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A FRAMEWORK FOR SIMULTANEOUS OPTIMIZATION OF CAPEX AND OPEX DURING DESIGN, RAMP-UP AND OPERATIONS FOR DISTRICT ENERGY SYSTEMS

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ABSTRACT

District energy systems have been shown to improve energy efficiency, GHG emission reduction, and air quality, yet they are not as widely adopted as these benefits would imply. Extensive studies have been conducted to optimize district energy system design but typically focus on optimization for low carbon emissions and low life cycle cost, ignoring optimization of capital expense (CAPEX) during critical ramp-up. This paper proposes an analytical framework using Integer Programming for district energy system design and installation to simultaneously optimize CAPEX phasing and OPEX (operating expense) including ramp-up and operations. A case study was conducted with preliminary results showing that CAPEX and OPEX could be reduced by 3% and 5% respectively. This approach brings significant advantages to the project predictability and profitability thus strongly promotes the use of district energy technologies.

Keywords: optimization, district energy, energy efficiency, ramp-up, installation phasing, operation

1. INTRODUCTION

Our world is rapidly urbanizing. Cities are responsible for 70-75% of energy use and GHG emissions, with a large portion coming from space heating and cooling [1]. To tackle these energy challenges, district energy systems are widely used. It has been widely accepted that district energy projects require coordination of different stakeholders and substantial investment and engineering efforts. Early buy-in of all stakeholders can be improved by demonstrating the ability to lower CAPEX and OPEX during early design phase, which incentivizes the wide use of district energy instead of individual HVAC (heating, ventilation, and air conditioning) systems. Typical engineering practices during conceptual design evaluate only simple design alternatives and make decisions based on past experience. This practice can easily lead to poor predictability and suboptimal system design. Extensive studies have been conducted to optimize the design of district energy systems. However, the majority have focused on optimization for low carbon emissions and low life cycle cost, ignoring optimization of CAPEX during ramp-up, which has significant impacts onto project long-term success.

This paper proposes a data-driven framework utilizing Integer Programming for district energy system design and installation to optimize CAPEX phasing and OPEX through ramp-up to operations. The framework consists of three steps: 1) Total Energy Demand Aggregation and Energy Supply Equipment Encoding; 2) Simultaneous Evaluation of CAPEX and OPEX; 3) Optimization Implementation. The proposed framework is then demonstrated by a case study to significantly improve project predictability and profitability.

2. LITERATURE REVIEW

2.1 Optimization in District Energy systems

District energy system design is a complex problem involving the choice of supply technology of different kinds and sizes, the layout of the distribution network and the operational strategies. Traditionally, engineers make design decisions from past experience in a “trial and error” manner [2]. In the recent few decades, optimization algorithms have been wildly used in the

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design and operation of district energy [3-5]. Several studies have focused on optimizing the design and operation of district energy system using Mix Integer Programming (MIP) [3,4]. Metaheuristic algorithms like Genetic Algorithms are sometimes used for nonlinear modeling and global optimization [5,6]. Past studies have covered a wide range of optimization problems: from single-objective to multi-objective, from centralized to decentralized to integration of both, from excluding to including of renewables/storage. However, they all failed to take the gradual increase of loads into consideration and performed optimization as if CAPEX was a one-time expense, which is usually not the case.

2.2 Ramp-up Period in District Energy System Design

In practice, when most greenfield district energy systems are constructed, CAPEX is not spent at one time and budget planning involves the consideration of installation phasing [7]. Ramp-up is a term used in economics and business domain to describe an increase in a firm's production in response to the anticipated increasing demand [8]. In the case of District Energy, ramp-up is characterized by large purchases of equipment, which follow the increase of occupancy rates and energy demand, over several months or years. It is of great importance because it could speed up/delay the cash flow, and affect payback and return on investment [9]. Therefore, it largely impacts financial advantage if installation and CAPEX is deferred [10].

