Quantifying the contribution of individual technologies in integrated urban energy systems – A system value approach✧

Rui Jing [a,b], Kamal Kuriyan [b], Jian Lin [a], Nilay Shah [b], Yingru Zhao [a,*]

a College of Energy, Xiamen University, Xiamen, China

b Department of Chemical Engineering, Imperial College London, London, UK

Abstract

Integrated urban energy systems satisfy energy demands in a cost-effective manner by efficiently combining diverse technologies and energy saving strategies. However, the contribution of an individual technology within a complex system is difficult to quantify. This study introduces a generalized "system value" approach to quantify the contribution of an individual design decision towards improving the system design (e.g., achieving a lower cost design). It measures the contribution of an individual technology to the whole system in the range between two benchmarks that respectively represent complete exclusion of the technology and the optimal penetration level. The method is based on a technology-rich Mixed Integer Linear Programming (MILP) model for optimal design of urban energy systems. The model considers multi-energy supply technologies, networks, storage technologies and various energy saving strategies. A stochastic formulation is further developed to quantify uncertainties of the system value. The system values of nine kinds of energy supply technologies and three categories of energy-saving strategies are quantified via a case study, which illustrates the variation in the system values for individual technologies with different levels of penetration, and multi-energy supply technologies can have a large impact in integrated systems.

Keyword: system value; LCOE; integrated urban energy system; technology valuation; supply and demand optimization; stochastic programming

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*Corresponding author. Tel.: +86 592 5952781. E-mail: yrzhao@xmu.edu.cn
First author E-mail: fafujingrui@126.com

Nomenclature

Abbreviations	
ATC	Annualized total cost
CAPEX	capital cost
CCS	carbon capture and storage
CHP	combined heating and power
CRF	capital recovery factor
GC	grid cost
HDD	heating degree day
LCOE	levelized cost of energy
MC	maintenance cost
MILP	mixed integer linear programming
OPEX	operation cost
PV	photovoltaic panel
SRI	solar radiation index
SV	system value
UES	urban energy system
WWR	window-to-wall ratio

Symbols	
C	cost
CAP	installed capacity
E	electrical power
DX	distance between buildings
M	big "M"
Q	thermal energy
prob	probability
Lo	Transmission loss

Greek symbols	
α	energy charge/discharge status
β	on/off status
η	efficiency
μ	grid connection status
χ	start frequency limit
δ	energy network built/not
γ	energy transfer direction
φ	implement saving strategies/not
λ	CHP heat-to-power ratio

Subscripts/superscript	
ac	absorption chiller
b	boiler
batt	battery
CAP	capital cost
cf	cooling energy flow
cha	energy charge
cool	cooling energy
c-pipe	cooling pipework
dem	demand
disc	energy discharge
DH	district heating
DC	district cooling
ec	electrical chiller
ex	electricity feed-back
h	hour
heat	heating
hf	heating energy flow
h-pipe	heating pipe
hp	heat pump
i	building serial number
im	imported electricity
in-st	in storage
j	building serial number
k	energy saving options
maint	O&M cost
n	project lifetime
NG	natural gas
pipe	energy network
r	interest rate
re	recovered heat
s'	scenario
s	season
st-in	electricity charging
st-out	electricity discharging
t	each technology
win	window
y	capacity increment index

1 Introduction and background

Urbanization is one of the most important trends globally and improving the sustainability of urban energy systems (UES) is a central element in the fight against global warming. As the share of people living in urban areas grows both regionally and globally, an increasing amount of energy is required to fulfill energy demands, particularly for buildings [1]. As of 2017, the urban buildings and construction sector accounted for 36% of final energy use and 39% of energy related emissions [2]. Compared with 2010, space cooling energy use had increased by more than 20% and appliance electricity demand had grown by 18% in 2017, corresponding to an increase of more than 6 exajoules (EJ) p.a. in global final energy consumption [3].

The application of optimization methods in UES design has considerable potential to improve sustainability [4]. UES have become increasingly complex with the development of decentralized technologies, e.g., intermittent renewable energy sources, co/tri-generation technologies, power-to-gas, electricity and thermal storage [5], but thanks to the improvement in mathematical programming techniques, these complex systems can be optimized to achieve specific objectives, among which the most frequently used and fundamental one is the energy cost [6]. Although the optimal system design, including the best technical configuration and dispatch strategies can be determined by the solution from a mathematical programming model, the value an individual technology contributes to that objective is not explicitly quantified. The approach presented in this paper quantifies the value lost if a technology may be excluded or unavailable for practical reasons and how its value may vary with the level of penetration.

1.1 Valuation of energy technologies in integrated systems

Valuation of a technology is particularly important for analyzing the integration of new technologies, e.g., intermittent renewable energy [7], large scale electricity storage [8], and carbon capture and storage (CCS) [9]. Kitapbayev et al. [10] investigated the flexibility that thermal storage can provide to district energy systems in terms of the real option value considering the stochastic price of electricity and gas. Cost reductions offered by thermal storage coupled with CHP were found to be robust even with unfavorable trends in energy price. Gottwalt et al. [11] calculated the cost savings for different groups of consumer devices resulting from demand side scheduling in a microgrid with an aggregator. The generation cost savings for the aggregator were normalized with respect to a benchmark without load control to rank the residential demand response flexibility of individual groups of appliances. The results showed that electric vehicles, batteries, and heaters with storage are the most promising devices for residential demand response.

The levelized cost of energy (LCOE) is one of the most frequently used valuation criteria when designing urban or other energy systems [12]. Schmidt et al. [13] applied an analogous concept, the levelized cost of storage (LCOS), to the valuation of nine electricity storage technologies in twelve possible applications. They highlighted the importance of evaluating a technology or system from a lifespan cost perspective and not merely on investment cost. Economic parameters contributing to energy system costs may include fuel prices, capital costs, operational costs, carbon taxes, subsidies and quotas [14]. Hirth et al. [15] evaluate the integration costs of wind and solar power where the integration costs may include costs associated with balancing services, more flexible operation of thermal plants and reduced utilization of infrastructure. A “system LCOE” for a technology type is obtained by combining the integration cost with the “technology LCOE”. To extend this valuation method to multi-region applications, Reichenberg et al. [16] incorporate the impact of transmission and storage capacities in the calculation of the “system LCOE”. This allows them to quantify the system costs with a high penetration rate of renewable energy.

Many of these approaches utilize the LCOE as the economic index of a particular energy technology in isolation, with a separate evaluation of integration costs based on the penetration level the technology and prevailing installations of other technologies. More systemic approaches are required that use a unified measure to quantify the contribution of a technology considering the interaction of all the relevant technologies. Pudjianto et al. [17] introduced a systemic measure based on an optimization model for comparing the value that bulk and distributed electricity storage technologies can contribute to electricity systems from a whole-system perspective. Their research indicated that electricity storage has potentially greater economic benefits than other demand-side technologies, e.g., flexible generation, demand response, and interconnections. Heuberger et al. developed a “system value” approach to quantifying the value of energy storage technologies in the long-term energy mix planning of electricity systems [18], and applied a similar concept to evaluate the benefit of CCS in future energy scenarios [9]. Nielsen et al. [19] proposed a yearly monetary savings index to compare the economic benefit of both heat pumps and electrical boilers coupled with heat accumulators and CHP units within a district heating system in Denmark. The results indicate that the largest value for these technologies is obtained with lower electricity prices which is of particular importance given the predicted impact of a larger share of wind in the Danish electricity mix. All these studies have made pioneering efforts in technology valuation from a systemic perspective, the idea could be applicable for evaluating the investment decisions of complex UES incorporating both supply and demand-side technologies.

1.2 Simultaneous optimization of energy supply and saving strategies

Optimization techniques have been widely applied to solve decision-making problems of complex systems in building energy saving research, as reported by Diakaki et al. [20], Senel et al. [21], and Gou et al. [22]; and in UES energy supply design problem, e.g., Scheller et al. [23], Jing et al. [24], and Zhang et al. [25]. However, less attention has been paid to the problem of simultaneously optimizing both the energy supply technologies and demand-side energy saving strategies. The possible difficulties lie in 1) the knowledge gap between building energy saving research and energy system planning research, 2) the difficultly of matching different modelling scales, or 3) integrating non-linear building energy expressions within linear urban energy system design models. Nevertheless, incorporating energy supply and saving strategies from a centralized planning perspective could achieve a better overall system planning. A few representative articles are as follows

Nielsen at al. [26] find that selecting the correct level of energy savings measures depends on the supply system type and the heat supply cost. They highlight the need to incorporate the impact of energy savings measures in specific buildings into the overall energy system planning. Meyer et al. [27] identify policy initiatives provided by the utility company, that can serve as incentives for investments in savings measures for the property owners and other stakeholders. They also stress the importance of synchronizing investments in energy conservation measures with that in the supply side to avoid overinvestment in the supply system. Jennings et al. [28] proposed a detailed urban energy system planning model considering both supply side and demand side technologies with explicit spatial and temporal resolution and illustrated its application with a detailed case study which presented guidance on technology upgrades at the concept design stage. Wu et al. [29] introduced a combined building envelope optimization and energy system design framework, and further applied this to a residential case study. The results indicate that the trade-off between cost and emissions will have a significant impact on the selection of retrofit options. Zheng et al. [30] conducted an industrial retrofitting case study considering both demand-side retrofits and supply side technical upgrades. The use of fossil fuels turns out to be essential during summer, and the technology mix is greatly affected by the grid electricity price. These papers explored the feasibility of centralized planning by simultaneous optimizing supply and demand-side technologies via one model, which laid a preliminary foundation for the present study.

1.3 Motivation and contribution

Based on the review of previous research, each energy technology's cost in isolation is typically quantified by an absolute monetary valuation of LCOE, with extensions to account for additional costs or benefits in the context of an integrated system. However, several challenges still exist:

- Although a lower overall cost of an integrated UES can be achieved through the combination of multiple energy technologies, it is difficult to quantify the contribution of an individual component in an integrated system in a general way and considering all interactions between different types of technologies, storage, and network designs.
- Insufficient efforts have been made on the valuation of the investment decisions in integrated UES considering the existence of both supply technologies and energy saving strategies, as well as the uncertainties.

Therefore, we introduce a generalized "system value" approach for the systemic valuation of individual investment decisions on a range of supply technologies and demand-side saving strategies. By using a unified and convenient measure, the contribution of individual energy supply technologies, energy storage technologies, and energy saving strategies can be quantified from a systemic perspective.

