utility company, and the demand for 2020 ~ 2030 is based on projections from Ref. [40]. The capital cost and O&M cost are expected to remain stable or decline, while the fuel cost would increase slightly. In addition, the emission factor for coal power, gas power, and waste incineration power is assumed to be 0.825, 0.391, and 0.358 tons $CO_2$/MWh, respectively. The emission factor for imported power during 2005 ~ 2017 is obtained from published government data [41] and future annual emission factors are based on best-fit exponential function with an $R^2$ value of 0.97 (with roughly 2 ~ 3% annual decline).

## 4. Result and discussion

### 4.1. System planning trade-off between cost, energy diversity, and emissions

Fig. 7 shows a trade-off between cost and energy diversity, as well as the trade-off between cost and $CO_2$ emissions. We present such a trade-off using the Pareto frontier, where each solution on the Pareto frontier denotes a certain scenario with the optimal system design and dispatch strategy. In Fig. 7(a), the diversity-optimal scenario maximises the diversity of energy mix with the least diversity index (HHI). Since the renewable energy potential (Wind, WI, and PV) is limited and accounts for less than 10% in total, imported power, coal power, and gas power remain the three main sources of energy supply, with each accounting

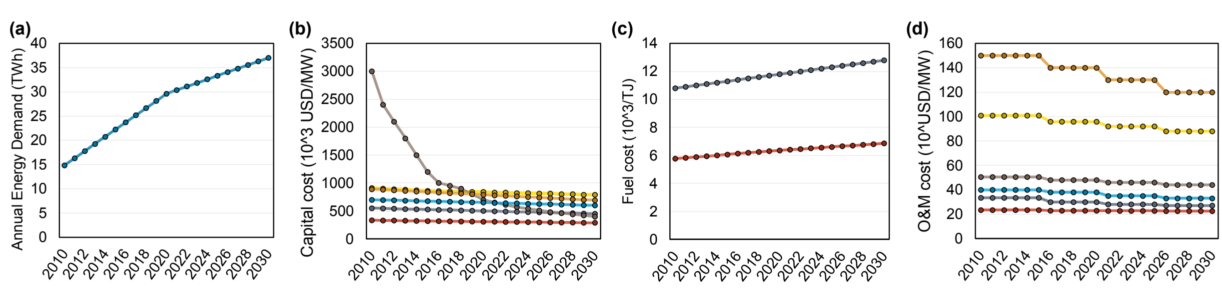


**Fig. 6.** Input parameters over planning horizon. (a) annual electricity demand [40], (b) capital cost of each technology [42,43], (c) fuel cost of coal and gas, (d) O&M cost of each technology [44].

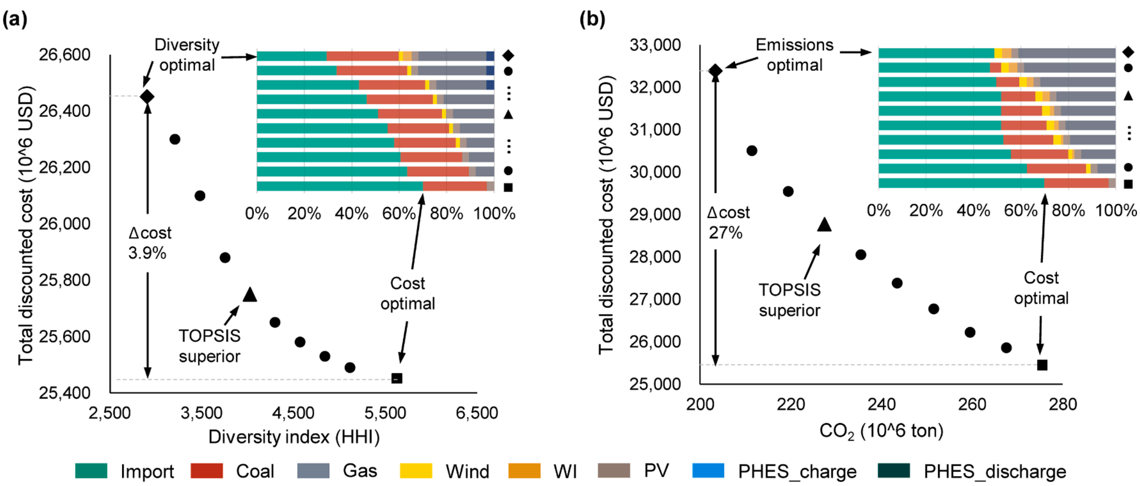


**Fig. 7.** Pareto frontier representing the trade-off between cost and diversity (a); the trade-off between cost and $CO_2$ emissions (b). The total discounted cost is the overall cost of 20-years horizon, the set of bar chart on the up-right corner represents the energy mix at 2030 for each optimal solution on the Pareto frontiers. Abbreviations: WI – waste incineration power, PV – photovoltaic, PHES – pumped hydro energy storage.