In summary, the additional time dimension of the design, represented by ramp-up, plays an important role in the project profitability, and is identified and addressed in this paper. The overall objective of this paper is to introduce a new framework for district energy system design and installation with optimization through ramp-up to operation stages.

3. METHODLOLGY

The framework utilizes an Integer Programming (IP) model for district energy system design and installation to optimize CAPEX phasing and annual OPEX through ramp-up to operations. It consists of three steps (see Fig 1): 1) Total Energy Demand Aggregation and Energy Supply Equipment Encoding; 2) Simultaneous Evaluation of CAPEX and OPEX; 3) Optimization Implementation.

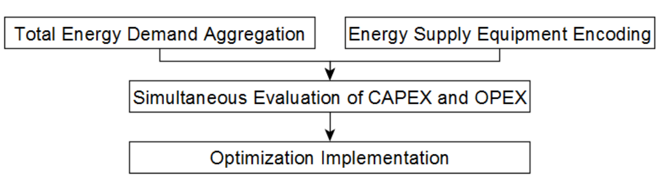

Fig 1. Diagram of the district energy system framework

3.1 Total Energy Demand Aggregation and Energy Supply Equipment Encoding

The first step is to aggregate energy demand of all buildings to get an overall load profile of the district over years. Hourly demand of each building per year is estimated by the historical weather data (hourly dry bulb temperature), occupied building floor area, building energy use intensity classified by building type (commercial, residential, etc.) and time of a day/week/year. It could be further adjusted if historical energy consumption data is provided. Besides, cost data and performance specification of each candidate equipment of the same type are gathered and processed to allow flexible selection of equipment of various sizes from different manufacturers. COP performance curves are preprocessed with 2D interpolation (temperature and partial load) so they could be accessed in later implementation.

3.2 Simultaneous Evaluation of CAPEX and OPEX

The design to be optimized is not as simple as the final set of installed equipment that continues over the project lifetime. Instead we evaluate various possible combinations of equipment sets and sequences during ramp up. Since ramp up is often as much as 30% of the project lifetime, this neglected period has great opportunities for optimization. Selection of equipment per year includes size, quantity of each type (chiller, thermal energy storage, etc.). Each unique set of equipment combination and sequence becomes a design alternative to be evaluated. Additional CAPEX of each year due to the newly installed equipment is discounted considering inflation and aggregated to calculate the “discounted CAPEX”. Annual OPEX is calculated through daily operational simulation (or optimization if the whole problem is formulated as a 2-level nested optimization problem). As for the constraints: 1) equipment to be installed each year is examined whether it could provide sufficient energy to cover the energy demand; 2) to secure the reliability of energy supply, a redundant equipment of each type is installed. The Integer Programming (IP) model is developed and the problem is defined as follows:

$$\min(\mathrm{CAPEX}(\mathbf{X}), \mathrm{OPEX}(\mathbf{X})),\ \mathbf{X} = \{x_{i,j,k}\}$$

$$\begin{aligned} \text{s.t. } & x_{i,j,k-1} \le x_{i,j,k} \\ & \mathbf{X_k} \text{ satisfies demand of year k}, \forall \mathrm{k} \\ & \mathbf{X_k^*} \text{ satisfies 80\% demand of year k}, \forall \mathrm{k} \end{aligned}$$

where:

$x_{i,j,k} =$ the number of equipment of type i and of size j installed in year k,

$\mathbf{X_k}$ = all equipment installed in year k,
$\mathbf{X_k^*}$ = all equipment without redundancy in year k,
$CAPEX(\mathbf{X}) = \sum_k \sum_i \sum_j x_{i,j,k} \cdot cost_{i,j} \cdot \frac{1}{(1+discount\_rate)^k}$,
$OPEX(\mathbf{X})$ = simulated opex of the final year,
$cost_{i,j}$ *is provided by manufacturers.*

3.3 Design and installation optimization

Having the multi-objective optimization problem formulated above, discounted CAPEX and annual OPEX are the two competing objectives concerning financial aspects of project success. Algorithms including metaheuristic search algorithms like Genetic Algorithms are implemented to explore the design space and find the optimal solutions to assist design decision making.

