OPTIMAL MULTI-OBJECTIVE PROBABEL MODELING FOR SUPPORTING OF THE POWER GENERATION, REFRIGERATION AND CCHP HEATING UNIT

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Abstract

This paper presents a multi-objective optimization model to optimize the performance of the Combined cooling, heat & power (CCHP) strategy in different climates based on cost, energy consumption and carbon gas production. In order to ensure the reliability of the CCHP's performance strategy and potential load power, potential constraints are added to the contingency model and the impact of increasing the level of reliability on contingency constraints on cost, energy consumption and carbon gas production is analyzed. To develop the proposed multi-objective analysis, a model is proposed to reduce primary energy consumption and carbon emissions, and for different atmospheric conditions, values of energy consumption and carbon gas production are determined. Finally, the proposed problem was applied to the cities of San Francisco, Boston, Miami, Minneapolis and Columbus and coded in the GAMS optimization software environment. Then, based on the numerical results, the capabilities of the proposed scheme in support of optimal CCHP performance planning are evaluated.

Keywords: Multi Objective Modeling, Power generation, CCHP Heating Unit and Combined Systems

I. Introduction

With the restructuring of the electricity market, electricity prices in the market can be affected by factors such as disruption of supply and demand, capacity constraints on transmission lines, changes in fuel prices in the market, and other factors. With the increasing demand for energy, the use of methods to control the above factors, as a result of controlling electricity prices in the market, seems
necessary. One way to control transmission capacity constraints is to use distributed
generation systems[1]. On the other hand, a large share of the energy consumption is
related to the cooling and heating energy that can be utilized from the thermal energy
of distributed generation systems. As a result, in addition to reducing electricity
demand from the grid, the efficiency of distributed generation systems is increased by
the simultaneous generation of electricity and heat. Today, in addition to price
changes in the electricity market and energy efficiency, there are also concerns about
the increase in greenhouse gases, which can reduce greenhouse gas emissions by co-
generating electricity and electricity. All of these factors have increased interest in
using co-production systems including CHP and CCHP.

At the same time as this rapid growth of electricity, there was a general decrease in
the costs of generating and delivering electricity, mainly due to economic problems
caused by the dimensions and sizes, efficient technologies and reduced fuel costs.
During this time, most industries abandoned their power generation for reasons such
as income tax laws, costs, the development of other similar technologies, and so
on[II].

Over the past decade, CCHP has received much attention in the past decade due to
the possibility of reducing CO2 emissions and air pollutants and increasing energy
efficiency to very high levels [III]. The CCHP can supply on-demand electrical power
through internal combustion energies, turbine engines or fuel cells simultaneously by
providing heat and cold (thermal and refrigerant) loads with recycled energy [IV]. In
order to efficiently distribute the energy generated by CCHP, extensive studies have
been provided to develop CCHP performance strategies ([V], [VI] and [VII]).

Existing CCHP performance strategies can be divided into two main groups. The first
group is related to simple rule based strategy and the second group is related to
optimal and near-optimal strategies. In addition to the optimal strategies of the CCHP
system, the performance of CCHP has been improved in a number of studies by
adding it to sources of dispersed generation such as biomass in reference [VIII] and
solar energy in references [IX] and[X].

In simple rule-based strategies, two strategies for CCHP performance are based on
the demand for electrical and thermal loads. In the case of the Electric Charge
Strategy (FEL), all electrical loads must be supplied through the CCHP through the
Power Generation Unit (PGU). In a heat-based strategy (FTL), enough heat is lost to
recover the heat and cooling load. The performance and effectiveness of these two
strategies have been reviewed in references ([XI] and [XII]).

However, FEL and FTL strategies perform less well than strategies based on
optimization models to reduce costs and reduce carbon emissions. Therefore, studies
in the literature have been conducted to develop optimal or near-optimal CCHP
performance strategies using optimization techniques in [XIII] and XIV]. In general,
two optimization models have been studied in scientific references, the first one being
the definitive one in [XV], [XVI], [XVII], [XVIII] and [XIX] and the second one
being the probabilistic one.

In the deterministic model, all information is assumed to be explicit and assumed
not to be random. In [14], a linear programming model (LP) to determine the optimal
strategy for CCHP in terms of cost, PEC and CDE is studied separately. In [XX], the
effect of different energy price policies is investigated using Particle Asset
Optimization (PSO) algorithm. In [XIII], a counting algorithm is proposed to study
the performance strategy of a new structure CCHP system and hybrid chillers. In [XIV], a simple three-part algorithm for studying CCHP performance by minimizing energy cost is investigated. Reference [XIX] provides a tool for studying the long-term optimization of the CCHP system based on the Mixed Linear Programming (MILP) model.

In addition to these single-objective models, a number of studies of multi-objective models to optimize the CHP system on energy and environmental benefits have been presented concurrently. A multi-objective optimization model is presented in [XXI] to optimize the CCHP system in efficiency, system production cost and environmental impact costs. In [XVIII], two objectives of fuel cost and environmental impact using a multi-objective linear competitive algorithm for economically optimizing CCHP distribution are presented. In [XVII], comparisons between FEL and FTL for a building with sustained heat load in cool climates are analyzed with a multi-constraint model including core energy storage, greenhouse gas reduction and annual cost reduction. Nature-based optimization algorithms such as PSO algorithm [XVI] and genetic algorithm ([XV] and [XXII]) have been used to study and optimize the multi-objective optimization of CCHP performance. Reference [XXIII] presents a matrix modeling for the CCHP system to optimize the performance strategy with several constraints.

uncertainties of heating load, natural gas prices, electricity prices and engine performance are studied and the performance of the CCHP system at the cost of performance, PEC, and CDE under uncertainty is investigated. In [VI], a non-deterministic programming model including the Monte Carlo method (MCM) and mixed nonlinear programming is presented to optimize the CCHP performance strategy under uncertainty. In [XXIV], a potential model for the economical distribution of the CHP system is presented which can simultaneously optimize the performance of the CCHP in terms of cost, power and heat generation using the PSO optimization algorithm in the proposed probabilistic model. Finally, it should be noted that based on previous studies, the following can be considered as the study gap for optimal CCHP utilization:

1- In most papers, the nonlinear model for CCHP operation is generally expressed and then evolutionary algorithms such as genetic algorithm and particle swarm are used to solve it. Note that these algorithms are generally based on the rule of random phenomena. Therefore, these algorithms guarantee the absolute optimal solution for a low probability optimal problem. In addition, these algorithms are based on the iterative process of solving the problem, so it is very time consuming to use the process in large volume problems.