The contributions of this paper are as follows:

- Develop a generalized "system value" approach based on a UES optimization model to quantify the benefit of a range of urban energy technologies in a systemic context that capturing cross-sector interactions among heating, cooling and electricity supply technologies, network design, and energy-savings measures;
- Propose a technology-rich model incorporating both urban energy supply technologies and energy saving strategies which considers the impact of energy saving strategies on the optimal level of supply technologies and vice versa;
- Quantify the uncertainty in the "system value" by applying both deterministic and stochastic modelling approaches.

The rest of the paper is organized as follows,

Section 2 introduce some concepts and the outline of this study. Section 3 applies the method to a case study. Section 4 analyzes the obtained results considering uncertainties. Some conclusions are drawn in Section 5. The detail model is provided as Appendix.

2 Methods

As energy systems become increasingly integrated and complex, it is necessary to evaluate an individual technology within an overall systemic context rather than in isolation. Hence, this paper introduces a generalized "system value" approach, which allows decision-makers to compare and prioritize different technologies from a systemic perspective.

2.1 System value approach

The system value for an individual technology depends on the technology itself, the system within which the technology is adopted, and the penetration level of that technology.

2.1.1 System value definition

Previous research defines the system value (SV) of a technology as the marginal benefit that the technology can bring to the integrated system as a function of its installed capacity (or investment). In their approach, the scenarios reflecting policy targets for large-scale power systems are used as benchmarks in the calculation of the system value. The system value is calculated as the reduction in the system cost obtained from the solution of an optimization model, using the benchmark scenario as a starting point, and gradually increasing the availability of the evaluated technology [9]. In this study, the ***technology exclusion benchmark*** where a technology is modelled but completely excluded in the optimal system design is used as the starting point since it is more convenient for the green-field design of an urban energy system. The system value is the cost reduction resulting from the incremental installation of that technology as determined from the solution of the optimization model described in the following sections. By collecting the cost reductions for each step of incremental installation, an aggregated curve of system value as a function of installed capacity can be plotted.

The system value approach is present study is derived based on the integrated UES, "energy cost" is chosen as the illustrative metric of the "system value"; the objective function normally includes the operational cost (*OPEX*) and the annualized capital cost (*CAPEX*) as defined in Eq. (1).

$$\begin{aligned} Obj &= OPEX + CAPEX \\ &= OPEX + \sum_t CAP_t \times \mathrm{C}_t^{\mathrm{Capital}} \times \mathrm{CRF}_t \end{aligned} \tag{1}$$

where subscript t denotes each type of technology within the system, CAP is the installed capacity, $\mathrm{C}^{\mathrm{Capital}}$ is the unitary capital cost, CRF is the capital recovery factor to annualize the capital cost.

Then, the ***benefit*** (***B***) is defined as the reduction in *OPEX* plus the reduction in *CAPEX* of other technologies due to increase in capacity of that specified technology, see Eq. (2).

$$B_y = (Obj_{y=0} - Obj_y) + TC_y \tag{2}$$

where subscript y represents the increment of installed capacity for that technology (y=0 denotes the technology is not installed in the system as the technology exclusion benchmark); TC is the ***technology cost*** and is equal to the *CAPEX* of that technology; when one technology is not installed (i.e. y=0), the $TC_{y=0}$ is zero obviously, and as previously defined in Eq. (1), the TC is linear with its installed capacity.

Fig. 1 brings forward an actual plot of aggregate system value for the CHP from the following case study. Based on the ***technology exclusion benchmark***, the aggregate system value as a function of installed capacity can be plotted. The maximum value is expected at the point where the slope of aggregate benefit is less than the slope of aggregate cost. Corresponding installed capacity reaches its optimal value in the original model. If the installed capacity exceeds that optimal value, the system value is expected to drop.

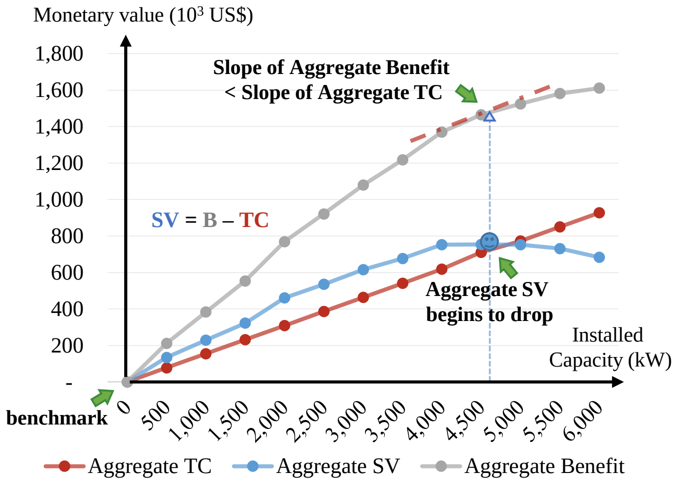

Fig 1 System values (SV), technology cost (TC), and benefit (B) for an individual technology as a function of installed capacity

2.1.2 Calculation procedure

Based on above definition, Fig. 2 illustrates the procedure of the system value approach. In Step 1, a technology-rich urban energy system (UES) model including both energy supply technologies and energy saving strategies is formulated and is defined as the **original model** without adding extra capacity control constraints. In Step 2, an optimal design of the system configuration involving specific types of energy supply technologies and energy-saving strategies is obtained (i.e., $t \in t_a$) by solving this model; the rest modelled but not installed technology/strategy are categorized as $t \in t_b$. In Step 3, extra capacity control constraints are applied to an individual technology or energy saving strategy, with three stages, Step 3.1 – **exclude** the technology or energy saving strategy (i.e., $t \in t_a$) from the optimal design obtained in Step 2, run the optimization, and consider the optimal objective value (i.e. cost in this case) as the **benchmark**; For the technology or saving strategy that is not installed (i.e., $t \in t_b$) in Step 2 but exist in the technology-rich original model, the optimal cost obtained in Step 2 is the **benchmark**. Step 3.2 – increase the installed capacity of that technology iteratively, run the optimization, and collect a series of optimal cost. Until Step 3.3 – **oversize** that technology beyond the optimal capacity obtained in Step 2, run the optimization, and collect the optimal cost. Note that when extra constraints are applied to an individual technology or energy-saving strategy, the remaining technologies and strategies are free to change. In Step 4, the "system value" of each technology and saving strategy can be calculated as the value difference between the optimal cost obtained in Step 3.2, 3.3 and that from Step 3.1 (if $t \in t_a$) or Step 2 (if $t \in t_b$). By plotting the aggregated curve of system value against installed capacity, the maximum value and corresponding installed capacity can be determined in Step 5. By changing the technology or energy saving strategy one at a time in Step 6, the system value of each technology or energy saving strategy can be obtained individually. To quantify the system value variations against uncertainties, a stochastic model which is an extension of the original deterministic model is developed in Step 7.

Two different formulations for calculating system value are defined for either maximization objective scenario or minimization objective scenario as shown in Eq. (3); the present example is an energy cost minimization scenario. The calculation here is based on the cost reduction ($Obj_{y=0} - Obj_y$) with respect to the ***technology exclusion benchmark***.

$$SV_{t,y} = \begin{cases} Obj_{t,y} - Obj_{t,y=0} & \text{for maximization objective} \\ Obj_{t,y=0} - Obj_{t,y} & \text{for minimization objective} \end{cases} \quad \forall t \text{ and } y=0,1,2,...\text{opt},...,\text{N} \tag{3}$$

where the energy cost is formulated as the objective function (Obj); t represents the technology; iteration y represents the increment of installed capacity by adding extra capacity control constraints in Step 3, where y=0 is the ***benchmark*** condition as in Step 3.1 (if $t \in t_a$) or Step 2 (if $t \in t_b$). This is accomplished by specifying a constraint on the value of the technology capacity variable CAP as defined in Eq. (1). For the first iteration (i.e., y=0), the capacity is set to zero. The number of y iterations (N) can be user-defined and should be sufficiently large to cover the optimal condition as obtained from the **original model** (y=opt) and may be extended to "over-size" conditions in Step 3.3. The maximum system value (SV) is expected to be achieved at the optimal condition (y=opt).

2.1.3 Features of the approach

In general, the system value approach in the paper shares a similar purpose with the sensitivity analysis via the traditional "shadow price" method for quantifying the additional benefit resulting from an increase in the capacity of a technology. The differences lie in: (1) The complex energy system model is a combinatorial discrete optimization model, formulated as a MILP, for which it is difficult to calculate the additional benefit by the traditional shadow price approach; instead, the system value approach directly calculates the additional benefit as the objective function differences obtained by adding additional capacity control constraints and is straightforward to implement. (2) The "shadow price" method calculates the additional benefit of a technology with respect to the optimal solution of the original model; in contrast, the system value approach evaluates the benefit of a technology in the entire range between the technology exclusion benchmark and the optimal solution of the original model, which is particularly useful for technology comparison in green-field energy system designs.

In the meantime, this system value definition has several attributes:

- In contrast to a "technology LCOE" approach, where the integration costs resulting from the penetration level the technology and prevailing installations of the remaining technologies are calculated separately, the system value method directly accounts for both of these factors in the technology valuation.
- The system value method can demonstrate the individual benefit that adding incremental units of capacity for a technology contribute to the integrated system; and it is not limited to a monetary valuation but can also be an environmental or other benefit valuation index.
- This approach is applicable for complex systems' model where at least one alternative exists for supply technologies to match the demand; if a system model only has only one supply technology matching one demand, then that technology would always be the first priority for decision-makers, and there is no need to quantify its value or compare it with other technologies.

Notice that the system values of different technologies and energy saving strategies are evaluated based on a green-field case. Urban energy retrofits can be considered as a straightforward extension with additional bounds on certain design variables.