4. CASE STUDY

4.1 Case study setup

To validate the performance of the framework, it is implemented in a district cooling system design project in the south of China. The served area contains residential, commercial, office, and hotel buildings, each of which has distinctive load patterns. The hourly cooling demand of each building is estimated as follows:

$$\begin{aligned} Demand_{b,h} = {} & Cooling\ Floor\ Area \times Cooling\ Load\ Index \\ & \times Min((Cooling\ Season\ Flag \\ & \times Cooling\ Weekly\ Schedule\ Flag \\ & \times Max(Dry\ Bulb\ Temp \\ & - Outdoor\ Base\ Temp, 0)) \\ & /(Design\ Outdoor\ Temp \\ & - Outdoor\ Base\ Temp), 1) \end{aligned}$$
$\forall b \in Buildings, \forall h \in [1,8760]$.

In this project ice storage is used for peak shaving due to space constraint. Therefore, a basic design configuration includes baseload chiller(s), dual-duty chiller(s) and ice storage. For easy maintenance and procurement, all equipment of each type is of the same size. The predicted demand ramp-up is shown in Fig.2.

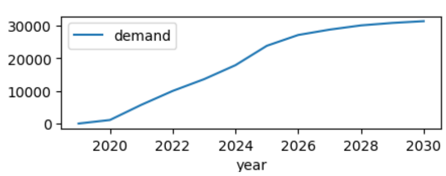

Fig 2. Ramp-up of cooling demand

Table 1. Design variables of case study

Variable	Description of the variable	Range
$size_{bl}$	capacity of baseload chiller	[2.8MW]
$size_{dd}$	capacity of dual-duty chiller	[3.3MW]
$x_{bl,k}$	quantity of baseload chiller installed in year k	[0, 1, 2 ,3]
$x_{dd,k}$	quantity of dual-duty chiller installed in year k	[0, 1, 2 ,3]
$x_{ice,k}$	quantity of ice storage installed in year k	[0, 1, 2 ,3]

The design variables are shown in Table 1. The Objectives and constraints are defined as follows:

$$CAPEX = \sum_k [Cost_{bl} \cdot x_{bl,k} + Cost_{dd} \cdot x_{dd,k} + Cost_{ice} \cdot x_{ice,k}] \cdot \frac{1}{(1 + discount\_rate)^k}$$
$OPEX$ = simulated opex,
$\mathbf{X_k}$ satisfies demand of year k, $\forall$k,
$\mathbf{X_k^*}$ satisfies 80% demand of year k, $\forall$k,
$discount\_rate$ = 6%.