2- Although the definitive and probabilistic models available in the studies are capable of improving CCHP science in terms of energy and environmental benefits. However, few studies have been performed to optimize the performance of CCHP with a multipurpose function while considering CCHP reliability as an example to determine how much CCHP can reliably meet the demand load.

3- In some articles, FEL and FTL schemes have only been considered for CCHP. But keep in mind that these two strategies have lower performance than strategies based on optimization models to reduce costs and reduce carbon emissions.

4- In most of the articles the deterministic model or random model is considered for the proposed problem. But it has to be said that the deterministic model is not...
capable of modeling the deterministic parameters, and the stochastic model takes into account the uncertainty parameters, but requires a high number of scenarios to ensure a reliable response.

Therefore, to offset the above, this paper presents a possible multi-objective optimal problem with uncertain load demand and adding probabilistic constraints to ensure the reliability of the CCHP's performance strategy. A possible equivalent model for compromise between the performance of CCHP under different climatic conditions will be presented. In addition, an incentive scheme to reduce PEC and CDE is proposed in this proposal, which is based on optimization of the Parato Front. Thus, one can summarize the major advantages of the proposed approach over previous research as follows:

1- Provide an optimization model including contingency constraints tailored to the uncertainty parameters in the proposed scheme that can create a high-reliability operational strategy for the CCHP.

2- Providing an optimal operation strategy for the CCHP based on the Parato Front that can provide an optimal reconciliation rule between several different objective functions such as energy cost, PEC and CDE.

3- Definition of an incentive strategy for optimal operation of CCHP proportional to reduction of environmental pollution indices.

4- Consider a linear optimization model that can be solved based on standard mathematical rules such as simplex in optimization software such as GAMS and can provide an absolute optimal solution.

The rest of the paper is as follows: section 2 presents the mathematical model of the CCHP planning. In this section some necessary constraint is given. Section 3 gives the proposed method of the paper. In the section 4, the main results of the proposed method is simulated and finally, section 5 conclude the paper.

II. Possible modeling to support CCHP planning

This section describes the problem of "optimal multi-objective probabilistic modeling to support the planning of the operation of the electricity, refrigeration and heat cogeneration unit". Hence the two mathematical models for the probabilistic problem are presented as a proposal which will be described in detail below. The fuel is transferred to the PGU unit, which can generate electricity and repel heat as a by-product in the CCHP system. The electrical energy produced is used to supply the building's power and its cooling and heating components. If the PGU is not able to generate enough electricity to supply the on-demand load, the difference in electrical energy can be obtained from the electricity grid. If there is excess electricity, it can be transferred out or sold to the grid. The recycled heat is used to generate heating and cooling to provide heating and cooling loads to the building. If the heat recovered from the PGU is not sufficient for heating and cooling the building, a boiler is used to supply the rest of the heat demanded. A flow network model for the CCHP system is shown in Fig. 1. In this model, CCHP performance can be optimized on the basis of performance cost, PEC and CDE based on the deterministic linear programming model. This paper considers uncertainties in the energy demanded (including electrical, cryogenic, and thermal energy) and defines linear programming as a
probabilistic constraint model to ensure that the performance strategy can be obtained. It has been developed, providing confidence and supplying the potential energy demanded. The following is the probabilistic model used and the equivalent formulation.

II.I. Probability model

In this model, three random parameters including \( E_{d} \), \( Q_{\text{cool}_d} \), and \( Q_{\text{heat}_d} \) are introduced to express uncertainties in electrical, cooling, and heating demand respectively, and 4 probability constraints based on Eq. 1 to Eq. 4 relationships to guarantee CCHP performance. A reliable way of supplying potential energy demand is presented. The four constraints are presented to ensure the energy balance in nodes 1, 9, 10 and 11 of Fig. 1. Probability constraints indicate that the probability of meeting the constraint must be higher than the confidence level \( r \).

\[
\begin{align*}
P \left\{ E_{\text{grid}}(t) + E_{\text{pcg}}(t) + E_{\text{subtotal}}(t) - E_{\text{excess}}(t) - E_{\text{loss}}(t) \right\} & \geq E_d(t) + Q_{\text{cool}_d}(t) + Q_{\text{heat}_d}(t) \geq r_i \\
\end{align*}
\]

(1)

\[
\begin{align*}
P \left\{ E_{\text{facility}}(t) \geq E_d(t) \right\} & \geq r_i \\
\end{align*}
\]

(2)

\[
\begin{align*}
P \left\{ Q_{\text{cool}}(t) \geq Q_{\text{cool}_d}(t) \right\} & \geq r_j \\
P \left\{ Q_{\text{heat}}(t) \geq Q_{\text{heat}_d}(t) \right\} & \geq r_k \\
\end{align*}
\]

(3)

The programming variables in this model are shown in Table 1. The lower range of all variables is equal to zero. In this model, three objective functions are studied. The first objective function (\( f_{\text{cost}} \)) is to minimize the cost of operating the entire CCHP system over time intervals \( T \). The second objective function (\( f_{\text{PEC}} \)) is to minimize the total core energy consumed in time periods \( T \). The third objective function (\( f_{\text{COE}} \)) is to minimize total CO2 emissions over time periods \( T \).
\begin{align*}
    f_{\text{cont}} &= \sum_{t=1}^{T} \left( c_{el} E_{\text{grid}}(t) + c_{f_{-\text{pgu}}} F_{\text{pgu}}(t) + c_{f_{-\text{boiler}}} F_{\text{boiler}}(t) \right) \\
    f_{\text{PEC}} &= \sum_{t=1}^{T} \left( ECF_{\text{PEC}} E_{\text{grid}}(t) + FCF_{\text{PEC-\text{pgu}}} F_{\text{pgu}}(t) + FCF_{\text{PEC-\text{boiler}}} F_{\text{boiler}}(t) \right)
\end{align*}