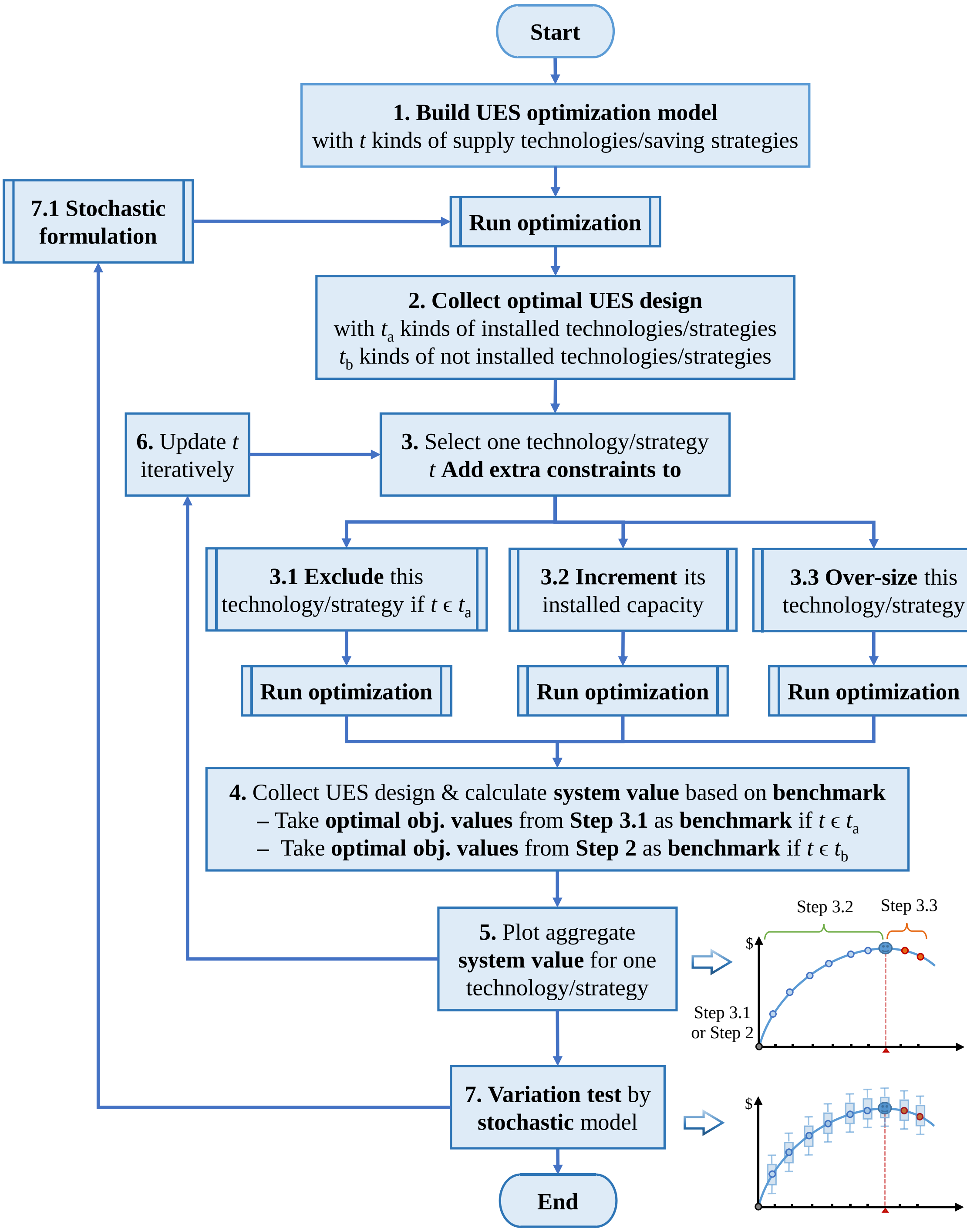

Fig 2 Calculating procedure of system value approach

2.2 Modelling with supply technologies and saving strategies

To evaluate system values of diverse technologies, a technology-rich model for optimal design of community-level UES is developed. As shown in Fig. 3, within each building, an integrated energy system may be implemented potentially incorporating a representative range of supply technologies and demand-side energy saving measures. Energy transfers between buildings and interactions with the utility grid are also considered. The optimization model would select a subset of these supply technologies, savings measures and transfer connections; and optimize the installed capacity, network design, and system operational strategy with the least energy cost and subject to a series of constraints.

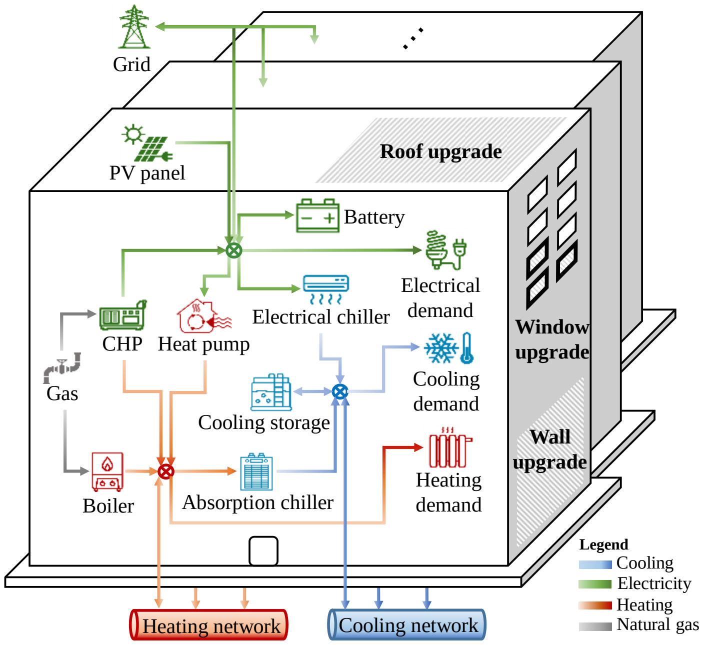

Fig 3 Technology-rich model for optimal design of multi-node community-level urban energy systems

As described in section 1.2, the modelling of energy supply technologies has been widely investigated in the UES research field [31], but relatively few articles have considered energy supply technologies and energy saving strategies simultaneously. Assuming the basic building design can meet relevant standards of building energy efficiency, applying energy saving strategies can further reduce cooling and heating demand at each time interval. The combined model should account for these savings and also the additional investment cost in the integrated system. The overall system capital cost (CAPEX) accounts for the energy saving upgrade cost as shown in Eq. (4).

$$\begin{aligned} CAPEX = & \sum_i \sum_t CAP_{i,t} \times \mathrm{C}_t^{\mathrm{Capital}} \times \mathrm{CRF}_t + \sum_i \sum_{j \neq i} \mathrm{DX}_{i,j} \times \mathrm{C}_{\mathrm{pipe}}^{\mathrm{Capital}} \times \mathrm{CRF}_{\mathrm{pipe}} \\ & + \sum_i \Big(\sum_{k=1,2,3} \varphi_{i,k}^{\mathrm{roof}} \times \mathrm{C}_{i,k}^{\mathrm{roof\text{-}Capital}} + \sum_{k=1,2,3} \varphi_{i,k}^{\mathrm{win}} \times \mathrm{C}_{i,k}^{\mathrm{win\text{-}Capital}} + \sum_{k=1,2,3} \varphi_{i,k}^{\mathrm{wall}} \times \mathrm{C}_{i,k}^{\mathrm{wall\text{-}Capital}} \Big) \end{aligned} \tag{4}$$

where the subscripts *t, k, i* represent *t* kinds of energy technologies, *k* options of energy saving upgrades, and serial number of buildings, respectively. *CAP* is the installed capacity, CRF is the capital recovery rate, based on an interest rate of 6% and a life of 20 years for each technology, 25 years for energy saving upgrades, and 30 years for pipework [32]. $\mathrm{C}^{\mathrm{Capital}}$ is the unitary capital cost of different technology types and upgrades, DX denotes distances between buildings, φ is a binary variable representing the choice of a particular energy saving strategy.

In the model formulation, instead of aggregating all energy saving strategies, this study considers upgrade actions on roof, walls and windows individually. Consistent with the approach for modelling energy supply technologies, all energy saving strategies are considered as “virtual” technologies and integrated into the model as linear items. Taking the heating balance as an example shown in Eq. (5).

$$(Q_{i,s,h}^{\text{h-dem}} - \sum_{k=1,2,3} \varphi_{i,k}^{\text{win}} \times Q_{i,s,h,k}^{\text{h-win}} - \sum_{k=1,2,3} \varphi_{i,k}^{\text{roof}} \times Q_{i,s,h,k}^{\text{h-roof}} - \sum_{k=1,2,3} \varphi_{i,k}^{\text{wall}} \times Q_{i,s,h,k}^{\text{h-wall}}) + \sum_{j \neq i} Q_{i,j,s,h}^{\text{hf}(i,j)} + Q_{i,s,h}^{\text{ac-heat}} = Q_{i,s,h}^{\text{re-heat}} + Q_{i,s,h}^{\text{hp}} + Q_{i,s,h}^{\text{b-heat}} + \sum_{j \neq i} Q_{j,i,s,h}^{\text{hf}(j,i)} \times (1 - Lo^{\text{h-pipe}}) \tag{5}$$

where Q represents heating energy, φ is a binary variable representing the selection of one energy saving strategy. k indicates the three options (i.e., basic, improved, and high standard) that are available for each energy saving strategy (upgrading window – win, roof, and wall) individually, i and j are the serial number of buildings, s and h denote seasons and hours, respectively. The superscripts h-dem, hf, re-heat, ac-heat, hp and b-heat indicate heating demand, heat flow, recovered heat from CHP, heat consumed by absorption chiller and heating supply from heat pump and boiler, respectively. $Lo^{\text{h-pipe}}$ is the heat loss rate of the heating network.

To maintain model linearity, the energy saving potentials of $Q^{\text{h-win}}$, $Q^{\text{h-roof}}$ and $Q^{\text{h-wall}}$ are all considered as input parameters, whose values can be calculated based on the U value difference as derived in Eq. (6a~c) [33].

$$Q^{\text{h-dem}} = 86.4 \times S \times \overline{U} \times HDD_{18} \tag{6a}$$

$$\overline{U} = (1 - \frac{1}{S \times H}) \times U_{e} + \frac{1}{S \times H} \times U_{\text{roof}} \tag{6b}$$

$$U_{e} = WWR \times U_{\text{win}} + (1 - WWR) \times U_{\text{wall}} \tag{6c}$$

where S is shape factor, $\overline{U}$ is external envelope average heat transfer coefficient [W/(m^2 ◦C)], HDD_{18} is heating degree days based on 18 ◦C. H is building height, U_e is window and wall heat equivalent transfer coefficient, U_{roof} is heat transfer coefficient for roof. WWR is window-to-wall ratio, U_{win} and U_{wall} are heat transfer coefficient for windows and wall, respectively.