for nearly one-third of the energy mix. From the diversity-optimal scenario to the cost-optimal scenario (i.e., the least-cost solution), imported power's share increases gradually with declining share of gas power, while the share of coal power remains constant. This is because the cost of local coal power remains lowest of all energy technologies, and the price of imported power is lower than the cost of local gas power in this case. Compared to the cost-optimal scenario, the diversity-optimal scenario requires 3.9% additional cost. This additional cost is mainly caused by the cost difference between imported power and local gas power. Meanwhile, the PHES technology is only used when the requirement for energy diversity is high. Its potential on cost-saving or providing flexibility has not been fully realised unless the import power price difference on peak/off-peak is more significant.

Fig. 7(b) shows that, in the emissions-optimal scenario (i.e., the least emissions solution), coal power is completely phased out, and imported power becomes the biggest contributor with roughly 45.2% share, followed by gas power with 40.1% share. This is based on the assumed gradual decline of the emission factor for the provincial utility grid, lower emissions factor for gas power compared to coal, and the limited local resource potential for other renewable energy. As the cheapest coal power is phased out, 26.8% additional cost is incurred under the emissions-optimal scenario when compared to the least-cost scenario.

In general, due to the limited potential of renewables, imported power, coal power, and gas power are three major drivers for balancing the Energy Trilemma of Xiamen. In the trade-off between cost and energy diversity, imported power and gas power are directly competing with each other. In the trade-off between cost and emissions, coal power and gas power are seen as the two major competitors. In addition, a superior solution on the Pareto frontier has been specified for Fig. 7(a) and (b) individually by the TOPSIS posterior decision-making approach. The identified superior solution has maximal rationality for representing the trade-off between conflicting objectives, and for the ease of policy-making if needed.

Fig. 8 presents the energy portfolio evolution over the planning horizon and the hourly dispatch strategies of typical days for the three representative scenarios of the cost-optimal scenario, the diversity-optimal scenario, and the emissions-optimal scenario, as well as two superior solutions on Pareto frontiers as plotted in Fig. 7(a and b), respectively.

For the cost-optimal scenario (Fig. 8a ~ c), the coal power capacity remains stable over the entire planning horizon due to its low operational cost, accounting for 72.9% of annual energy output in 2030. Solar PV enters the energy mix in 2021 when the installation and O&M cost gradually drops to a competitive level. The capacity slowly increases under the annual build rate limit, leading to an annual energy out of 2.4% in 2030. From the system dispatch perspective, the system operational trends remain similar for different typical days; the hourly output of coal power remains stable, the output of PV only occurs during the daytime (6:00 ~ 17:00), and the remaining demand gap is met by imported power.

For the diversity-optimal scenario (Fig. 8d ~ f), the capacities of all technologies start to increase at the beginning of the planning horizon so as to maximise the diversity of power supply while considering the annual build rate limits. Among which, the renewables of solar, wind, and waste incineration power account for 2.4%, 5.4% 2.8% of the annual energy output in 2030. In terms of system dispatch, gas power, coal power, and waste incineration power output remain constant, while PV and wind power output are determined by climatic and resources availability conditions. PV output only occurs during the daytime, while wind power output is larger during the night-time than the daytime. PHES charging by surplus power occurs during the off-peak hours (1:00 ~ 9:00) while PHES discharge occurs during the peak hours (12:00 ~ 21:00). For different seasons, no significant difference is observed in the outputs of all local power generation technologies, and seasonal variations in demand are met by flexible imported power.

For the emissions-optimal scenario (Fig. 8g ~ i), coal power is completely phased out. Gas power and imported power are two major supply sources, accounting for 40.1% and 49.0%, respectively; while solar, wind, and waste incineration power together account for the remaining 11% of total supply. In terms of the hourly dispatch strategy, similar to other scenarios, both the output of gas power and waste incineration power are stable during the whole day; solar and wind output depend on the climate condition; and unmet demand is fulfilled by imported power. The seasonal demand variations are covered by the imported power, while the operational strategies of the other technologies remain unchanged.