Table. 1: The DVs variables for the first model

| DVs | Explains |
|-----|----------|
| $E_{\text{grid}}$ | Extracted energy from grid |
| $F_{\text{pgu}}$ | PGU Consumption |
| $F_{\text{boiler}}$ | Boiler Energy consumption |
| $E_{\text{pgu}}$ | PGU electrical power |
| $Q_{\text{rcv}}$ | PGU losts |
| $Q_{\text{boiler}}$ | Generated energy in boiler |
| $E_{\text{facility}}$ | Consumed energy in the building |
| $Q_{\text{th\_cool}}$ | Thermal energy required for cryogenic components |
| $Q_{\text{th\_heat}}$ | Thermal energy required for heating components |
| $Q_{\text{cool}}$ | Thermal energy generated by cryogenic components |
| $Q_{\text{heat}}$ | Thermal energy generated by heating components |
| $E_{\text{excess}}$ | Extra energy generated by PGU |
| $\text{Energyloss}_{\text{pgu}}$ | PGU energy losses |
| $\text{Energyloss}_{\text{boiler}}$ | Boiler energy losses |
| $\text{Energyloss}_{\text{c}}$ | Energy losses of CCHP cryogenic components |
| $\text{Energyloss}_{\text{h}}$ | Energy losses of CCHP thermal components |
| $\text{Energyloss}_{\text{total}}$ | Total system energy losses |

\begin{align*}
    f_{\text{CDE}} &= \sum_{t=1}^{T} \left( ECF_{\text{CDE}} E_{\text{grid}}(t) + FCF_{\text{CDE-\text{pgu}}} F_{\text{pgu}}(t) + FCF_{\text{CDE-\text{boiler}}} F_{\text{boiler}}(t) \right)
\end{align*}

In the above relationships $t$ time period indices ($t = 1, \ldots, T$), $c_{el}$, $c_{f_{-\text{pgu}}}$, and $c_{f_{-\text{boiler}}}$ respectively represent the cost of purchasing 1kW of electricity, the cost of fuel used to generate 1kW of energy in PGU, and the cost of fuel for producing 1kW of energy in the boiler. Is. $ECF_{\text{PEC}}$, $FCF_{\text{PEC-\text{pgu}}}$ and $FCF_{\text{PEC-\text{boiler}}}$ are the site-to-primary energy conversion factors for electricity, fuel used in PGU and fuel used in boilers,
respectively. $ECF_{CDE}$, $FCF_{CDE\_pgu}$ and $FCF_{CDE\_boiler}$ are emission conversion factors for electricity, fuel used in PGU and fuel used in boilers, respectively.

In Eqs 8 to 14, the energy balance constraints are expressed at nodes 3, 4, 5, 6, 7, 8 and 12 of Fig. 1. In Eq. 15, conversion of fuel to electrical energy is provided by PGU. Eq. 16 to Eq. 19 provide energy efficiency constraints for PGU, boiler, cooling and thermal components.

\[
E_{pgu}(t) + Q_{rev}(t) + Energy_{loss\_pgu}(t) - F_{pgu}(t) = 0
\]  
(8)

\[
Q_{boiler}(t) + Energy_{loss\_boiler}(t) - F_{boiler}(t) = 0
\]  
(9)

\[
E_{excess}(t) + E_{facility}(t) - E_{grid}(t) - E_{pgu}(t) = 0
\]  
(10)

\[
Q_{th\_cool}(t) + Q_{th\_heat}(t) - Q_{rev}(t) - Q_{boiler}(t) = 0
\]  
(11)

\[
Q_{cool}(t) + Energy_{loss\_c}(t) - Q_{th\_cool}(t) = 0
\]  
(12)

\[
Q_{heat}(t) + Energy_{loss\_h}(t) - Q_{th\_heat}(t) = 0
\]  
(13)

Energy_{loss\_total}(t) - Energy_{loss\_pgu}(t) - Energy_{loss\_boiler}(t) - Energy_{loss\_c}(t) - Energy_{loss\_h}(t) = 0
(14)

\[
F_{pgu}(t) = \begin{cases} 
aE_{pgu}(t) + b & E_{pgu}(t) > 0 \\ 0 & E_{pgu}(t) = 0 \end{cases}
\]  
(15)

\[
Q_{rev}(t) - \eta_{pgu\_th} F_{pgu}(t) = 0
\]  
(16)

\[
Q_{boiler}(t) - \eta_{boiler} F_{boiler}(t) = 0
\]  
(17)

\[
Q_{cool}(t) - \eta_{cool\_comp} Q_{th\_cool}(t) = 0
\]  
(18)

\[
Q_{heat}(t) - \eta_{heat\_comp} Q_{th\_heat}(t) = 0
\]  
(19)

In the above equations a and b the two parameters of converting fuel energy to electrical energy and $\eta_{pgu\_th}$, $\eta_{pgu\_th}$, $\eta_{pgu\_th}$ and $\eta_{pgu\_th}$ are respectively the fuel conversion efficiency of PGU heat, boiler heat, thermal and cryogenic components respectively.
In the first likelihood programming model, a number of planning variables can be eliminated by converting equality constraints to inequality constraints. Hence a second equivalent planning model is presented to simplify the first planning model. In this model, the decision variables of \(E_{\text{grid}}, F_{\text{boiler}}, E_{\text{facility}}, Q_{\text{cool}}\) and \(Q_{\text{heat}}\) are retained and a number of Spgu binary variables are defined to express the PGU status during the \(T\) interval. The way these binary variables are defined is that 1 represents the PGU method and 0 represents its off. The objective functions are similar to the first probabilistic model and are defined as Eq. 5 to Eq. 7. The constraints in Eq. 1 to Eq. 4 and Eq. 8 to Eq. 19 are equivalent to the constraints stated below in Eq. 20 to Eq. 27.