By varying the U value before and after energy saving upgrades, the saving potential can be estimated. As energy savings could be affected by other factors, e.g., occupants, equipment and lighting [34], the cost data for each energy saving upgrade option varies significantly in the literature, e.g., in Ref. [35] and Ref. [36], conservative saving values, from Ref. [37] and Ref. [38], are selected as the model inputs. In this case, the assumed cost only includes the material related cost, while the labor cost and any other cost (e.g. finishes) are not included as they should be part of the original building construction plan.

Table 1 energy saving strategies' performance and cost

Energy saving strategies	Parameters	Basic*	Improved#	High standard^
Window insulation upgrade	U_{win} (W/m^2 K)	2.76	1.89	1.15
	unit cost (\$/m^2)	90	140	170
Roof insulation upgrade	U_{roof} (W/m^2 K)	0.53	0.26	0.19
	unit cost (\$/m^2)	12	24	38
Wall insulation upgrade	U_{wall} (W/m^2 K)	0.43	0.36	0.24
	unit cost (\$/m^2)	9	17	30

*Basic: 6cm wall insulation, 6cm roof insulation, 6/12/6 windows; #Improved: 8cm wall insulation, 14cm roof insulation, 3/12/3 Low-E windows; ^High standard: 14cm wall insulation, 20cm roof insulation, 4/16/4/16/4 windows.

Only one out of three discrete options (i.e., basic, improved, and high standard) for each energy saving strategy (i.e., window, roof, and wall insulation upgrades) is allowed as constrained by Eq.

(7a~c). If needed, decision-makers can control the implementation of any strategy by pre-defining the value of φ.

$$\sum_{k=1,2,3} \varphi_{i,k}^{\text{roof}} \leq 1 \tag{7a}$$

$$\sum_{k=1,2,3} \varphi_{i,k}^{\text{win}} \leq 1 \tag{7b}$$

$$\sum_{k=1,2,3} \varphi_{i,k}^{\text{wall}} \leq 1 \tag{7c}$$

2.3 Stochastic programming

Various kinds of uncertainties exist when establishing the model, e.g., uncertain energy demand, energy prices, and climate conditions [39]. Stochastic programming is a widely used approach to deal with uncertainties in practice [40]. A stochastic model is formulated to quantify the uncertainty in the "system value" results. Since this study focuses on introducing the generalized "system value" approach, the proposed stochastic model only features the main principles of dealing with uncertain inputs, while not aiming to innovate in stochastic programming. The scenario generation procedure and the mathematical formulation of the optimization model are discussed in the next two sub-sections.

2.3.1 Scenario generation

In this study, multiple uncertainties from cooling demand, heating demand and solar radiation index (SRI) are considered and built as a scenario tree. Building cooling and heating demands are estimated by building energy simulation software in a conservative manner. Then, three levels of cooling demand, i.e. high, medium, and low, are assumed as 100%, 75%, and 50% of the simulated cooling demand, respectively; two levels of heating demand, i.e. high and low, are assumed as 100% and 70% of the simulated heating demand, respectively; and two levels (i.e. high and low) of SRI values are assumed as detailed in the following paragraph. An overview of the scenario tree is presented in Fig. 4 with 12 scenarios in total, the probability of each scenario is calculated by the multiplication of the probability of corresponding uncertain parameters.

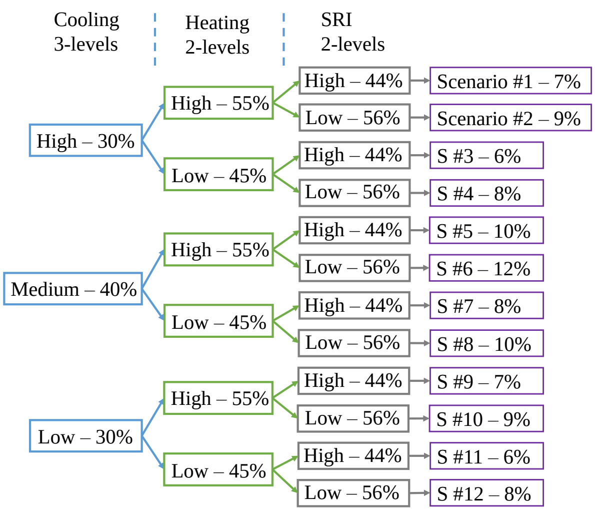

Fig 4 Illustrative stochastic scenario tree with probability assigned to each uncertain parameter

The k-means clustering technique is applied to generate SRI scenarios based on historical data for the previous three years, following an approach similar to that of Ref. [41]. By plotting hourly SRI values discretely as shown in Fig. 5, the k-means clustering technique can categorize all points within each hour into a pre-defined number of clusters (two in this case). Then, the centroid of each cluster is considered as the representative SRI value for each hour. By connecting the corresponding centroids, two SRI profiles can be generated as shown by the green and blue curves. The weight (W_{high} or W_{low}) of each cluster is calculated from the number of points belonging to that cluster. The rest of the input parameters are assumed as constants.

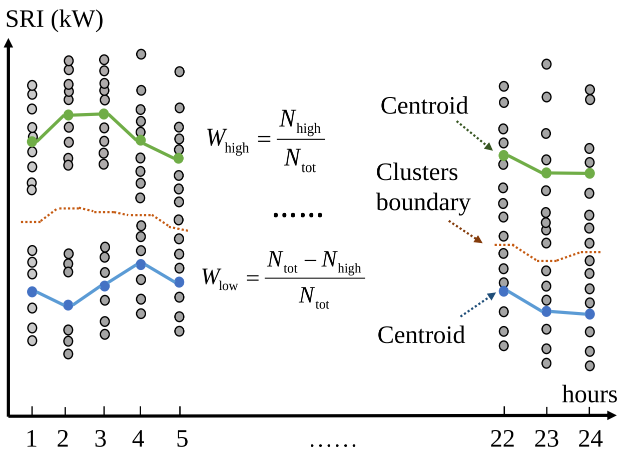

Fig 5 K-means clustering based approach to generate SRI scenarios and corresponding weights

2.3.2 Stochastic formulation

By introducing an additional index *s'* to represent different scenarios, the deterministic model can be converted to a stochastic model. For a UES model, the design variables, e.g., installed capacity and implementation of energy saving strategies, should remain constant in all scenarios; while the values of operational variables, e.g., hourly energy input/output from each technology, could be different due to parameter differences in various scenarios.

Taking Eq. (5) as an example, the stochastic formulation is shown in Eq. (8), in which the binary variable (φ), which controls the decision of adopting energy saving strategies, should remain constant in all scenarios. In contrast, operational variables, e.g., heating output from technologies, can vary in different scenarios. The rest of modelling constraints are presented in the **Appendix**.

$$\begin{aligned}&(\mathrm{Q}^{\text{h-dem}}_{s',i,s,h} - \sum_{k=1,2,3} \varphi^{\mathrm{win}}_{i,k} \times \mathrm{Q}^{\mathrm{win}}_{s',i,s,h,k} - \sum_{k=1,2,3} \varphi^{\mathrm{roof}}_{i,k} \times \mathrm{Q}^{\mathrm{roof}}_{s',i,s,h,k} - \sum_{k=1,2,3} \varphi^{\mathrm{wall}}_{i,k} \times \mathrm{Q}^{\mathrm{wall}}_{s',i,s,h,k}) + \sum_{j \neq i} Q^{\mathrm{hf}(i,j)}_{s',i,j,s,h} + Q^{\text{ac-heat}}_{s',i,s,h} = \\ &Q^{\text{re-heat}}_{s',i,s,h} + Q^{\mathrm{hp}}_{s',i,s,h} + Q^{\text{b-heat}}_{s',i,s,h} + \sum_{j \neq i} Q^{\mathrm{hf}(j,i)}_{s',j,i,s,h} \times (1 - Lo^{\text{h-pipe}})\end{aligned} \quad (8)$$

The overall energy cost formulations are different from the deterministic model as shown in Eq. (9).

$$\begin{aligned}&\mathrm{Min} \quad Obj_{\mathrm{total}} = CAPEX + \sum_{s'=1}^{N} \mathrm{prob}_{s'} \times OPEX_{s'} \\ &OPEX_{s'} = \sum_{s} \sum_{h} \sum_{i} [FC_{s',s,h,i} + MC_{s',s,h,i} + GC_{s',s,h,i}]\end{aligned} \quad (9)$$

where Obj_{total} is the overall energy cost including the capital cost (*CAPEX*) and the expected value of operation cost (*OPEX*); $prob_{s'}$ represents the probability of different scenarios; *FC*, *MC*, and *GC* are fuel cost, maintenance cost, and grid electricity cost (including electricity purchasing cost minus electricity feed-back revenue), respectively. Detailed calculations of the objective are presented in **Appendix**.

3 Case study

To demonstrate the system value approach, a case study is conducted for a newly designed business zone in Shanghai, China. Six commercial buildings with network availabilities are illustrated in Fig. 6(a). Each building has its own energy demand profiles as shown in Fig. 6(b~d), where a whole year is divided into summer/winter/transition seasons, cooling is required in summer and heating is provided in winter. In addition, the solar radiation index, that will affect the solar PV output, is displayed in Fig. 6(e).

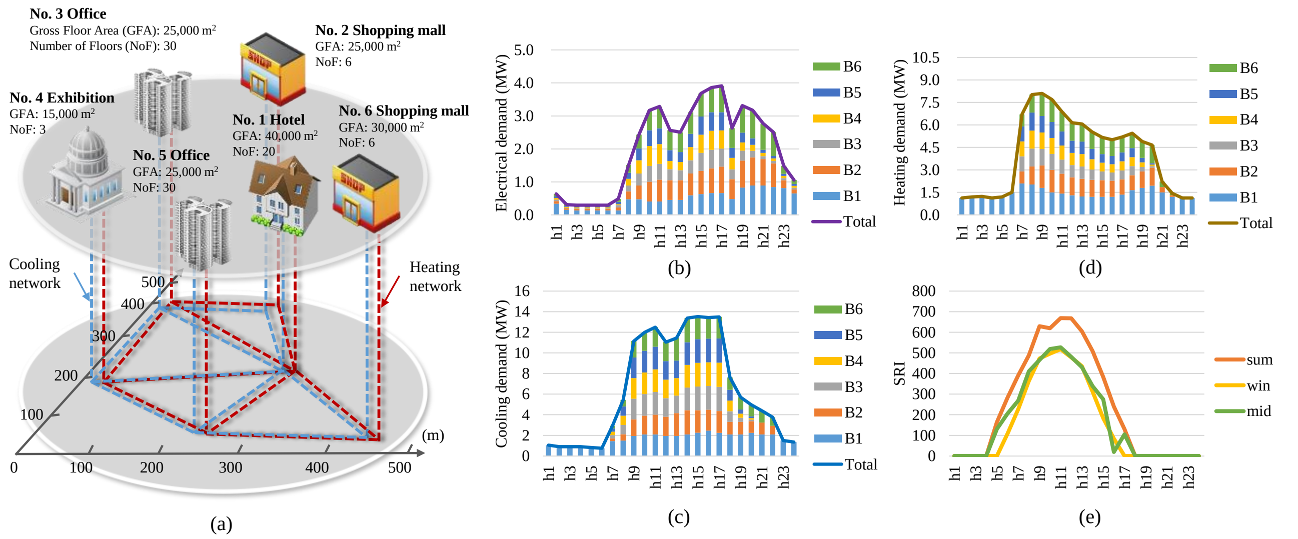

Fig 6 Illustrative community-level case study with 6 buildings (a); hourly electrical load profile (b), original (before energy saving upgrade) cooling profile (c), original heating profile (d); and original Solar Radiation Index (SRI) (e)

The overall problem is formulated as a Mixed Integer Linear Programming (MILP) model in GAMS 25.0.3, calling CPLEX to solve the model. The deterministic model has roughly 35,000 variables (including 9,000 binary variables), 48,000 constraints, and the solution time varies from 2 to 21 minutes. The stochastic model has roughly 360,000 variables, 480,000 constraints with the solution time varying from 1 to 8 hours.

