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Research Paper

A stochastic evaluation of investments in combined cooling, heat, and power systems

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HIGHLIGHTS

- The stochastic effects of CCHP system design were investigated in investment level.
- Parametric method has given the widest range of probability.
- Monte Carlo method has given the highest mean value.
- Scenario-based is the most appropriate method due to comparisons and contrasts.
- The proposed methods provide a broader point of view to evaluate the CCHP systems.

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ABSTRACT

CCHP (Combined Cooling, Heat, and Power) systems, by their nature, work under uncertainties during their economic life. This study aims to use stochastic methods to forecast whether or not a CCHP system with long-term uncertainties will be feasible. To understand how uncertain parameters that affect profitability unfold over time, the system was analyzed with four different simulation methods, the results of which were compared: the parametric method, the Monte Carlo method, the historical trend method, and the scenario-based method. The parametric method gave the widest range of probabilities for the objective function, which provided an unclear prediction about the possible results of the projected years. The Monte Carlo method gave the highest mean value, while the historical trend method gave probabilities in a narrower range. The scenario-based method, which offered a broader prediction than the historical trend method, can be considered to be the most appropriate method to adopt given the comparisons and contrasts it provides. The methods proposed in this study provide decision-makers with a broader point of view to evaluate the amortization of CCHP systems.

1. Introduction

Nowadays, limited energy sources force the use of energy to be more efficient and economic. Generally centralized power generation approaches are characterized by high rates of energy losses due to waste heat and distribution inefficiencies [1]. Auto-production enables more efficient energy usage by eliminating losses that stem from the distribution system of energy plants [2]. Accordingly, CCHP (Combined Cooling, Heat, and Power) systems are the best-known technology for efficient energy usage, usually referring to the simultaneous production of cooling, heating, and power from a single energy source. CCHP plants are built as decentralized systems and are operated close to where they are needed. Thus, CCHP systems are considered to be more efficient, profitable, reliable, and environmentally friendly than conventional generating plants [3,4].

There are many studies of CCHP systems, some of which focus on optimization in the design and operation stages, while others involve simulation models or selection approaches and planning solutions, as discussed below with related references.

As with other energy-conversion systems, CCHP systems should be designed and operated efficiently to gain the expected advantages, which is clearly an issue falling under optimization. There are many studies concerning CCHP optimization [5] and multi-criteria decision-making methods [6,7]. generally encompassing the steps of design and operation.

Several studies have used linear programming to optimize CCHP systems [8,9]. Lozano et al. [10] used a simple linear programming model to minimize the variable operational cost of a CCHP system. Similarly, Unal and Ersoz [11], proposed the same model to minimize the total annual variable operational cost and the maintenance cost of a

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Nomenclature

Symbols

α	shape factor
β	shape factor
$\triangle$	change in variable
δ_{smc}	specific maintenance cost per hour [USD]
η_{ab}	auxiliary boiler efficiency
η_{hrs}	heat recovery system efficiency
η_{pgu}	PGU efficiency
μ	average
σ	standard deviation
θ	occurrence probability
a	regression constant
awh	annual working hours of the plant
b	slope of regression
C_{gc}	specific gas consumption of PGU
COP_{ac}	coefficient of performance of AC
COP_{mc}	coefficient of performance of MC
E_d	electricity demand [kW]
E_r	electricity power needs of MC
E_{ac}	electricity power needs of AC
$Icchp$	investment cost of CCHP [USD]
J	number of simulation
n	years
OC_{CCHP}	operational cost of CCHP system
OC_{SP}	operational cost of separate production
P_{ep}	electricity price [USD/kWh]
P_{fa}	AB fuel price
P_{fc}	natural Gas price [USD/m^3]
Q_c	heating power of PGU [kWh]
Q_d	heating demand [kW]
Q_l	waste heat
Q_r	driving heat for absorption system [kWh]
Q_{ab}	heat generated by AB
R_d	cooling demand [kW]
R_e	cooling capacity of mechanical chiller [kWh]
R_q	cooling capacity of absorption chiller [kWh]
tas	total annual saving
tns	total number of scenario
W_{pgu}	generated electricity by PGU