\[
(1 + a\eta_{\text{pgu\_th}} - a)F_{\text{pgu}}(t) - bS_{\text{pgu}}(t) \leq 0 \quad (20)
\]

\[
aE_{\text{facility}}(t) - aE_{\text{grid}}(t) - F_{\text{pgu}}(t) + bS_{\text{pgu}}(t) \leq 0 \quad (21)
\]

\[
\frac{Q_{\text{cool}}(t)}{\eta_{\text{cool\_comp}}} + \frac{Q_{\text{heat}}(t)}{\eta_{\text{heat\_comp}}} - \eta_{\text{pgu\_in}} F_{\text{pgu}}(t) - \eta_{\text{boiler}} F_{\text{boiler}}(t) = 0 \quad (22)
\]

\[
F_{\text{pgu}}(t) \leq MS_{\text{pgu}}(t) \quad (23)
\]

\[
P\{E_{\text{facility}}(t) + Q_{\text{cool}}(t) + Q_{\text{heat}}(t) \geq E_d(t) + Q_{\text{cool\_d}}(t) + Q_{\text{heat\_d}}(t)\} \geq r_1 \quad (24)
\]

\[
P\{E_{\text{facility}}(t) \geq E_d(t)\} \geq r_2 \quad (25)
\]

\[
P\{Q_{\text{cool}}(t) \geq Q_{\text{cool\_d}}(t)\} \geq r_3 \quad (26)
\]

\[
P\{Q_{\text{heat}}(t) \geq Q_{\text{heat\_d}}(t)\} \geq r_4 \quad (27)
\]

Assuming that the three probable energy demands at each time interval \(t\) are independent and consistent with the normal distribution in which 95% of the total area is within the 20% range of mean energy demand [XXV]. According to the four probability constraints of Eq. 23 to 27, when normal parameters in probability constraints are normally distributed, equivalent to 4 definite constraints on Eq. 23 to Eq. 27 is:
\( E_{\text{facility}}(t) + Q_{\text{cool}}(t) + Q_{\text{heat}}(t) \geq Z_1(t) \) \hspace{1cm} (28)

\( E_{\text{facility}}(t) \geq Z_2(t) \) \hspace{1cm} (29)

\( Q_{\text{cool}}(t) \geq Z_3(t) \) \hspace{1cm} (30)

\( Q_{\text{heat}}(t) \geq Z_4(t) \) \hspace{1cm} (31)

\[ Z_1(t) = \mu_{E_d}(t) + \mu_{Q_{\text{cool,d}}}(t) + \mu_{Q_{\text{heat,d}}}(t) + z_{a_1} \sqrt{\sigma_{E_d}^2(t) + \sigma_{Q_{\text{cool,d}}}^2(t) + \sigma_{Q_{\text{heat,d}}}^2(t)} \] \hspace{1cm} (32)

\[ Z_2(t) = \mu_{E_d}(t) + z_{a_2} \sigma_{E_d}(t) \] \hspace{1cm} (33)

\[ Z_3(t) = \mu_{Q_{\text{cool,d}}}(t) + z_{a_3} \sigma_{Q_{\text{cool,d}}}(t) \] \hspace{1cm} (34)

\[ Z_4(t) = \mu_{Q_{\text{heat,d}}}(t) + z_{a_4} \sigma_{Q_{\text{heat,d}}}(t) \] \hspace{1cm} (35)

Where \( Z_{a1}, Z_{a2}, Z_{a3} \) and \( Z_{a4} \) are reliability indices corresponding to the reliability levels \( r_1, r_2 \) and \( r_3 \) and \( r_4 \). And the inverse transfer function is the standard normal distribution function.

Assuming that there is no interaction between variables at different time intervals, the second probabilistic model can be expressed as T-independent problems that are linear binary hybrid programming problems. For this purpose, one can derive a profit function to combine all three objective functions as follows:

\[ \min f(t) = c_{\text{grid}} E_{\text{grid}}(t) + c_{\text{pgu}} F_{\text{pgu}}(t) + c_{\text{boiler}} F_{\text{boiler}}(t) \] \hspace{1cm} (36)

In the above relation, \( c_{\text{grid}} \), \( c_{\text{pgu}} \) and \( c_{\text{boiler}} \) are the coefficients of electricity, fuel used in PGU and fuel used in boilers. For example, if the cost function is defined to minimize the cost function then \( c_{\text{grid}} = \text{cel} \) and \( c_{\text{pgu}} = \text{cf}_{\text{pgu}} \) and \( c_{\text{boiler}} = \text{cf}_{\text{boiler}} \). In order to solve the sub-problem at any time interval \( t \), the problem is divided into two linear programming sub-problems: the first problem is the state of PGU off \( (c_{\text{pgu}} = 0) \) and the second problem is the state of PGU off \( (\text{Spgu} = 1) \). The optimal solution is obtained by minimizing the relationship cost function of Eq. 36.

In this case, silent PGU means that \( C_{\text{pgu}}(t) = 0 \) and \( F_{\text{pgu}}(t) = 0 \). Thus the linear programming model in time interval \( t \) is obtained as follows:
\[
\min f(t) = c_{\text{grid}}(t)E_{\text{grid}}(t) + c_{\text{boiler}}(t)F_{\text{boiler}}(t)
\]  
\tag{37}
\]

\[
E_{\text{facility}}(t) - E_{\text{grid}}(t) \leq 0
\]  
\tag{38}
\]

\[
Q_{\text{cool}}(t)/\eta_{\text{cool\_comp}} + Q_{\text{heat}}(t)/\eta_{\text{heat\_comp}} - \eta_{\text{boiler}}F_{\text{boiler}}(t) = 0
\]  
\tag{39}
\]

\[
E_{\text{facility}}(t) + Q_{\text{cool}}(t) + Q_{\text{heat}}(t) \geq Z_1(t)
\]  
\tag{40}
\]

\[
E_{\text{facility}}(t) \geq Z_2(t)
\]  
\tag{41}
\]

\[
Q_{\text{cool}}(t) \geq Z_3(t)
\]  
\tag{42}
\]

\[
Q_{\text{heat}}(t) \geq Z_4(t)
\]  
\tag{43}
\]