4. Result and discussion

4.1 Optimal solution

Fig. 7 presents the annualized energy supply/demand balances for the optimal solution obtained from the deterministic model. The diagram consists of three charts representing the balance for electricity, heating, and cooling; b1 ~ b6 denote each of 6 buildings. Each charts shows both the energy supply side and the demand side, different band colors represent energy flows generated by different technologies to fulfill the demand, and the width of bands indicates the magnitude of the energy flow.

As seen in Fig. 7(a), CHP is the main electricity source for all buildings. Each building purchases a significant amount of electricity from the grid during the off-peak period and feeds a relatively smaller amount of electricity back to the grid mainly during the morning peak (7-8 a.m.) and evening peak (6-7 p.m.). A full capacity of PV panels is installed in each building, however, due to the limits on available space, the PV power contribution is not very significant compared to other sources. Battery storage only plays a role in building 3, 4, and 5 which have distinct on/off operation schedules, but not in building 1, 2, and 6 which have a relatively high electrical demand even during the evening off-peak period.

As for the heat balance in Fig. 7(b), CHP is the main source of heating supply for every building. Heat pumps also contribute significantly during the midnight period when CHP may be switched-off. Boilers are only used during the morning peak. To further reduce cost, b1 (the hotel) receives heating supply from b5 and b6 via a network connection particularly during the evening peak as most guests tend to return and take a shower. The other buildings remain standalone without connecting to others. The demand savings are represented by flows originating and terminating within the same building.

Fig. 7(c) describes the annual cooling balance, where electric chillers and absorption chillers are the two main cooling suppliers with different proportions of cooling supplied in each building, but the total amount of cooling generated is similar for 6 buildings in total. Meanwhile, cooling energy is only transferred from b5 to b1 particularly during the evening peak period, at which time the cooling demand is mainly in b1 (the hotel) since most of guests tend to return. The cooling storage tanks are actively utilized to discharge cooling during the morning peak and afternoon hotter period (2-4 p.m.) in all buildings.

A significant amount of savings in both heating and cooling demands is achieved in all buildings through the use of wall and roof upgrades. Window upgrades are not selected due to the higher investment costs even though they can provide greater energy savings.

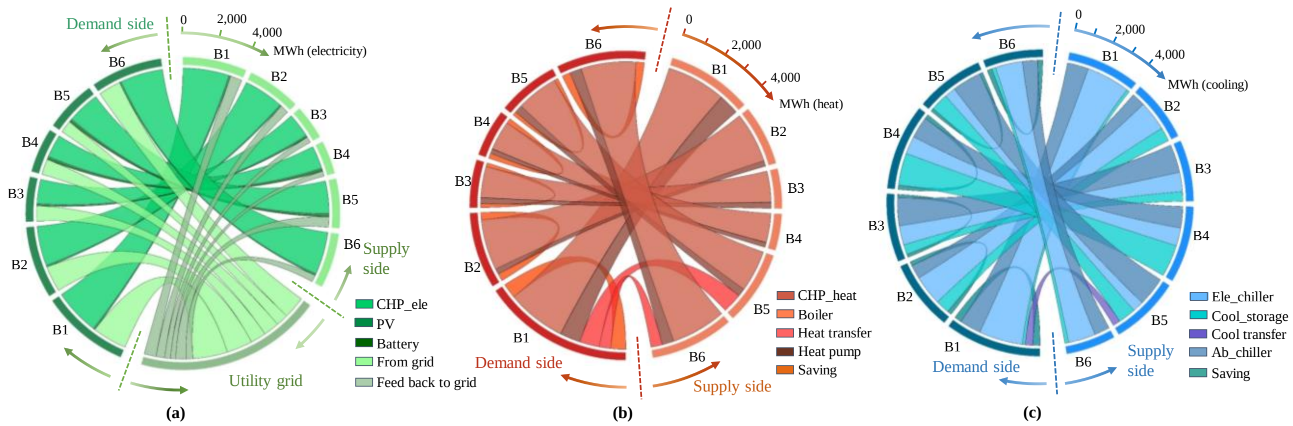

Fig 7 Annualized energy breakdown for optimal solution – electricity (a), – heating (b), – cooling (c)

4.2 Deterministic system value

Fig. 8 shows the aggregated curve of system values for each energy supply technology and saving strategy obtained from the deterministic model in this case, in which the vertical axis indicates the system value, and the horizontal axis is the incremental installed capacity of each individual technology from (a) ~ (g). The horizontal axis of (h) to (j) is different and denotes a series of discrete energy saving options, i.e., basic, improved, and high standard options.

4.2.1 Energy supply technologies

As shown in Fig. 8, there is a wide variation in system values across technology types and savings measures. The aggregated curves illustrate the development in system value over the range of capacities starting from the exclusion benchmark up to the optimal value. Oversizing the technology illustrates the decline in system values beyond this point.

CHP has the highest system value (US\$ 750×10^3) as shown in Fig. 8(a). This is due to the ability to feed electricity to the grid in peak hours while also being able to supply heat and electricity demands simultaneously. The available installation space limits, the maximal system value of PV panels to US\$ 39×10^3. However, the trend of system value curve in Fig. 8(b) indicates that this value could be larger if more installation space were available. Fig. 8(c) shows that a relatively small capacity of electricity storage (i.e., battery) can make a significant amount system value around US\$ $86\text{x}10^3$. The underlying reason could be that the installed capacity of the battery has a significant impact on the amount of electricity imported from the utility grid during the off-peak (cheaper) period, which affects the operation cost of the integrated system significantly. Interestingly, its system value develops slowly until a threshold value is reached and develops much more rapidly thereafter. The storage capacity must be chosen carefully as there is a relatively narrow range in which the storage has a high system value

Comparing cooling storage as shown in Fig. 8(f) with the battery storage, although a significantly larger capacity of cooling storage is adopted, the system value (i.e., US\$ 63×10^3) is slightly less than that of the battery storage. Although a larger amount of cooling is stored than the electricity, the latter tends to be more “valuable” for storage than the former in terms of the monetary and the energy grade. As for the cooling supply technologies, both electric chillers and absorption chillers have similar system values, the higher COP for the electrical chiller being offset by the requirement for a more valuable energy resource.

The technologies that can only supply heating have relatively low values suggesting that they are primarily used to supplement the heat supply from the CHP. Heat pumps have a maximal system value of US\$ 35×10^3 as shown in Fig. 8(d), and boilers have an even lower system value of US\$ 8.2×10^3 as shown in Fig. 8(h). Fig. 8(j) and 8(k) show that energy savings measures have a significantly greater impact on the energy system.

4.2.2 Energy saving strategies

System values of three energy saving strategies (window, wall and roof upgrade) are displayed in Fig. 8(i~k). For each strategy, three discrete upgrade options are available. The optimal solution lies between the basic and improved options for both wall and roof upgrades, in other words, the basic upgrade option is implemented some in buildings and the improved option is implemented in others. However, the window upgrade is not implemented anywhere in the optimal solution since the cost reduction due to the savings cannot offset its high investment cost.

Wall and roof upgrades have system values of similar magnitude, i.e., US\$ 68×10^3 and 82×10^3, respectively. In contrast, since no window upgrade is adopted in the original optimal design, a negative system value is observed if the window upgrade is enforced. Fig. 8(i) verifies such a phenomenon – the higher the standard of the forced upgrade, the larger the system value loss.