The Superior-1 solution (Fig. 8j ~ l), considering the trade-off between cost and diversity, is similar with the Superior-2 solution (Fig. 8m ~ o), considering the trade-off between cost and emissions from the overall transition perspective over the planning horizon. The renewables of solar, wind, and waste incineration power account for 6.1% and 7.2% in total for the annual energy output of Superior-1 and Superior-2 solution, respectively, in 2030. The difference exists on the share of import power and gas power, where the import power and gas power account for 57.9% and 15.2% of annual energy output, respectively, in 2030 for Superior-1 solution; whereas the values are 50.8% and 20.2% for Superior-2 solution in 2030. The two superior solution are similar in terms of dispatch strategy, i.e. gas power and coal power keep stable all-

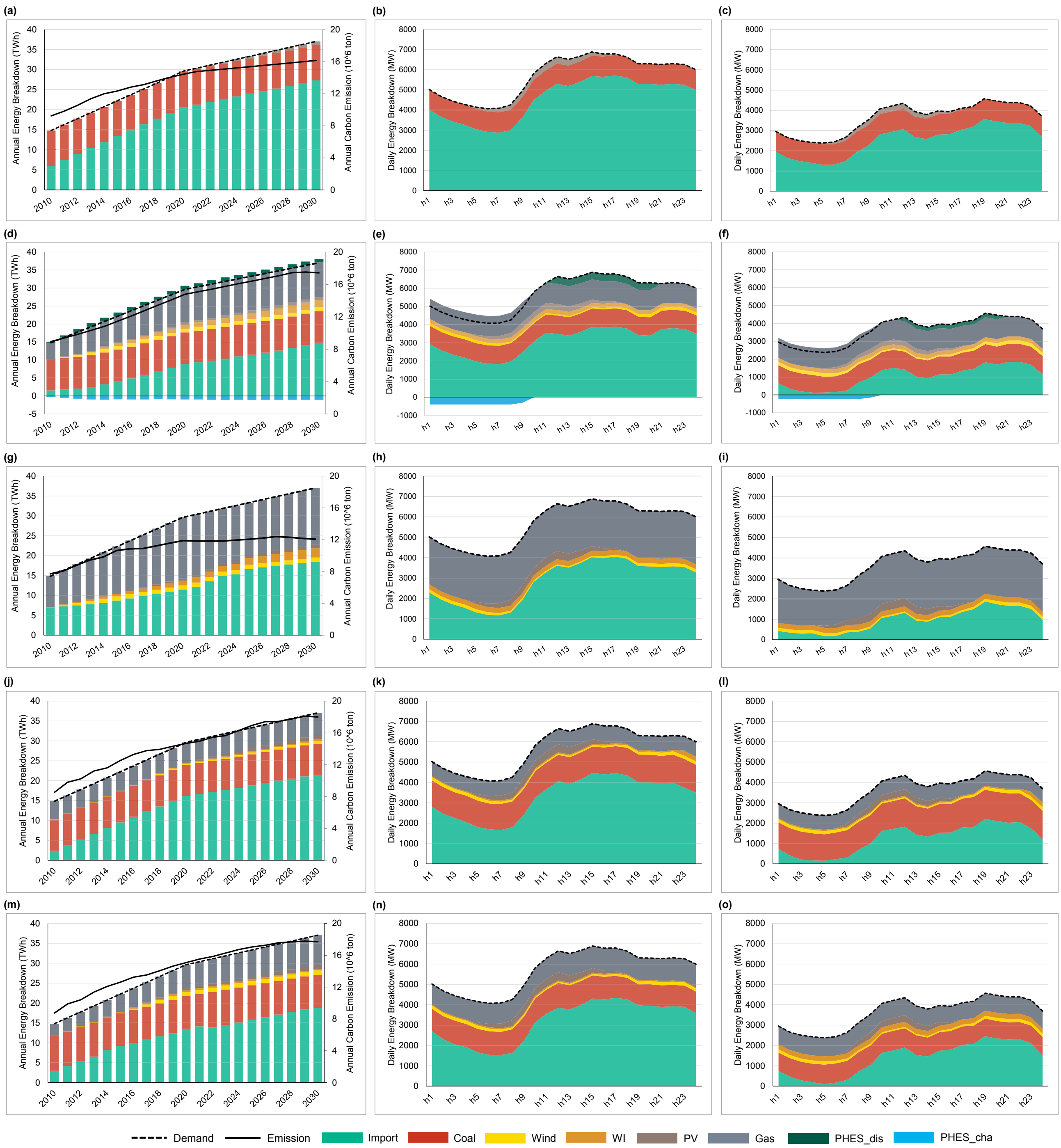


**Fig. 8.** Comparison of the cost-optimal scenario (a ~ c), the diversity-optimal scenario (d ~ f), the emissions-optimal scenario (g ~ i), the superior solution identified (known as Superior-1) considering the trade-off between cost and diversity (j ~ l), as well as the superior solution (known as Superior-2) considering the trade-off between cost and $CO_2$ emissions (m ~ o). Both Superior-1 and 2 are identified by the TOPSIS approach. Energy mix per year over the planning horizon (a, d, g, j, and m), energy balances for the representative summer-weekday by 2030 (b, e, , h, k, and n), energy balances for the representative winter-weekday by 2030 (c, f, i, l, and o). Abbreviations: WI – waste incineration power, PV – photovoltaic, PHES_cha/dis – power charge/discharge for the pumped hydro energy storage.

day, solar power output only occurs during the daytime, and the rest fluctuating demand is covered by import power.

As seen from three representative scenarios and two superior solutions, the outputs of combustion-based technologies, i.e., gas, coal, and waste incineration power, generally remains stable all-day, and the demand fluctuations are mainly covered by imported power. The output of renewable solar and wind power varies depending on the climate conditions, but their impacts on the overall power supply are insignificant due to the limited local resource potential, less than 9% of the annual energy output in 2030. In addition, as