It can be seen that the relation constraint Eq. 38 must be provided by the optimal solution. The optimal solution for this linear programming model is:

\[
E_{\text{facility}}(t) = \begin{cases} 
\max(Z_1(t)-Z_2(t)-Z_3(t), Z_2(t)) & \text{if } c_{\text{grid}}(t)\eta_{\text{boiler}}/c_{\text{boiler}}(t) \\
\leq \min(1/\eta_{\text{cool\_comp}}, 1/\eta_{\text{heat\_comp}}) \\
Z_2(t) & \text{otherwise}
\end{cases}
\]  
\tag{44}
\]

\[
E_{\text{cool}}(t) = \begin{cases} 
\max(Z_1(t)-Z_2(t)-Z_3(t), Z_2(t)) & \text{if } 1/\eta_{\text{cool\_comp}} \leq \min(c_{\text{grid}}(t)\eta_{\text{boiler}}/c_{\text{boiler}}(t) \\
1/\eta_{\text{heat\_comp}}) \\
Z_3(t) & \text{otherwise}
\end{cases}
\]  
\tag{45}
\]

\[
E_{\text{heat}}(t) = \begin{cases} 
\max(Z_1(t)-Z_2(t)-Z_3(t), Z_3(t)) & \text{if } 1/\eta_{\text{heat\_comp}} \leq \min(1/\eta_{\text{cool\_comp}}, \\
\eta_{\text{boiler}}/c_{\text{boiler}}(t)) \\
Z_4(t) & \text{otherwise}
\end{cases}
\]  
\tag{46}
\]

In this case, PGU is on, which means Cpgu \((t) = 1\). Therefore, the linear programming model can be simplified as follows:
A linear programming problem to obtain the optimal solution is solved at any time interval $t$ when PGU is switched on. Finally, note that Problem Sections 3-3 and 3-4 can be implemented based on the following flowchart.

III. Proposed Strategy

It is noteworthy that the proposed problem model is linear in the previous sections. This paper also uses a mathematical principle such as simplex to solve this problem that has a robust and reliable solution. So, different software can solve optimization problems. But among these software, GAMS software is a powerful software optimization based on mathematical methods. One of the advantages of this software is that the coding process in this software is very simple. It also has many problem solvers for each model that is ready as a package. Therefore, the user error in coding the problem solving method will be very low[XXVI]. In the following, the coding process of a problem is expressed in the GAMS software environment. To this end, consider the following:
\[
\min_{x_j} \sum_{j \in \varphi_2} C_j x_j \tag{53}
\]

If
\[
f_i = \sum_{j \in \varphi_2} a_{i,j} x_j \quad \forall i \in \varphi_2 \tag{54}
\]
\[
f_i \geq 1 \quad \forall i \in \varphi_2 \tag{55}
\]
\[
\sum_{j \in \varphi_2} x_j = N_{\text{max}} \tag{56}
\]
\[
x_j \in \{0,1\} \quad j \in \varphi_1 \tag{57}
\]

Where sets 1 and 2 are \{1, 2, ..., 8\}, and Nmax is 3. Also the parameter C for all elements of the set is 1 to 100 and the matrix a is as follows.

\[
a = \begin{bmatrix}
1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 1 & 1 & 0 & 0 & 1 & 1 \\
0 & 0 & 1 & 1 & 1 & 0 & 0 & 1 \\
0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 \\
0 & 0 & 1 & 0 & 0 & 1 & 1 & 0 \\
0 & 0 & 1 & 1 & 0 & 0 & 0 & 1
\end{bmatrix} \tag{58}
\]

IV. Simulation Results

This section presents the numerical results of the Problem of "Optimal Multi-Objective Possible Modeling to Support Planning Performance of Cogeneration Unit". Note that this is coded in the GAMS optimization software environment. Following is a discussion of the details of the problem and the results of the various case studies carried out in this section, so that the capabilities of the proposed scheme can be evaluated.

In this section, CCHP exploitation studies are evaluated under the uncertainty of energy demand as a stochastic problem presented in the previous sections. For this purpose, in this paper, five Columbus, Minneapolis, San Francisco, Boston and Miami sites with different electric, thermal and cooling load curves are used. It is worth noting that hourly electrical, thermal, and cooling load information was obtained from the reference [III]. Also, electricity and gas prices for the sites under study, site-to-primary energy conversion factors for gas and electricity purchased for PEC evaluation, and CDE conversion factors for gas and electricity sites in Table. 1. The values of the coefficients used in Eq. 15 to Eq. 19 are also expressed in[III]. According to [XXVII] and [XXVIII], the electrical, thermal and cooling demand at
any time \( t \) are normal distributions. The average value of \( \mu \) is the normal distribution of the time value in the load profile and \( Q \) is a standard deviation of 20% of \( \mu \).

Table 2: Price, location-to-primary energy conversion factor, CDE conversion factor used in the simulation

| City                          | Price(kWh) | Location-to-primary energy conversion factor | CDE conversion factor (ton/year-kWh) |
|-------------------------------|------------|---------------------------------------------|-------------------------------------|
|                               | Electricity | Gas                                         | Electricity | Gas | Electricity | Gas |
| Columbus                      | 0.078      | 0.028                                       | 3.34        | 1.047 | 0.000749    | 0.0002 |
| Minipolyis                    | 0.074      | 0.034                                       | 3.34        | 1.047 | 0.000826    | 0.0002 |
| San Francisco                 | 0.119      | 0.028                                       | 3.34        | 1.047 | 0.000439    | 0.0002 |
| Boston                        | 0.108      | 0.039                                       | 3.34        | 1.047 | 0.000455    | 0.0002 |
| Miami                         | 0.076      | 0.037                                       | 3.34        | 1.047 | 0.000662    | 0.0002 |

The choice of reliability levels depends on the importance of probability constraints. In this paper, four probability constraints Eq. 23 to Eq. 27 are considered to be of equal importance, hence the level of reliability for each probability constraint \( r \) is considered in this section. Be. Also in this section, optimization of three objective functions in Eq. 5 to Eq. 7 individually with different reliability levels \( r \) ie 0.2, 0.5, 0.8, 95 0. and 0.99 are performed. In the future study, the effects of the unequal level of reliability on the operational strategy are examined. In reality and in practice, the level of reliability is set to over 0.8. But in this case study, values of less than 0.8 for the reliability level have also been investigated, which is to provide a full discussion of the proposed operation strategy. Finally, consider the optimal values of operating cost \( f_{\text{cost}} \), PEC \( f_{\text{PEC}} \) and CDE \( f_{\text{CDE}} \) for the five sites considered under different reliability levels in Fig. 2 to Fig. 5. It is worth noting that for all five sites considered in this section, operating costs, PECs and CDEs increase if reliability levels are increased, as the level of reliability also increases with the level of energy demand. Also note that for the level of reliability the problem model will be equal to 0.5, since the parameters \( \sigma_{\text{Ed}} \), \( \sigma_{\text{Qcool,d}} \) and \( \sigma_{\text{Ed}} \) for all simulation times based on Eq. 32 to Eq. 35 are equal to zero. Also, it can be seen from Fig. 2 to Fig. 5 that the operating cost, PEC and CDE are less than 0.5 if the uncertainty level is less than 0.5 (definitive problem). The corresponding values in the problem are deterministic, but this is more than 0.5 for the uncertainty level. For future reviews of operating costs, PEC and CDE, an effect index (1) is defined as follows:

\[
\Delta = \frac{f_{\text{sto}} - f_{\text{det}}}{f_{\text{det}}}
\]  