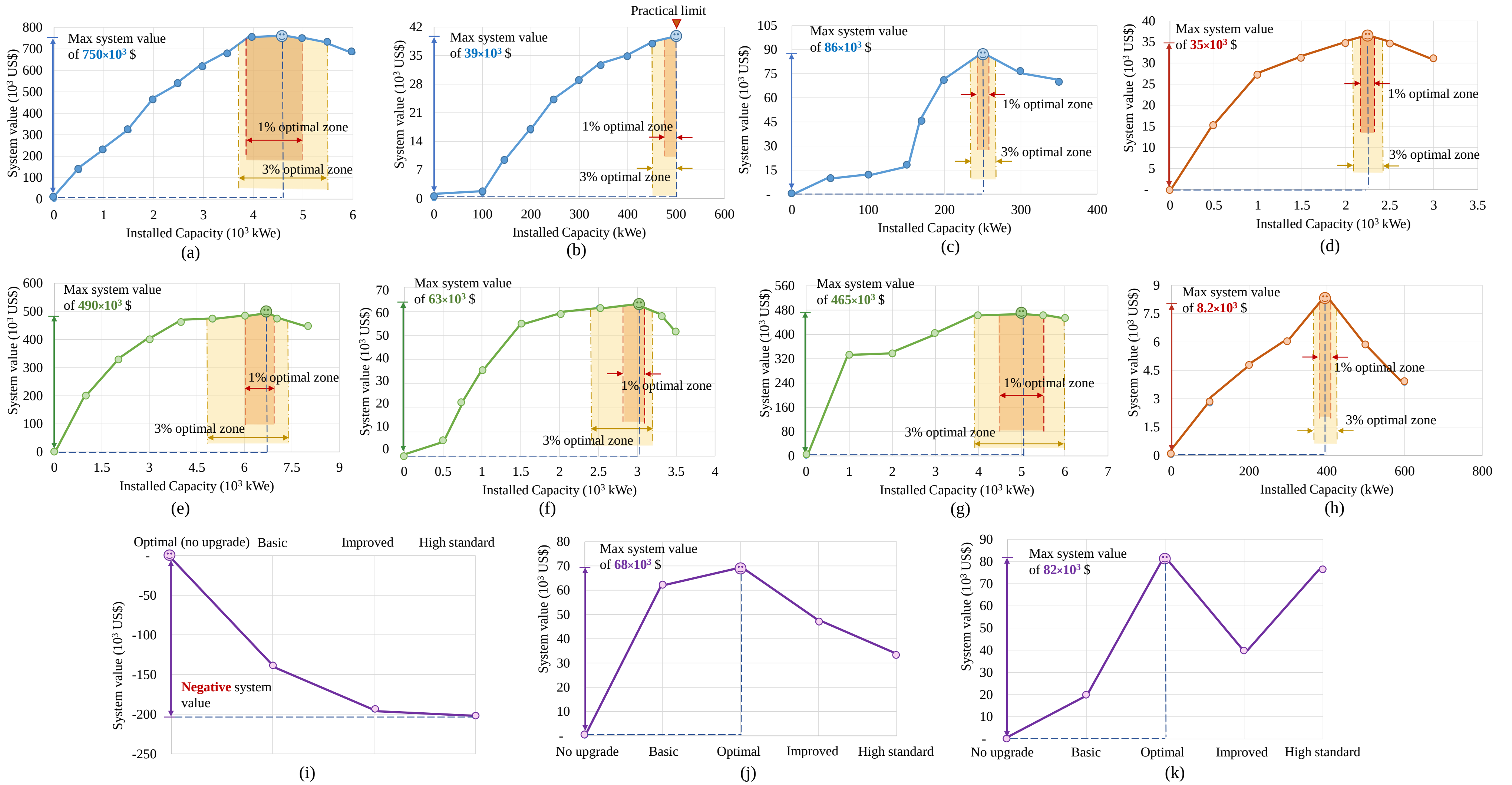

Fig 8 System values (deterministic) of different supply technologies and energy saving strategies, (a) CHP, (b) PV panel, (c) battery, (d) heat pump, (e) electric chiller, (f) cooling storage, (g) absorption chiller, (h) boiler, (i) window insulation upgrades, (j) wall insulation upgrades, (k) roof insulation upgrades. Note that: from (a) ~ (h), the installed capacities of technologies are modelled as continuous variables, two areas in each figure with light and dark orange represent the optimal design zones for 1% or 3% system value drop, respectively; whereas, for (i) ~ (k), the energy saving strategies are modelled as discrete options without optimal design zone.

4.3 System value with uncertainties

To quantify the variations in system values with multiple uncertainties, a stochastic model is formulated as described in Section 2.3. The corresponding results are discussed below.

4.3.1 Comparison between deterministic and stochastic system value

Fig. 9 shows the comparison of system values between the deterministic and stochastic models, where the weighted mean system values are used as the primary representation of the stochastic model results. Box and whisker diagrams are plotted for every aggregated curve of system value to show the variation in system values at each capacity level. It is seen that the trends of system value aggregated curves for both deterministic and stochastic formulations are generally consistent, but value differences exist for all technologies and energy saving strategies. These observations can be explained by the parametric assumptions in stochastic scenario settings, in which (1) the parametric variation ranges are relatively large in the present case study (i.e., heating demand 100%/70%, cooling demand 100%/75%/50%, and SRI 100%/70%), (2) while the deterministic model assumes each type of demand is maintained at 100%, which is larger than that of the stochastic model.

4.3.2 System value's variation with uncertainty

When uncertainties are considered, the system value could vary within a certain range. Taking the maximum system values of the CHP and PV panels as examples, the probability distributions for 12 scenarios as displayed in Fig. 10(a) and (b), respectively. For the ease of risk visualization and management, 12 scenarios are sorted from the lowest to highest of the maximum system value, e.g., the maximum system values for CHP could vary between US\$ 600×10^3 and 850×10^3 with a weighted average value of 750×10^3. Note that the number of scenarios is determined during the scenario setting in stochastic modelling considering the modelling scale and computational cost. In this case study, 12 scenarios are selected for a sufficiently accurate characterization of probability distributions.

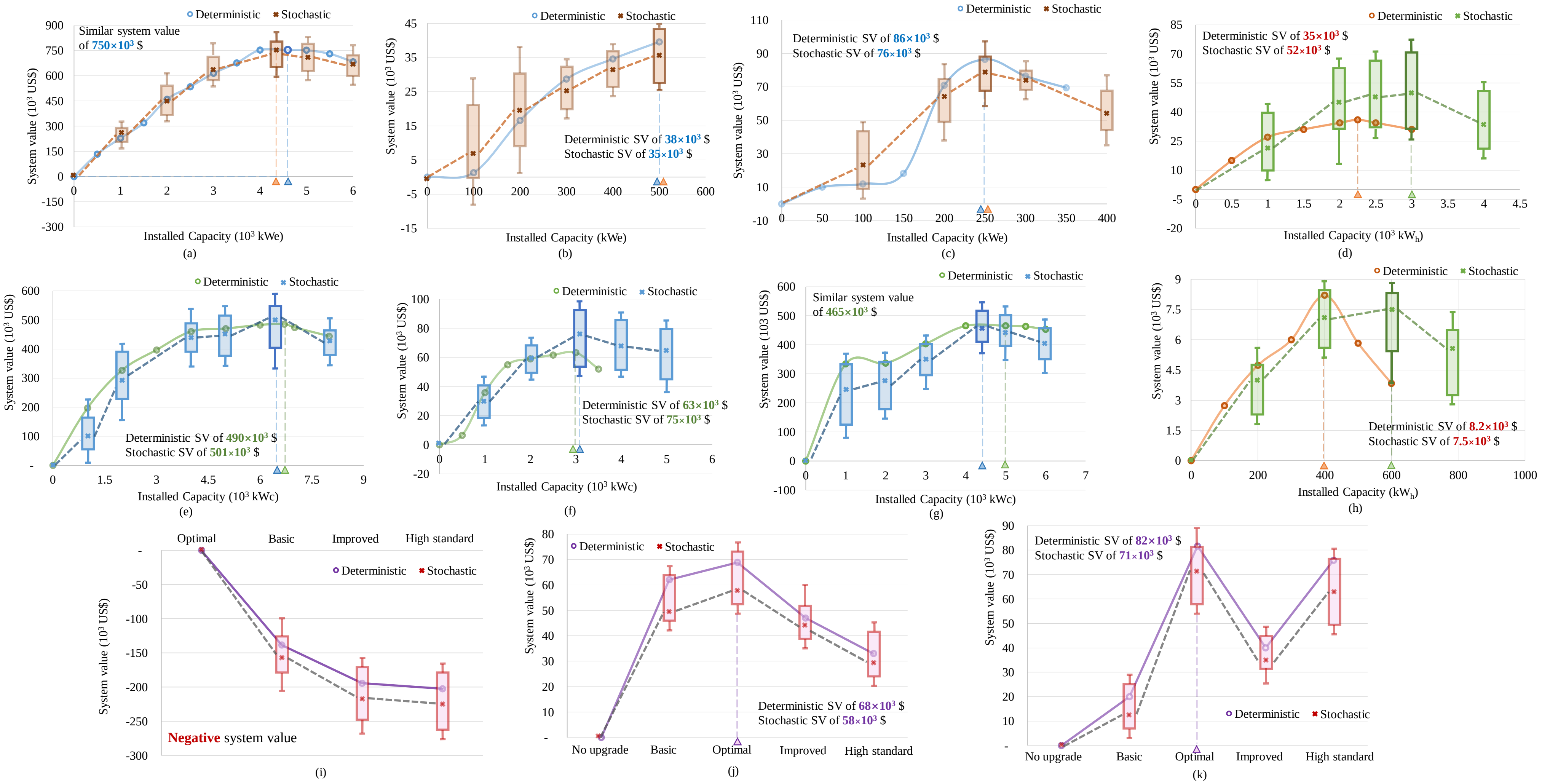

Fig 9 System value comparisons between deterministic and stochastic models: (a) CHP, (b) PV panel, (c) battery, (d) heat pump, (e) electric chiller, (f) cooling storage, (g) absorption chiller, (h) boiler, (i) window insulation upgrades, (j) wall insulation upgrades, (k) roof insulation upgrades. Note that: for the results of the stochastic model, the representative point (with a crossing mark) is the weighted average system value of 12 uncertain scenarios (i.e., No. 1 ~ 12 from the smallest to the biggest), which is also the optimal value of the objective function; for plotting the box diagram, the 1st quartile is calculated by the weighted value of No. 3 and 4 scenarios (reaching 25% cumulative probability), and the 3rd quartile is calculated by the weighted value of No. 9 and 10 scenarios (reaching 75% cumulative probability).

