Risk and Uncertainty Analysis of Cooling Demand in Multi-Chiller System Using Downside Risk Constraints Method

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ABSTRACT The optimal performance of a multi-chiller system (MCS) is the crucial factor in managing the expected power consumption (EPC). Also, the uncertainty of cooling demand in the industrial or residential sector plays a crucial role, which should be modeled and managed. So, the stochastic risk-constrained performance of the optimal chiller loading is studied in an uncertain environment in this paper. Scenario-based stochastic programming is applied to the provided case study to model the cooling demand uncertainty (CDU), and the downside risk constraints (DRC) are implemented to model the associated risks. The risk-averse performance of the MCS is compared with the risk-neutral one to show the positive effects of the DRC. The proposed model is implemented under the DICOPT solver in GAMS software. The comparison results show that the expected power consumption of MCS is increased slowly, while the expected risk-in-power consumption (ERIPC) is decreased promptly.

INDEX TERMS Cooling demand uncertainty (CDU), downside risk constraints (DRC), expected power consumption (EPC), expected risk-in-power consumption (ERIPC), multi-chiller system (MCS), risk-neutral and risk-averse performances.

NOMENCLATURE

ABBREVIATIONS

CDU Cooling demand uncertainty
DRC Downside risk constraints
EPC Expected power consumption
ERIPC Expected risk-in-power consumption
GAMS General Algebraic modeling system
MCS Multi-chiller system
PLR Partial load ratio

PARAMETERS

\(Q^t_{i,s}\) The cooling demand
\(Q^n_i\) The nominal capacity of MCS
\(\alpha_i, \beta_i, \gamma_i, \zeta_i\) Operating coefficients of the MCS
\(\rho_i\) Probability of each scenario
\(\lambda\) Control the risk level

VARIABLES

\(PC\) Expected power consumption of the MCS
\(Q_{i,t,s}\) Cooling load of the MCS
\(PLR_{i,t,s}\) PLR of the MCS
\(P_{i,t,s}\) Power consumption of the MCS

I. INTRODUCTION

Nowadays, the MCS as air-conditioning system [1] is widely used in the residential sector to provided convenience [2]. Also, they are used in the industrial sector to increase the obtained profit through improving the quality of their products [3]. It should be noted that the electrical power consumption of the MCS can be increased by improper control [4].
Therefore, optimal management of the MCS to minimize electrical power consumption can be considered as a crucial point [5]. Finally, the risk associated with the cooling demand uncertainty should be managed in the studied test system.

The optimal chiller loading problem has been optimized in [6] with different techniques to minimize the consumption of electricity under the cooling demand uncertainty. Determining the PLR for each chiller is the primary purpose of the paper mentioned above.

Various heuristic and conventional algorithms such as dynamic programming [7], [8], genetic algorithm (GA) [9], multi-phase GA [10], GA in coupling MATLAB and TRNSYS software [11], firefly algorithm [12], particle swarm optimization [13], [14], cuckoo search [15], evolution strategy [16], simulated annealing [17], differential evolution [18], equal loading rate [19], neural network [20] and GAMS [21] have been applied to optimize the chiller loading problem.

By evaluating the references [7]–[21], it can be seen that the optimization problem has been analyzed with different techniques without considering the uncertainty of the cooling demand. On the other hand, the worthy reference [22], [23] modeled the cooling demand uncertainty with the use of the robust optimization approach. Also, different methods are presented in [24] to increase the robustness of the chiller sequencing control considering the different load indicators. It is noteworthy that managing the associated risk has not been considered in these works. But, the different strategies of optimal chiller loading namely risk-seeker, risk-neutral and risk-averse are obtained via info-gap decision theory in [25].

In this work, the stochastic risk-constrained performance of the optimal chiller loading problem has been studied under the uncertain environment. At first, the scenario-based stochastic programming has been used to model the cooling demand uncertainty. Then the downside risk constraints (DRC) method has been applied to model and manage the risk associated with cooling demand uncertainty and reduce the expected risk-in-power consumption (ERIPC) in the studied MCS system.

The main contributions and novelty of this article can be summarized as follows:

1) Optimizing the consumption of the electricity in the MCS under uncertain environment.

2) Applying the scenario-based stochastic programming to model the cooling demand uncertainty.

3) Modeling the risk associated with cooling demand uncertainty with the use of downside risk constraints (DRC).

4) Obtaining the risk-averse performance of the MCS to show the effects of the DRC.

The rest of this paper is categorized as follows: The stochastic risk-constrained model of the MCS is provided in Section II. The simulation results in both risk-averse and risk-neutral points of view are presented and compared in Section III. Finally, the conclusion is provided in Section IV.