(59)

Fsto and fdet represent the objective function values in the stochastic and deterministic models, respectively. Different values of effect index for operating cost, PEC and CDE corresponding to different reliability levels are given in Table. 2. The NG/E column is calculated as follows:
1- Price of natural gas divided by the price of electricity corresponding to the Cost line
2- Primary location-to-primary conversion factor divided by corresponding electricity-to-primary conversion factor for PEC line
3- CDE conversion factor Natural gas divided by CDE conversion factor Corresponding electricity for CDE row

Fig. 2: The cost function versus different levels of reliability

Fig. 3: The function PEC versus different level of reliability

Fig. 3: The function CDE versus different level of reliability

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Table 3: Effectiveness Index (%) for different reliability levels and cities

| City          | R   | 0.2 | 0.5 | 0.8 | 0.95 | 0.99 | Medium | NG/E |
|---------------|-----|-----|-----|-----|------|------|--------|------|
| Columbus      | Cost| 6.78| 0.00| 7.47| 14.55| 20.53| 9.88   | 0.28 |
|               | PEC | 6.90| 0.00| 7.58| 14.78| 20.86| 10.02  | 0.31 |
|               | CDE | 6.92| 0.00| 7.64| 14.90| 21.03| 10.10  | 0.33 |
| Minapolis     | Cost| 6.83| 0.00| 7.36| 14.34| 20.24| 9.75   | 0.29 |
|               | PEC | 6.89| 0.00| 7.46| 14.53| 20.50| 9.87   | 0.31 |
|               | CDE | 6.71| 0.00| 7.05| 13.71| 19.37| 9.37   | 0.26 |
| San Francisco | Cost| 6.64| 0.00| 6.66| 12.90| 18.10| 8.86   | 0.21 |
|               | PEC | 7.42| 0.00| 7.67| 14.92| 21.04| 10.21  | 0.31 |
|               | CDE | 7.35| 0.00| 8.59| 16.78| 23.74| 11.29  | 0.66 |
| Boston        | Cost| 6.88| 0.00| 7.21| 13.95| 19.56| 9.52   | 0.27 |
|               | PEC | 7.01| 0.00| 7.46| 14.52| 20.47| 9.89   | 0.31 |
|               | CDE | 7.06| 0.00| 7.55| 14.70| 20.72| 10     | 0.33 |
| Miami         | Cost| 6.49| 0.00| 7.55| 14.72| 20.78| 9.91   | 0.38 |
|               | PEC | 6.45| 0.00| 7.42| 14.48| 20.48| 9.77   | 0.31 |
|               | CDE | 6.45| 0.00| 7.40| 14.47| 20.45| 9.75   | 0.31 |

It is worth noting that for Columbus, San Francisco and Boston sites, the level of reliability has a large impact on CDE and has a small effect on operating cost. The level of reliability also has a large effect on PEC and a small effect on CDE for Minneapolis. In the case of Miami, the level of reliability has a large impact on operating costs and it has a small effect on CDE. It is noteworthy that increasing the level of reliability results in an increase in energy demand, which in turn increases the demand for natural gas for estimating thermal and cooling loads. Therefore, this paper argues that the change of electricity proportional to natural gas has major effects on increasing CDE for the Columbus, San Francisco, and Boston sites. It also has a huge impact on increasing the cost of operating the Miami site. Ultimately, it will have a major impact on increasing the PEC for the Minneapolis site. It also follows the same path as the NG/E coefficient as in Table 3. In this section, CCHP exploitation studies using the multi-objective stochastic problem model presented in the next section will be discussed. This section defines an incentive to reduce PEC and CDE for the CCHP system. Hence, this incentive to reduce PEC and CDE appears in the objective function along with the minimization of operating cost, thus creating a single-objective problem. The objective function formulation is as follows:

$$\min f_{\text{total}} = f_{\text{cost}} + p_{\text{PEC}} (f_{\text{PEC}} - f_{\text{PEC,ref}}) + p_{\text{CDE}} (f_{\text{CDE}} - f_{\text{CDE,ref}})$$

That is, the terms and, respectively, represent the amount of PEC and CDE for reference studies. Also pPEC and pCDE are incentives to reduce PEC and CDE, which are in dollars per kWh and dollars, respectively. In this section, the results of the Paratou Front are evaluated for 95% confidence level at various sites. In this section, the primary energy storage incentive is considered, so pPEC must be greater than zero and pCDE must be equal to zero. Note that the average retail price of electricity in the United States is approximately $ 0.1 per kWh. Hence, in this section, the coupling model is evaluated by changing pPEC to the set of 0.02, 0.04, 0.06, 0.08 and 0.1 for the 95% confidence level and the results of this section are presented in the Table 4. It is worth noting that based on the results of Table 4, it is observed that...
at the Columbus, Boston and Miami sites, increasing $p_{\text{PEC}}$ for primary energy storage reduces the total cost expressed in Eq. 60, PEC and CDE. And the cost of operating will increase. For the city of San Francisco, PCE and CDE decrease, but operating costs increase, while $p_{\text{PEC}}$ increases. Ultimately, increasing $p_{\text{PEC}}$ reduces total cost and PEC, while operating cost and CDE increase.