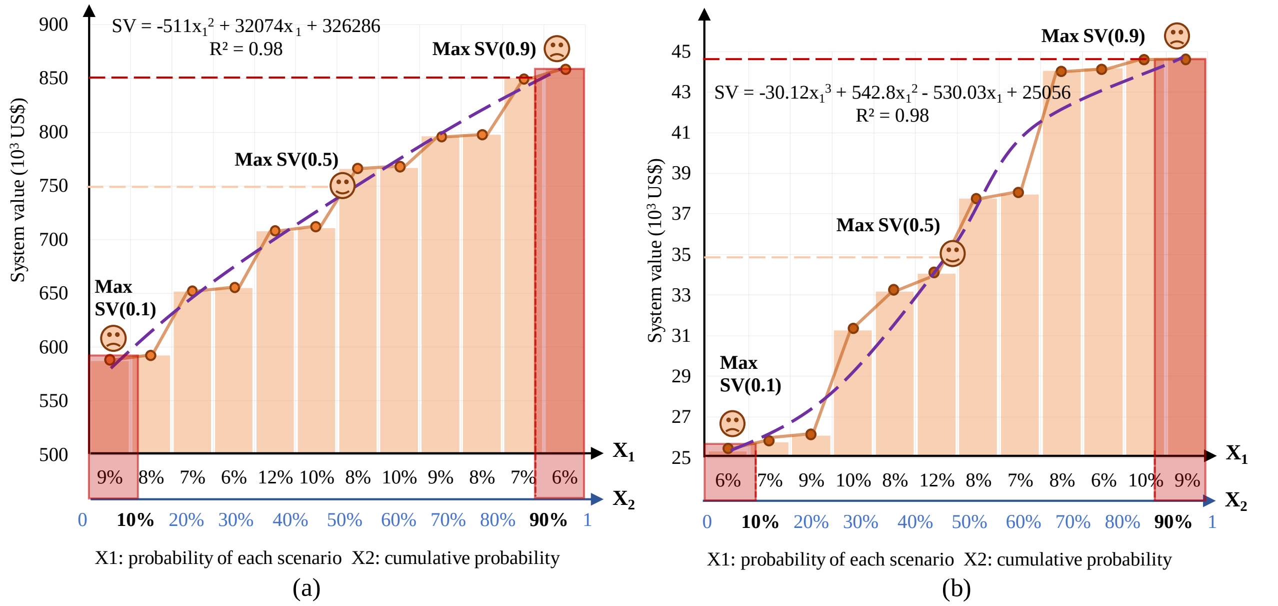

Fig 10 Cumulative probabilities of achievable maximum system values based on various scenarios' probabilities, (a) CHP, and (b) PV panels

4.4 Implications for decision-makers

Based on above deterministic and stochastic system value comparisons, several implications are noteworthy,

- The system values of energy saving strategies are significant at around 10-15% of the system values for the primary heating and cooling supply technologies (i.e., CHP, absorption chiller, electric chiller). This observation further highlights the importance of embedding demand-side strategies into the decision-making of energy system design. The valuation method used in this paper is based on a cost metric that does not account for greenhouse gas emissions. Adding a carbon cost to the objective function or specifying an emissions target would enhance the values of the savings strategies relative to the supply technologies and make the higher performance options more attractive.
- If we consider that a 1% or 3% drop of aggregate system value still represents a good design (as marked in red and yellow in Fig. 7), then optimal design zones for each technology can be identified instead of merely optimal design points. This optimal design zone represents the range that a technology's installed capacity can vary and still achieve a "good enough" solution, which provides meaningful flexibility for system designs.

In general, the case study demonstrates the system value approach and quantifies the individual benefit of a representative range of supply technologies and saving strategies in an integrated UES. The system value quantifies the impact of the technology by the objective function in the optimization model and accounts for all the system constraints, costs, and interactions with other technologies. This method is particularly useful for highly complex, in which multiple technologies with similar functionality can potentially fulfill the demands. Through the system value approach, the decision-makers or system-designers can prioritize all feasible technologies systemically.

5. Conclusions

This study introduces a system value approach for the valuation of an individual technology within a complex urban energy system. The approach can be used to show the development in system values over a range of capacities up to the optimal penetration level. Moreover, the system value method is not limited to monetary valuation, it is also suitable to quantify other performance measures, e.g., emissions. In particular, the method presents a unified measure to evaluate technologies that are not easy to compare directly, e.g., supply technologies and savings strategies. Several conclusions can be summarized as follows.

(1) A technology-rich urban energy system Mixed-Integer Linear Programming model is established incorporating commonly used energy supply technologies and energy saving strategies.

(2) A stochastic model considering multiple uncertainties is used to quantify the uncertainty in the system value. Although the obtained maximum system values are not always similar, deterministic and stochastic models generally show similar system value trends.

(3) The case study illustrates the application of the system value approach and indicates that combined heating and power (CHP) provides the largest system value. Energy savings strategies have a significant impact with system values of around 10-15% of those for the main energy supply technologies.

(4) The proposed system value approach identifies the penetration level at which a technology has a maximal system value and the range within this value can be maintained without a significant decrease. Hence, the proposed approach could be an effective decision-support tool for decision-makers to determine the most beneficial investment ratio and to avoid over-investment.

This study introduces the generalized system value approach in a case with a representative range of supply technologies and savings strategies. The case study results could vary in other cases, but the system value approach should be broadly applicable, particularly for comparison of different technologies within integrated and complex systems. Overall, the system value method presents an additional viewpoint for decision-makers to evaluate new technologies or systems from a systemic perspective.

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Declaration of interest

There are no conflicts to declare.

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Appendix

This Appendix provides more information for the MILP model in this paper. The deterministic model in the present study is based on our previous work [42]. Here the stochastic formulations are described in detail as follows.

A.1 Cost objective

The overall cost objective can be formulated as shown in Eq. (A1).

$$\begin{aligned} &\text{Min} \quad Obj_{\text{total}} = CAPEX + \sum_{s'=1}^{N} \text{prob}_{s'} \times OPEX_{s'} \\ &OPEX_{s'} = \sum_{s,h,i} [FC_{s',s,h,i} + MC_{s',s,h,i} + GC_{s',s,h,i}] \end{aligned} \tag{A1}$$

where Obj_{total} is the overall project cost including the capital cost (*CAPEX*) and the expected value of operation cost (*OPEX*); $\text{prob}_{s'}$ represents the probability of different scenarios; *FC*, *MC*, *GC* are fuel cost, maintenance cost, and grid cost (including the electricity feed-back revenue), respectively. Note that the subscripts of *s'*, *s, h* are scenarios, seasons, and hours, respectively, if not specified in the following content.

Alternatively, the cost objective can be formulated by adding one extra variable as shown Eq. (A2). The two formulations of Eq. (A1) and Eq. (A2) are equivalent; the benefit of Eq. (A2) is the ease of extracting the individual cost value for various scenarios.

$$\begin{aligned} &\text{Min} \quad Obj_{\text{total}} = \sum_{s'=1}^{N} \text{prob}_{s'} \times SC_{s'} \\ &SC_{s'} = CAPEX + OPEX_{s'} \\ &OPEX_{s'} = \sum_{s,h,i} [FC_{s',s,h,i} + MC_{s',s,h,i} + GC_{s',s,h,i}] \end{aligned} \tag{A2}$$

where *SC* is an auxiliary variable used to extract various scenarios' cost values.

The *CAPEX* is the capital cost for all energy devices and energy networks. *CAPEX* is annualized by the capital recovery factor (*CRF*) with a commonly used interest rate (r) of 6%. Meanwhile, different lifetime are considered, i.e., 20 years for energy supply devices and 30 years for pipework.

$$\begin{aligned} CAPEX = &\sum_{i} \sum_{t} CAP_{i,t} \times \text{C}_{t}^{\text{Capital}} \times \text{CRF}_{t} \\ &+ \sum_{i} \Big(\sum_{k=1,2,3} \varphi_{i,k}^{\text{roof}} \times \text{C}_{i,k}^{\text{roof-Capital}} + \sum_{k=1,2,3} \varphi_{i,k}^{\text{win}} \times \text{C}_{i,k}^{\text{win-Capital}} + \sum_{k=1,2,3} \varphi_{i,k}^{\text{wall}} \times \text{C}_{i,k}^{\text{wall-Capital}} \Big) \\ &+ \sum_{i} \sum_{j \neq i} \text{DX}_{i,j} \times \text{C}_{\text{pipe}}^{\text{Capital}} \times \text{CRF}_{\text{pipe}} \end{aligned} \tag{A3}$$

$$CRF = \frac{\text{r} \times (1+\text{r})^{n}}{(1+\text{r})^{n} - 1} \tag{A4}$$

where the subscripts of *t, k* represent *t* kinds of energy technologies, and *k* options of energy saving upgrade, respectively. *CAP* is the installed capacity, $\text{C}^{\text{Capital}}$ is the capital cost per unit, DX is the distance between buildings. φ is a binary variable representing whether implementing one certain energy saving strategy or not. Note that if not specified in the following content, the subscripts of *i, j,*

t are building serial number i and j ($j{\neq}i$), as well as t categories of energy technologies, respectively.

In the *OPEX*, fuel cost (*FC*) is the cost of consumed gas by all devices as derived in Eq. (A5).

$$FC_{s'} = \sum_{i,s,h}\left(\frac{E^{\text{CHP}}_{s',i,s,h}}{\eta_{\text{CHP}}}\times C^{\text{CHP-NG}}_{h} + \frac{Q^{\text{b-heat}}_{s',i,s,h}}{\eta_{\text{b}}}\times C^{\text{b-NG}}_{h}\right) \tag{A5}$$

where E^{CHP} denotes the power generation from CHP, $Q^{\text{b-heat}}$ represents the heating supply from boiler, η is the efficiency, and C^{NG} is the cost of natural gas.

Maintenance cost (*MC*) can be calculated as displayed in Eq. (A6).

$$MC_{s'} = \sum_{i,s,h}\left(E^{\text{pv/CHP}}_{s',i,s,h} + Q^{\text{b-heat/hp}}_{s',i,s,h} + Q^{\text{ec/ac-cool}}_{s',i,s,h} + Q^{\text{in-st}}_{s',i,s,h} + E^{\text{in-st}}_{s',i,s,h}\right)\times C^{\text{maint}}_{t} \tag{A6}$$

where $E^{\text{pv/CHP}}$ is electricity generated from PV panels and CHP, respectively. $Q^{\text{ec/ac-cool}}$ are cooling energy provided by electric chillers and absorption chillers, respectively. $E^{\text{in-st}}$ and $Q^{\text{in-st}}$ are cooling and electricity in storage, respectively.

The grid cost (*GC*) is shown in Eq. (A7).

$$GC_{s'} = C^{\text{im}}_{h}\times\sum_{i,s,h}E^{\text{im}}_{s',i,s,h} - C^{\text{ex}}_{h}\times\sum_{i,s,h}E^{\text{ex}}_{s',i,s,h} \tag{A7}$$

where C^{im} and C^{ex} are unit prices for electricity purchasing and feed-in, respectively. E^{im} and E^{ex} are the amount of electricity purchased and feed-in, respectively.