OPEX is calculated and constraints are checked based on a predefined daily operational strategy shown as the pseudocode in Fig 3. Enumeration of the equipment selection in all years was carried out and the equipment selections of each year were linked to get the complete design alternatives (equipment sequencing) (See Fig 4). Each distinct final year configuration corresponds to many different sets of equipment selection of previous years. Shortest path method was used to find the cheapest design alternative for each final year configuration.

```
demand = array containing cooling demand of 24 h

\\ store as much ice as possible
charged_hours = hours when tariff is cheapest (night time)
dd_available = number of dual-duty chillers that can make ice
               during charged_hours
\\ all dual-duty chillers are available if baseload chiller
   alone is sufficient to provide night time cooling demand
ice_max = min(ice storage, capacity provided by dd_available)

\\ discharge ice when chiller capacity is not sufficient
for h = 0 to 23
    discharge[h] = max(0, demand[h]-size_bl*x_bl-size_dd*x_dd)
    if discharge[h] > max_discharge: \\ can't meet peak demand
        return "failed"
if sum(discharge) > ice_max: \\ ice storage not enough
    return "failed"

discharge_order = hours sorted in a pre-defined order
\\ first sort key is tariff in descending order
\\ second sort key is the hour in descending order

ice_left = ice_max - sum(discharge)
for h in discharge_order:
    if ice_left > 0:
        discharge[h] = min(demand[h], max_discharge, ice_left)
        update ice_left
    else:
        break

chillers run in the same load to satisfy demand for each hour
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Fig 3. Pseudocode for daily operational strategy

4.2 Results and Discussion

Preliminary results show that discounted CAPEX and OPEX could be reduced simultaneously by 3% and

5% respectively compared to the engineer's manual design (see Fig 5). It should be noted that project lifespan is key to making the final decision and choosing which design/installation plan. Short project lifespan would favor larger saving in CAPEX than in OPEX, and vice versa. The optimal design varies as different decision makers view it with different weightings of the objectives and with different additional considerations. These results demonstrate the performance of the proposed framework in project predictability and profitability, which are of significant importance to enhance and complement engineering decision making for district energy systems.

5. CONCLUSIONS

In order to increase the predictability and controllability for the implementation of district energy systems, this paper proposes a data-driven framework utilizing Integer Programming for district energy system design and installation to optimize CAPEX phasing and annual OPEX through ramp-up to operations. The framework is extensible to equipment of different sizes and energy supply technologies, as well as different optimization algorithms. The main contribution of the proposed work is taking into consideration CAPEX phasing optimization during ramp-up period which greatly impacts project financial performance.

There are several limitations that will be addressed in future work: 1) the case study includes few equipment for the enumeration of equipment selection. As more equipment data is collected, a holistic optimization will be performed to efficiently search the bigger design space; 2) cost and performance specification of more equipment will be collected and included; 3) a simpler version of Integer Programming model is used for the proof-of-concept of the methodology. Different optimization algorithms are being systematically tested to examine the impacts of algorithms and expedite the search of appropriate design solutions; 4) a pre-defined operational strategy is used in the evaluation. Different operational strategies and operation optimization are to be examined to improve the operation simulation.

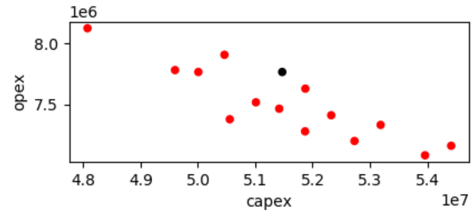

Fig 5. CAPEX and OPEX trade-off: red dots show the lowest discounted CAPEX solution for each final year plan, while the black dot represents the original design

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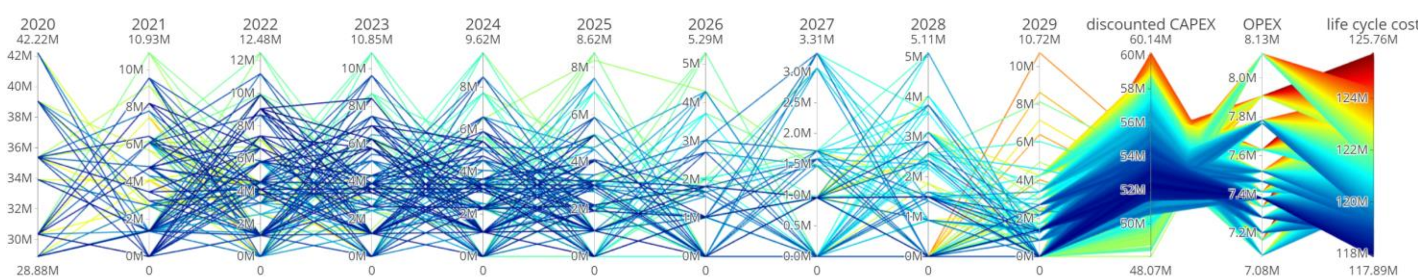

Fig 4. Design Space: from left to right, first ten coordinates show the CAPEX spent in each year during ramp-up (without discounting), next two coordinates are the two objectives (discounted CAPEX and OPEX), the last one is the life cycle cost.