Table 4: The total cost of Eq. 60

| City            | variable | PPEC  | Cost  | Ref   |
|-----------------|----------|-------|-------|-------|
|                 | 0.00     | 0.02  | 0.04  | 0.06  | 0.08  | 0.10 |
| Columbus        | $f_{\text{total}}$ | 5502  | 5351  | 5197  | 5042  | 4887  | 4732  | 6047.9 |
|                 | $f_{\text{cost}}$   | 5502  | 5504  | 5506  | 5508  | 5508  | 5509  | 6047.9 |
|                 | $f_{\text{PEC}}$    | 207.19| 206.86| 206.80| 206.77| 206.76| 206.76| 214.53 |
|                 | $f_{\text{CDE}}$    | 35.81 | 35.07 | 35.68 | 35.67 | 35.67 | 35.66 | 35.74  |
| Minipolysi s    | $f_{\text{total}}$ | 5427  | 5083  | 4737  | 4390  | 4032  | 3696  | 6064   |
|                 | $f_{\text{cost}}$   | 5427  | 5427  | 5429  | 5430  | 5431  | 5431  | 6064   |
|                 | $f_{\text{PEC}}$    | 222.13| 221.89| 221.85| 221.84| 221.84| 221.84| 239.2  |
|                 | $f_{\text{CDE}}$    | 41.22 | 41.31 | 41.33 | 41.35 | 41.35 | 41.36 | 48.29  |
| San Francisco   | $f_{\text{total}}$ | 5378  | 5444  | 5477  | 5494  | 5494  | 5380  | 6804   |
|                 | $f_{\text{cost}}$   | 5378  | 5405  | 5418  | 5524  | 5524  | 5757  | 6804   |
|                 | $f_{\text{PEC}}$    | 183.6 | 178.65| 178.18| 176.1 | 176.19| 172.92| 176.7  |
|                 | $f_{\text{CDE}}$    | 28.77 | 26.7  | 26.43 | 24.89 | 22.35 | 21.92 | 15.50  |
| Boston          | $f_{\text{total}}$ | 7795  | 7570  | 7331  | 7087  | 6843  | 6598  | 8851   |
|                 | $f_{\text{cost}}$   | 7795  | 7808  | 7815  | 7878  | 7823  | 7825  | 8851   |
|                 | $f_{\text{PEC}}$    | 201.45| 199.24| 199   | 198.91| 198.85| 198.83| 211.1  |
|                 | $f_{\text{CDE}}$    | 35    | 34.46 | 34.40 | 34.37 | 34.35 | 34.34 | 35.69  |
| Miami           | $f_{\text{total}}$ | 7460  | 7265  | 7066  | 6866  | 6665  | 6463  | 6731   |
|                 | $f_{\text{cost}}$   | 7460  | 7463  | 7466  | 7468  | 7469  | 7470  | 6731   |
|                 | $f_{\text{PEC}}$    | 219.62| 218.34| 218.27| 218.22| 218.22| 218.21| 228.26 |
|                 | $f_{\text{CDE}}$    | 38.78 | 38.53 | 38.51 | 38.5  | 38.5  | 38.49 | 40.94  |

In this section, carbon dioxide pollution is encouraged, so $p_{\text{PEC}}$ must be zero and $p_{\text{CDE}}$ must be greater than zero. Note that according to [40], the price of carbon pollution is approximately $30 / tonne. Hence, in this section, the coupling model by changing $p_{\text{CDE}}$ to set 0, 10, 20, 30, 40 and 50 is evaluated for 95% confidence level and the results of this section are presented in Table 5. It is worth noting that based on the results of Table 5, the following results will occur for different cities with increasing $p_{\text{CDE}}$ to reduce carbon dioxide pollution:

1- In Columbus, PEC and CDE decrease, if operating costs increase.
2- In Minneapolis, CDE and total cost are reduced, while operating cost and PEC increase
3- In San Francisco, CDE and PEC decrease, while operating costs and total costs increase.
Table 5: The total cost for different $P_{PEC}$

| City        | variable | $P_{PEC}$ | $C_{DE}$ | Ref |
|-------------|----------|-----------|----------|-----|
| Columbus    | $f_{total}$ | 5502      | 5503     | 5503 | 5503 | 5503 | 6047.9 |
|             | $f_{cont}$ | 5502      | 5502     | 5502 | 5503 | 5503 | 5504 | 6047.9 |
|             | $f_{PEC}$  | 207.19    | 207.07   | 207.01 | 206.96 | 206.93 | 206.90 | 214.53 |
|             | $f_{CDE}$  | 35.81     | 35.77    | 35.74 | 35.73 | 35.73 | 35.72 | 35.74 |
| Minipolysis | $f_{total}$ | 5427      | 5356     | 5285 | 5214 | 5143 | 5072 | 6064 |
|             | $f_{cont}$ | 5427      | 5427     | 5427 | 5428 | 5428 | 5428 | 6064 |
|             | $f_{PEC}$  | 222.13    | 222.21   | 222.25 | 222.29 | 222.37 | 222.43 | 239.2 |
|             | $f_{CDE}$  | 41.22     | 41.20    | 41.19 | 41.19 | 41.17 | 41.17 | 48.29 |
| San Francisco | $f_{total}$ | 5378      | 5504     | 5624 | 5741 | 5853 | 5964 | 6804 |
|             | $f_{cont}$ | 5378      | 5382     | 5388 | 5398 | 5406 | 5413 | 6804 |
|             | $f_{PEC}$  | 183.6     | 180.92   | 179.90 | 179.1 | 178.59 | 178.3 | 176.7 |
|             | $f_{CDE}$  | 28.77     | 27.27    | 27.30 | 26.93 | 26.67 | 26.53 | 15.65 |
| Boston      | $f_{total}$ | 7795      | 7787     | 7775 | 7758 | 7746 | 8851 |
|             | $f_{cont}$ | 7795      | 7796     | 7798 | 7800 | 7803 | 780 | 8851 |
|             | $f_{PEC}$  | 201.45    | 200.89   | 200.43 | 199.94 | 199.57 | 199.41 | 211.1 |
|             | $f_{CDE}$  | 35        | 34.86    | 34.75 | 34.63 | 34.54 | 34.51 | 35.69 |
| Miami       | $f_{total}$ | 7460      | 7437     | 7413 | 7390 | 7366 | 7342 | 6731 |
|             | $f_{cont}$ | 7460      | 7461     | 7461 | 7461 | 7461 | 7462 | 6731 |
|             | $f_{PEC}$  | 219.62    | 218.63   | 218.59 | 218.52 | 218.49 | 218.44 | 228.26 |
|             | $f_{CDE}$  | 38.78     | 38.58    | 38.58 | 38.56 | 38.56 | 38.55 | 40.94 |

In Miami and Boston, CDE, PEC and total costs are reduced, while operating costs increase. So it's always the worst case if CCHP is used in Miami for economic acceptance if $p_{CDE}$ is $50$ / tonne. It is also always good if CCHP is used for Columbus, Minneapolis, San Francisco and Boston, although no CDE incentives are provided.