II. STOCHASTIC RISK-CONSTRAINED MODEL OF THE MCS

In the stochastic risk-constrained model of the MCS, first the scenario-based stochastic programming is used to model the cooling demand uncertainty. After that the downside risk constraints are utilized to model the associated risk.

A. STOCHASTIC MODEL

Chillers, as the air-conditioning system, consume high electrical energy in the industrial or residential areas. The consumption of electrical energy in industrial or residential sectors will be decreased if the performance of MCS managed properly [26]. The objective function (1) in the chiller loading problem is minimizing the expected power consumption of MCS. Also, the limitations of the MCS are provided in constraints (2)-(5), which should be considered in the optimization problem.

\[
\text{Min } PC = \sum_{s=1}^{S} \rho_s \times \sum_{i=1}^{T} \sum_{l=1}^{I} P_{i,t,s}
\]

Subject to : \( P_{i,t,s} = \alpha_i + \beta_i \times PLR_{i,t,s} + \gamma_i \times PLR_{i,t,s}^2 + \zeta_i \times PLR_{i,t,s}^3 \) \( (2) \)

\[
\text{PLR}_{i,t,s} = \frac{Q_{i,t,s}}{Q_{i,n}}
\]

\[
0.3 \leq PLR_{i,t,s} \leq 1 \rightarrow 0.3 \times Q_{i,n} \leq Q_{i,t,s} \leq Q_{i,n}
\] \( (3) \)

\[
\sum_{i=1}^{I} Q_{i,t,s} = Q_{i,n}
\] \( (5) \)

According to [27], [28], the consumption of electrical power in each chiller of the MCS is the polynomial function of PLR, which is presented in constraint (2). The PLR (3) is obtained by the division of the cooling load of each chiller by the nominal capacity. According to equation (4), PLR should be limited between 0.3 and 1. In other words, according to manufacturer suggestion, the minimum amount of PLR should be assumed to be 0.3 and the maximum amount of PLR should be equal to 1 if the chiller operated with the nominal capacity. Finally, the cooling demand balance is provided in constraint (5).

B. RISK MODEL

The risk associated with the cooling demand uncertainty is modeled in this subsection. In other words, the constraints between expected risk-in-power consumption and MCS’s expected power consumption are expressed. The operator of the MCS tries to have expected power consumption lower than the predetermined one (Target\(_{\text{power}}\)). The MCS will be satisfied once the power consumption of the MCS in each scenario be lower than the Target\(_{\text{power}}\). Otherwise, it will be considered as the downside risk. Therefore, the downside risk constraints for power consumption can be defined as follows:

\[
\text{If } PC_s > \text{Target}_{\text{power}} \text{ then } \text{Risk}_s = PC_s - \text{Target}_{\text{power}}
\]

\[
\text{otherwise } \text{Risk}_s = 0
\] \( (6) \)
In (6), \( PC_s \) and \( Risk_s \) are respectively the consumption power of the MCS and risk-in-power consumption at the \( s \)th scenario. The constraint (6) can be rewritten as Eq. (7).

\[
0 \leq Risk_s - (PC_s - Target_{power}) \leq M \times (1 - U_s)
\]

\[
0 \leq Risk_s \leq M \times U_s
\] (7)

In which, \( M \) is a large and positive number. \( U_s \) is a binary variable which will be 1 if the condition \( PC_s > Target_{power} \) be satisfied.

So, according to the provided description, the expected downside risk (EDR) for the consumption power of the MCS can be formulated as follows [29]–[31]:

\[
\sum_{s=1}^{S} \rho_s \times Risk_s \leq \lambda \times EDR
\]

\[
EDR = \sum_{s=1}^{S} \rho_s \times (PC_s^{No risk} - Target_{power})
\] (8)

In Eq. (8), \( PC_s^{No risk} \) is the consumption power in each scenario without considering downside risk constraints. \( \lambda \) is the number between 0 and 1 and it is used to control the risk level. It should be mentioned that \( \lambda = 1 \) indicates the risk-neutral performance of the studied test system while \( \lambda = 0 \) indicates the risk-averse performance.

The flowchart of the proposed risk-constrained economic chiller dispatch strategy is illustrated in Fig. 1. The presented stochastic risk-constrained model of the MCS is solved with the use of the DICOPT solver [32] in GAMS software [33].

It should be noted that the uncertainty parameters in worst condition is considered in the robust optimization approach which it rarely happens. Also, the robust cost in worst strategy is considered in the robustness function of info-gap decision theory which it rarely happens. But, all scenarios in best and worst condition are considered in the proposed stochastic optimization in the presence of DRC which is the most important advantage in versus the mentioned methods.