A.2 Model constraints

A.2.1 Energy balances

Three energy balances are considered, i.e., electrical, heating, and cooling balance. The heating balance has been described by Eq. (5) in Section 2.3 and is not repeated here. Similar to the heating balance, the cooling balance is displayed in Eq. (A8).

$$\begin{aligned}&\left(\mathrm{Q}^{\text{c-dem}}_{s',i,s,h} - \sum_{k=1,2,3}\varphi^{\text{win}}_{i,k}\times\mathrm{Q}^{\text{c-win}}_{s',i,s,h,k} - \sum_{k=1,2,3}\varphi^{\text{roof}}_{i,k}\times\mathrm{Q}^{\text{c-roof}}_{s',i,s,h,k} - \sum_{k=1,2,3}\varphi^{\text{wall}}_{i,k}\times\mathrm{Q}^{\text{c-wall}}_{s',i,s,h,k}\right) + \sum_{j\neq i}Q^{\text{cf}(i,j)}_{s',i,j,s,h} = \\ &Q^{\text{ac-cool}}_{s',i,s,h} + Q^{\text{ec-cool}}_{s',i,s,h} + \sum_{j\neq i}Q^{\text{cf}(j,i)}_{s',j,i,s,h}\times(1-\mathrm{Lo}^{\text{c-pipe}}) + Q^{\text{disc}}_{s',i,s,h} - Q^{\text{cha}}_{s',i,s,h}\end{aligned} \tag{A8}$$

where the left hand side of the cooling balance includes cooling demand ($Q^{\text{c-dem}}$); potential cooling demand reduction ($\mathrm{Q}^{\text{c-win}}$, $\mathrm{Q}^{\text{c-roof}}$, $\mathrm{Q}^{\text{c-wall}}$) by implementing energy saving strategies on window, roof, and wall, respectively; and cooling energy flowing from building i to j ($Q^{\text{cf}(i,j)}$). The right hand side consists of cooling energy supplied by electrical chillers ($Q^{\text{ec-cool}}$) and absorption chillers ($Q^{\text{ac-cool}}$); cooling energy flowing from building j to i ($Q^{\text{cf}(j,i)}$) with a cooling loss rate ($\mathrm{Lo}^{\text{c-pipe}}$); cooling charge ($Q^{\text{cha}}$) or discharge ($Q^{\text{disc}}$) from cooling storage. φ is the same binary variable to control the selection of energy saving options as in the heating balance.

The electrical balance is presented in Eq. (A9).

$$E^{\text{ec}}_{s',i,s,h} + E^{\text{ex}}_{s',i,s,h} + E^{\text{hp}}_{s',i,s,h} + E^{\text{st-in}}_{s',i,s,h} + E^{\text{dem}}_{s',i,s,h} = E^{\text{st-out}}_{s',i,s,h} + E^{\text{pv}}_{s',i,s,h} + E^{\text{im}}_{s',i,s,h} + E^{\text{CHP}}_{s',i,s,h} \tag{A9}$$

where the left-hand side items are defined as follows: E^{ec} is power consumption by electrical chiller, E^{ex} is the amount of electricity fed-in back to the grid, E^{hp} is power consumption by the heat pump, $E^{\text{st-in}}$ is power charging to battery, and E^{dem} is electrical demand of each building. The right-hand side items are defined as follows: $E^{\text{st-out}}$ is electricity discharge from battery storage, E^{pv} is power generated by PV panels, E^{im} is electricity purchased from the grid, and E^{CHP} is onsite power supply from CHP.

A.2.2 Capacity and conversion constraints

The energy output is equal to the input multiplied by an efficiency, where the value of efficiency is assumed constant to maintain a linear model. The energy output at each time-step would not exceed corresponding installed capacity as shown in Eq. (A10).

$$Q^{\text{re-heat}}_{s',i,s,h} = \lambda \times E^{\text{CHP}}_{s',i,s,h} \tag{A10a}$$

$$E^{\text{CHP}}_{s',i,s,h} \leq CAP^{\text{CHP}}_{i} \tag{A10b}$$

$$E^{\text{ec-cool}}_{s',i,s,h} \leq CAP^{\text{ec}}_{i} \tag{A10c}$$

$$Q^{\text{b}}_{s',i,s,h} \leq CAP^{\text{b}}_{i} \tag{A10d}$$

$$E^{\text{ac-cool}}_{s',i,s,h} \leq CAP^{\text{ac}}_{i} \tag{A10e}$$

$$Q^{\text{hp}}_{s',i,s,h} \leq CAP^{\text{hp}}_{i} \tag{A10f}$$

where CAP denotes installed capacity of various technologies at different buildings, λ is the heat-to-power ratio for CHP.

A.2.3 Storage modelling

Both battery and cooling storage are available. Since the constraints for storage devices are similar, Eq. (A11a~e) takes the battery storage model as an example. The in-storage of electricity ($E^{\text{in-st}}$) for each time-step should not larger than the installed capacity of battery storage (CAP^{batt}). The charging and discharging rate are constrained by a "big M" value. In addition, charging and discharging cannot happen simultaneously, this is modelled by introducing binary variable (α).

$$E^{\text{in-st}}_{s',i,s,h} = \eta^{\text{in-st}} \times E^{\text{in-st}}_{s',i,s,h-1} + \eta^{\text{cha}} \times E^{\text{cha}}_{s',i,s,h} - E^{\text{disc}}_{s',i,s,h} / \eta^{\text{disc}} \tag{A11a}$$

$$E^{\text{in-st}}_{s',i,s,h} \leq CAP^{\text{batt}}_{i} \tag{A11b}$$

$$E^{\text{cha}}_{s'i,s,h} \leq \alpha^{\text{cha}}_{s'i,s,h} \times \mathrm{M}_1 \tag{A11c}$$

$$E^{\text{disc}}_{s',i,s,h} \leq \alpha^{\text{disc}}_{s',i,s,h} \times \mathrm{M}_2 \tag{A11d}$$

$$\alpha^{\text{disc}}_{s',i,s,h} + \alpha^{\text{cha}}_{s',i,s,h} \leq 1 \tag{A11e}$$

where η^{cha}, η^{disc}, and $\eta^{\text{in-st}}$ are charging, discharging, and in-storage efficiency, respectively.

A.2.4 Operation constraints

The CHP should not operate at a very low-load, i.e., less than 30% of full capacity, as derived by Eq. (A12).

$$E^{\text{CHP}}_{s',i,s,h} \leq \beta^{\text{CHP}}_{s',i,s,h} \times M_3 \tag{A12a}$$

$$E^{\text{CHP}}_{s',i,s,h} \geq (\beta^{\text{CHP}}_{s',i,s,h} - 1) \times M_4 + 0.3 \times CAP^{\text{CHP}}_{i} \tag{A12b}$$

where β^{CHP} is a binary variable for modelling the on/off status of the CHP ($\beta^{\text{CHP}} = 1$ is on).

Additionally, the CHP is only allowed to switch on/off for one cycle per day as constrained in Eq. (A13).

$$\sum_{h} \chi_{s',i,s,h}^{\mathrm{CHP}} \leq 1 \tag{A13a}$$

$$\chi_{s',i,s,h}^{\mathrm{CHP}} \geq \beta_{s',i,s,h}^{\mathrm{CHP}} - \beta_{s',i,s,h-1}^{\mathrm{CHP}} \tag{A13b}$$

$$\chi_{s',i,s,h}^{\mathrm{CHP}} \leq 1 - \beta_{s',i,s,h-1}^{\mathrm{CHP}} \tag{A13c}$$

$$\chi_{s',i,s,h}^{\mathrm{CHP}} \leq \beta_{s',i,s,h}^{\mathrm{CHP}} \tag{A13d}$$

where χ is a binary variable for modelling the on/off cycling frequency.

Finally, the CHP is not allowed to vary its output drastically by Eq. (A14).

$$E_{s',i,s,h}^{\mathrm{CHP}} - E_{s',i,s,h-1}^{\mathrm{CHP}} \leq 0.5 \times CAP_{i}^{\mathrm{CHP}} \tag{A14a}$$

$$E_{s',i,s,h-1}^{\mathrm{CHP}} - E_{s',i,s,h}^{\mathrm{CHP}} \leq 0.5 \times CAP_{i}^{\mathrm{CHP}} \tag{A14b}$$

A.2.5 Grid connection and network modelling

Electricity purchasing from the grid and feed-in back to the grid are modelled by Eq. (A15).

$$0 \leq E_{s',i,s,h}^{\mathrm{ex}} \leq \mu_{s',i,s,h}^{\mathrm{ex}} \times M_5 \tag{A15a}$$

$$0 \leq E_{s',i,s,h}^{\mathrm{im}} \leq \mu_{s',i,s,h}^{\mathrm{im}} \times M_6 \tag{A15b}$$

$$\mu_{s',i,s,h}^{\mathrm{ex}} + \mu_{s',i,s,h}^{\mathrm{im}} \leq 1 \tag{A15c}$$

where μ^{ex} and μ^{im} are binary variables for modelling the power flow directions and prevent simultaneous power feed-in and purchasing.

The cooling and heating transfer among buildings can only happen when the pipework is built as shown in Eq. (A16).

$$\sum_{j \neq i} Q_{s',i,j,s,h}^{\mathrm{hf}(i,j)} \leq \delta_{i,j}^{\mathrm{DH}} \times M_7 \tag{A16a}$$

$$\delta_{i,j}^{\mathrm{DH}} + \delta_{j,i}^{\mathrm{DH}} \leq 1 \quad \forall j \neq i \tag{A16b}$$

$$\sum_{j \neq i} Q_{s',i,j,s,h}^{\mathrm{cf}(i,j)} \leq \delta_{i,j}^{\mathrm{DC}} \times M_8 \tag*{(A16a)}$$

$$\delta_{i,j}^{\mathrm{DC}} + \delta_{j,i}^{\mathrm{DC}} \leq 1 \quad \forall j \neq i \tag*{(A16b)}$$

δ^{DH} and δ^{DC} are binary variables to represent the heating and cooling pipework connections between buildings (1 is connected, 0 is not), respectively.

A building cannot receive energy and transfer out simultaneously.

$$\sum_{j \neq i} Q_{s',i,j,s,h}^{\mathrm{cf}(i,j)} \leq \gamma_{s',i,s,h}^{\mathrm{DC}} \times M_9 \tag{A17a}$$

$$\sum_{j \neq i} Q_{s',j,i,s,h}^{\mathrm{cf}(j,i)} \leq (1 - \gamma_{s',i,s,h}^{\mathrm{DC}}) \times M_{10} \tag{A17b}$$

$$\sum_{j \neq i} Q_{s',i,j,s,h}^{\mathrm{hf}(i,j)} \leq \gamma_{s',i,s,h}^{\mathrm{DH}} \times M_{11} \tag{A17c}$$

$$\sum_{j \neq i} Q_{s',j,i,s,h}^{\mathrm{hf}(j,i)} \leq (1 - \gamma_{s',i,s,h}^{\mathrm{DH}}) \times M_{12} \tag{A17d}$$

where γ^{DC} and γ^{DH} are binary variables for modelling the transfer/receive status, for heating and cooling respectively.