As seen in the previous sections, with increasing $p_{PEC}$, PEC decreases but the operating cost increases. Also with the increase of $p_{CDE}$, CDE decreases and the operating cost increases. Therefore, in this section, the effects of increasing $p_{PEC}$ and $p_{CDE}$ are observed simultaneously. $p_{PEC}$ changes in the set of 0.02, 0.04, 0.06, 0.08 and 0.1, while $p_{CDE}$ changes 10, 20, 30, 40 and 50 in total. Results for the 95% confidence level are shown in Fig. 6 to 10. Finally, based on these Figures, it can be seen that by increasing $p_{PEC}$ and $p_{CDE}$ in order to save the initial energy and reduce carbon dioxide pollution, the following results are obtained:

1. In Columbus City, the total cost, PEC and CDE are reduced if the effect of primary energy storage and carbon dioxide pollution is increased, while the cost of operation increases. Therefore, compared to the reference system (excluding PEC and CDE incentives), the conditions are economic for CCHP.
2. For Minneapolis, increasing $p_{PEC}$ reduces total cost and PEC and increases operating cost and CDE. Also note that increasing $p_{CDE}$ reduces total cost, operating cost, and CDE, if it increases PEC. Finally, like the city of Columbus, the CCHP is also economic in comparison to the city.
3. For the city of San Francisco, with the increase in PEC and CDE incentives, PEC and CDE decrease, and operating costs and total costs increase. The CCHP also has economic conditions in the city, even if there are no PEC and CDE incentives.

4. For the city of Boston, PEC, CDE, PEC, CDE and costs decrease with the increase of PEC and CDE incentives and the operating cost increases. It is worth noting that, like the city of San Francisco, the CCHP also has economic conditions in the city, even when PEC and CDE incentives are not needed.

5. For Miami, the PEC and CDE incentives increase as PEC, CDE and costs decrease and operating costs increase. CCHP conditions in this city are lower than the economic reference if the pPEC is less than 0.08.
Fig. 6: The variations a) Total cost, b) Cost of operation, c) PEC, d) CDE for Columbus.
Fig. 7: The variations a) Total cost, b) Cost of operation, c) PEC, d) CDE for Minipolysis
Fig. 7: The variations a) Total cost, b) Cost of operation, c) PEC, d) CDE for San-Fransisco
Fig. 7: The variations a) Total cost, b) Cost of operation, c) PEC, d) CDE for Boston.
Fig. 7: The variations a) Total cost, b) Cost of operation, c) PEC, d) CDE for Miami

Given the above diagrams and reference values in the cities of Columbus, Minneapolis and Boston, even without the incentives of PPEC and PCDE, CCHP systems are cost-effective and follow the pattern of energy consumption and pollution. For the City of San Francisco, even without incentives, it is cost-effective and the PPEC energy consumption pattern is 0.06 or higher, but despite the maximum PCDE incentive, its contaminant value is still within the reference range. Intended more, for the City of Miami, regardless of incentives, the amounts of energy consumption and pollutant production in the suffering are allowed, but not economically feasible. But the PPEC incentive range would be 0.08 or higher.

V. Conclusion

Optimizing energy supply has a positive impact on the economies of countries and enhancing their role in global energy markets. One of the results of optimizing energy supply is improving efficiency and reducing environmental pollutants caused by energy production. In recent years, distributed generation units due to benefits such as reduced distribution system losses (which account for 21% of total installed capacity in Iran - less than 8% in advanced countries), liberalization of transmission capacity are negligible. The cost of operating, contributing to the stability of the network, and so on has been much appreciated. One of the most important technologies in this field is CHP and CCHP. The basis of these systems is the use of heat losses from the local electricity source for use in heating applications. Normally the efficiency of the most efficient plants with natural gas is about 35%. In contrast, using CHP cogeneration systems or CCHP systems with energy recovery can increase its efficiency rating by up to 95%. Over the last half century, low prices have led to a tendency to consume more energy, and a widespread lack of attention to environmental protection has resulted in market decisions that, in most cases, lead to the release of pollutants and the use of energy in the same way. Low yields have come to fruition. Fortunately, today, market pricing and public policy efforts are encouraging energy use and environmental protection. Therefore, in some countries, the government encourages investors to invest in cogeneration systems.

The growth of electricity consumption in Iran in recent years is such that if the current trend continues and fossil fuel production is restricted, the country will become an importer of energy and electricity. Or demand-side management activities

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to pursue strategies to increase fuel efficiency and replace renewable energies instead of fossil fuels, so given the significant decline in fossil fuel resources and environmental issues, one can expect the future prospects of energy generation to move further. The benefits of consuming and minimizing losses as well as increasing the share of energy obtained from scattered and renewable sources of production. Given that these systems have just arrived in Iran and are expanding, to assist decision makers in the field of energy systems and sustainable development, this paper presents a multi-objective optimization model to optimize the CCHP performance strategy in the situation. Different climates were expressed by cost, energy consumption and carbon emissions. In order to ensure the reliability of the CCHP performance strategy to provide potential load energy, potential constraints were added to the contingency model, and the impact of increasing the level of reliability on contingency constraints on cost, energy consumption and carbon gas production was analyzed. To develop the proposed multi-objective analysis, a model was proposed to reduce primary energy consumption and carbon emissions, and for different atmospheric conditions, energy consumption and carbon gas production values were determined. Finally, the proposed problem was applied to the cities of San Francisco, Boston, Miami, Minneapolis and Bolumbas, and then based on the numerical results, the following general results were derived:

Increasing the level of reliability increases energy demand.

1- Increased level of reliability increases PEC.
2- Increased level of reliability increases CDE.
3- Increased level of reliability increases the cost of operating CCHPs.
4- Increasing PEC incentives generally reduce total costs and PECs in most cities, while increasing operating costs.
5- Increasing CDE incentives generally reduces total costs and CDEs in most cities, while increasing operating costs.
6- Simultaneous increases in PEC and CDE incentives generally reduce the overall cost of CDE and PEC in most cities, while increasing operating costs.
7- Given the PEC and CDE incentives, CCHP will generally be economical in most cities.

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