a representative of demand-side technology, PHES is only adopted when energy diversity is considered as the objective function. From the emissions perspective, the emissions-optimal scenario generates the least emissions as expected; while the cost-optimal scenario has lower emissions than the diversity-optimal scenario in 2030 as a result of declining emission factor for imported power from the Fujian provincial grid.

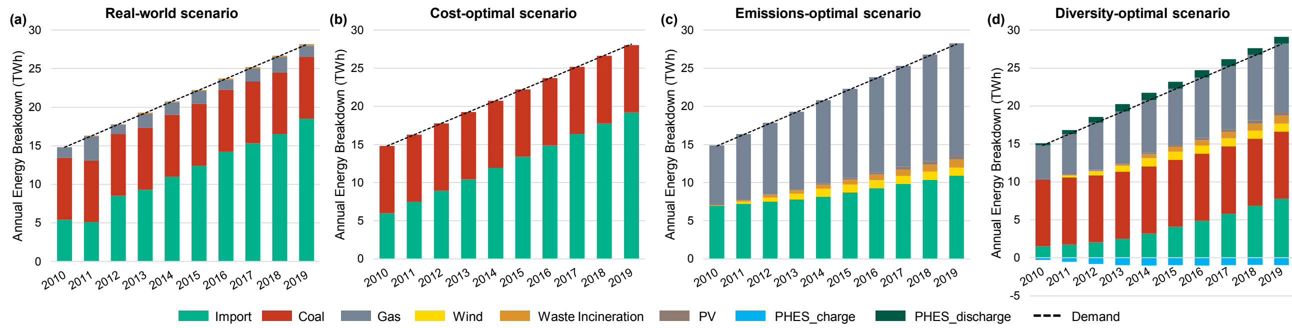


**Fig. 9.** Annual energy breakdown comparison (2010 ~ 2019) between the real-world scenario (a) and cost-optimal scenario (b), emissions-optimal scenario (c), diversity-optimal scenario (d). Abbreviations: PV – photovoltaic, PHES – pumped hydro energy storage.

### 4.2. Comparison of modelled results with real data and implications

For validation purposes, we compare the annual energy breakdown (2010 ~ 2019) of the three modelled scenarios with the real-world scenario based on actual reported historical data as shown in Fig. 9. In the real-world scenario, the proportion of coal power remains stable due to its low operational cost, and no significant increase in the proportion of gas power is observed over the time horizon due to the relatively high price of natural gas. The increase in electricity demand is mainly met by imported power from the provincial grid, while the total share of waste incineration power and PV is less than 2%.

Several policy insights can be generated by comparing three representative scenarios with the real-world scenario. (1) The cost-optimal scenario in Fig. 9(b) turns out to be most similar to the real-world scenario as the economy has remained a key factor for guiding decision-making. (2) Increasing the proportion of natural gas power is an effective measure for emissions reduction when the resource potential of solar and wind is limited as indicated in Fig. 9(c). (3) Implementing demand-side PHES will contribute to energy diversity, but coal, gas, and imported power remain the three major contributors for a diversity-optimal solution as shown in Fig. 9(d). In addition, because Xiamen's power supply relies on imported power to a considerable extent under all three scenarios, the electricity tariff, emission factor, and energy portfolio of the imported power would greatly affect the city's Energy Trilemma outcomes.