III. NUMERICAL STUDY

A. DATA

In this work, three chillers are considered as the MCS which the nominal capacities are 800 RT (1 RT = 3.5168525 kW). The mentioned system is similar to the system of a semiconductor plant in Hsin Tsu Science-based Park [9]. The power coefficients of the MCS associated with the performance curve is adopted from [22]. The forecasted amount of the cooling demand curve during a sample day (24-h) is adopted from [22]. All scenarios of cooling demands are depicted in Fig. 2 in which the normal distribution function is used to generate scenarios. Other generation units can be added in the proposed work [34], [35].

B. CASE STUDIES

Two case studies are used to investigate the performance of the proposed risk-constrained model of the MCS from the risk-neutral and risk-averse perspectives. So, the mentioned case studied can be summarized as follows:

Case study 1: Stochastic scheduling of the MCS without considering DRC, which known as the risk-neutral performance.

Case study 2: Stochastic scheduling of the MCS with considering DRC, which known as the risk-averse performance.

C. COMPARISON & RESULTS

In case study 1, the performance of the MCS is optimized without considering DRC. Obtained results are provided in Table 1. It should be noted that the average of the
consumption power, as well as the average of the risk-in-power, can be calculated with the use of the reported results in Table 1. So, the average of the consumption power and the average risk-in-power consumption are 29,592.4 kWh and 221.2 kWh, respectively. The predefined power consumption in case study 2 is assumed to be equal to the expected power consumption in case study 1. In case study 2, the performance of the MCS is optimized in the
presence of DRC. Obtained results in the second case study, in 10 scenarios and different values of $\lambda$ are presented in Tables 2–4.

Table 2 presents the power consumption in each scenario in case 2 in versus the risk control indicator which is slowly increased due to consider the cooling demand uncertainty. Also, the risk-in-power consumption in each scenario in case 2 in versus the risk control indicator is provided in Table 3. It is seen that the risk in power is significantly decreased due to implement the proposed DRC method which is the most important advantage of proposed risk model in this work.

Finally, the Pareto curve between average power consumption and average risk-in-power consumption in case study 2, is illustrated in Fig. 3. According to Table 4 and Fig. 3, in ${\lambda} \approx 0.3$, the average risk-in-power consumption is reduced significantly, 70%, in case study 2 in comparison with case study 1 while the average power consumption is increased slowly, 1.1768%, in case study 2.

D. RISK-CONSTRAINED PERFORMANCE OF MCS

The risk-constrained performance of the MCS is analyzed and compared in the third scenario of two risk-averse and risk-neutral case studies. Figs. 4–6 illustrate the risk-constrained PLR of the first, second and third chillers in the MCS in the risk-averse and risk-neutral viewpoints. It can be concluded that the PLR of the first chiller is reduced at hours 4 and 5 while it is increased at hours 14, 15, 17 and 20 in the risk-averse case study in comparison with risk-neutral one. Furthermore, it is shown that the PLR of the second chiller is increased at hours 4, 5, 15 and 17 in the risk-averse case study in comparison with risk-neutral one. Finally, it can be seen that the PLR of the third chiller is decreased at hours 4-6, 14-17 and 20 in the risk-averse case study in comparison with risk-neutral one to cope with the cooling demand uncertainty. So, this behavior makes the average power consumption of MCS to be increased while the average risk-in-power consumption is reduced significantly.

Figs. 7–9 illustrate the risk-based consumption power of first, second, and third chillers in the MCS in two risk-averse
and risk-neutral case studies. It is shown that the consumption power of the first chiller is decreased at hours 4 and 5 while it is raised at hours 14, 15, 17 and 20 in the risk-averse in comparison with the risk-neutral. Furthermore, it can be seen that the consumption power of the second chiller is increased at hours 4, 5, 15 and 17 in the risk-averse in comparison with the risk-neutral one. Finally, it can be concluded that the consumption power of the third chiller is reduced at hours 4-6, 14-17 and 20 in the risk-averse cases study in comparison with the risk-neutral to manage the cooling demand uncertainty which leads the average risk-in-power consumption to be decreased significantly and the average power consumption of the MCS to be increased slowly.

IV. CONCLUSION

The risk-averse stochastic performance of the MCS was studied under the cooling demand uncertainty. First of all, a scenario-based stochastic programming approach was used to model the cooling demand uncertainty. Then, downside risk constraints were implemented to model the associated risk in the provided case studies. So, two different case studies named risk-averse and risk-neutral were analyzed in this paper to study the performance of the MCS model under the uncertain environment. In the second case study 2, with considering the DRC, the average consumption power of the MCS was increased slowly while the risk-in-power consumption of the MCS was reduced significantly in comparison to case study 1. The electrical power consumption by the water pumps and the cooling towers of the chiller plants can be considered in the risk-constrained optimization process in the future works.

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