Abbreviations

AB	Auxiliary Boiler
AC	Absorption Chiller
CCHP	Combined Cooling Heat and Power
CHP	Combined Heat and Power
ED	Energy Demand
EP	Energy Price
HRS	Heat Recovery System
HTM	Historical Trend Method
LCV	Lower Calorific Value
MC	Mechanical Chiller
MCM	Monte Carlo Method
NGC	Natural Gas Consumption
PDF	Probability Density Function
PGU	Power Generation Unit
PM	Parametric Method
PP	Payback Period
SM	Scenario-based Method
SP	Separate Production

generic CCHP system. The results showed that CCHP systems reduce total annual costs for all operational cases, with the system driven by a gas engine having better performance than the one driven by a gas turbine. Additionally, linear programming was used for the sizing and operational optimization of CCHP in [12]. In [13], mixed integer linear programming was used to plan the short-term operation of CCHP systems. Moreover, several detailed simulation models were proposed in [14].

Li et al. [15] employed the weighting method and fuzzy optimum selection theory to evaluate the integrated performance of CCHP systems using various operational strategies. Cho et al. [16] summarized the methods used to perform energetic and exergetic analyses, system optimization, performance improvement studies, and the development and analysis of CCHP systems. Another review work [4] classified different types of CCHP systems based on the prime mover, size, and energy sequence usage, suggesting a general approach to select the appropriate CCHP system depending on specific needs. As in CCHP systems, Carpaneto and Chicco [17] specified the models and analyses to select the best CHP planning solution in the presence of uncertainties on a long-term timescale. Their study illustrated and discussed various technological alternatives operated under different control strategies.

The control strategy of a system plays a crucial role in optimization. As in CHP systems, CCHP systems can be operated under one of the following control strategies: on-off operation, FEL (following electricity load), and FTL (following heat load) [1,18]. With respect to these control strategies, [19] demonstrated that different seasonal load conditions and energy prices result in a reduction in total daily cost from 8% to around 100% in total daily cost. Apart from control strategies, component optimization is also important in overall optimization; however, the optimization of the whole system is a better solution than optimizing only the components [20].

Apart from the deterministic optimization method adopted in the studies mentioned above, stochastic optimization has also been performed. For example, [21] proposed a stochastic, multi-objective model to optimize CCHP operation strategy. Gomez-Villalva and Ramos [22] presented multi-objective stochastic optimization models to manage the energy of industrial consumers in liberalized energy markets. To analyze the risk that stems from energy price uncertainty, they developed a two-stage stochastic program by improving a deterministic optimization model.

In another example of stochastic optimization, Wang [23] proposed an improved multi-objective particle swarm optimization algorithm, which turned out to be effective in dealing with the CHP dispatch problem. Alipour et al. [24] also worked to solve a scheduling problem of CHP systems experienced by an industrial customer using a stochastic programming framework, where an auto-regressive, integrated moving-average technique was used to generate scenarios for electricity price and customer demand. Zhou et al. [25] proposed a two-stage stochastic programming model for the optimal design of distributed energy systems. To solve the optimization problem, they decomposed a two-stage strategy: a genetic algorithm conducted the first-stage search, while the Monte Carlo method handled uncertainty in the second stage.

A probabilistic model was proposed by Zamani et al. [26] for the optimal electrical/thermal scheduling of a virtual power plant to participate in both energy and spinning reserve markets. In that work, a simultaneous energy and reserve scheduling method was presented in light of demand-response programs. Meanwhile, Smith et al. [27] analyzed a CCHP system model under different operating strategies in terms of input and uncertainty. They revealed the significance of conducting uncertainty and sensitivity analyses in predicting CCHP system performance through a case study of a small office building. The uncertainties in the model predictions of primary energy consumption,