### 4.3. Methodological implications

The proposed optimisation framework of this study has the following advantages: (1) hourly temporal-resolution that can capture the demand-side flexibility such as utilisation of energy storage technology. (2) representative temporal-resolution in terms of years-seasons-days-scenarios-hours to capture the fluctuation of renewables and to evaluate short-term dispatch impacts on the long-term planning for the whole system. (3) ability to evaluate energy transition pathways considering the energy trilemma factors that are difficult to reconcile. Additionally, the bottom-up optimisation framework can be further extended to model several other sectors, including heating supply, transportion energy, and hydrogen planning, and re-formulated to capture parametric uncertainties through stochastic programming.

Our current approach has some limitations. To meet the goal of resilience; we introduce the diversity index as an objective function, which leads to a non-linear model with significantly greater computational requirements than a linear model. Although the concept of energy resilience is still not clearly defined, we introduced the diversity index in attempt to capture resilience goals because it is acknowledged that strengthening the vulnerable elements by increasing redundancy and energy storage; and enhancing the diversity of alternatives in the energy system can enhance energy systems' resilience at the design level [45]. We also adopted PHES as a demand-side management measure and introduced the diversity index as an objective function. A variety of indices [46], including the Herfindahl–Hirschman Index, Stirling Index, and Shannon-Wiener Index [47], can quantify the diversity of energy systems with different insights. But because all diversity indices found in literature causes non-linearity, more computationally efficient approaches are needed to evaluate the goal of resilience other than the diversity index.

Due to the computational complexity induced by the non-linearity from the diversity objective, the proposed model is deterministic without considering parametric uncertainties. Parametric uncertainties might have significant impact on the modelling results, including the future energy demand, fuel prices, and technology developments. Once again, more efficient ways of modelling resilience need to be explored so that the stochastic model could be further developed (based on the existing deterministic model) to address parametric uncertainties.

Another shortcoming of this study is the assumption on the perfect foresight of fully rational decision-makers over the time horizon. Though the assumption on the perfect foresight is widely applied in research field [48], in reality, investment decision-making is much more complex than simply cost minimisation. However, incorporating complex heterogeneous behavioral and any social aspects into the municipal-level planning model requires extensive research on relevant data and tools, as well as large remaining uncertainties. Thus, even though the gap between planning and real-world actions persists, energy planning can nevertheless still generate valuable insights by evaluating different possible scenarios and corresponding costs and benefits.

## 5. Conclusions

In this work, we developed a municipal-level, bottom-up optimisation framework with hourly temporal resolution and demand-side flexibility, and applied it to explore the sustainable transition pathways for the electricity sector of Xiamen City. Various scenarios based on the trade-offs among the Energy Trilemma of cost, emissions, and resilience are developed and analysed using multi-objective optimisation and decision-making approaches. The modelled scenarios are further verified by comparison with real-world conditions. The key findings include the following:

(1) Compared to the least-cost scenario, 3.9% additional cost is required for an optimal diversity solution for supporting energy resilience; and 26.8% additional cost is required to achieve a least-emission solution as the natural gas price is relatively high.
(2) Coal power is still a cost-efficient technology. Meanwhile, with limited local renewable resourced potential, natural gas and imported power play key roles in both the low-emissions and high-diversity electricity transition of Xiamen. As a demand-side technology, pumped hydro energy storage is only adopted

when optimising the diversity index but not considered to contribute to the goals of minimising cost or emissions.

(3) The non-linearity caused by the diversity index significantly increases the computational requirements for the model, and more computationally efficient ways of formulating energy resilience considerations need to be developed in future work.

By evaluating different possible pathways for a sustainable transition of Xiamen's electricity sector to help guide the decision-making processes of local policymakers, this study also offers important insights for other similar coastal cities considering energy transition pathways to balance Energy Trilemma.

## CRediT authorship contribution statement

**Rui Jing:** Conceptualization, Writing - original draft. **Yufeng Lin:** Resources. **Nina Khanna:** Writing - review & editing. **Xiang Chen:** . **Meng Wang:** Validation. **Jiahui Liu:** . **Jianyi Lin:** Supervision, Writing - review & editing.

## 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.

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