Applied Thermal Engineering 149 (2019) 1114–1124

Contents lists available at ScienceDirect

Applied Thermal Engineering

journal homepage: www.elsevier.com/locate/apthermeng

Research Paper

The chiller's electricity consumption simulation by considering the demand response program in power system

Zehui Shao[a,b], Ehsan Gholamalizadeh[c,*], Albert Boghosian[d], Behnam Askarian[e], Zhenling Liu[f]

[a] Institute of Computing Science and Technology, Guangzhou University, Guangzhou 510006, China
[b] School of Information Science and Engineering, Chengdu University, Chengdu 610106, China
[c] Department of Mechanical Engineering, Sejong University, Seoul, Republic of Korea
[d] Phd in Economics, University of Tehran, Kish International Campus, Iran
[e] Department of Electrical and Computer Engineering, Texas Tech University, Lubbock, TX 79409, USA
[f] University of California Irvine, CA 92697 USA

HIGHLIGHTS

- Risk-averse strategy is also considered.
- Using the aforementioned methods, precise planning is proposed.
- Consumption of the finally, cooling demand management is suggested.

ARTICLE INFO

Keywords:
Solar photovoltaic
Multi-chiller system
Cooling demand uncertainty and management
Robust optimization approach

ABSTRACT

One of the main challenges in multi-chill system issues by considering the uncertainty of cooling demand is total energy consumed and energy buying cost. Therefore, it is necessary to optimize power consumption in these issues. This paper provides a robust optimization method with uncertainty modeling in multi-chiller systems to obtain accurate planning. It should be noted that one of the energy supply sources for multi chiller system is photovoltaic system (in addition to the network). In order to improve cooling demand profile, using demand response program, demand levels are shifted through peak periods of energy consumption to low consumption periods. In this work, the minimization of energy procurement cost of multi-chiller systems from the upstream network is assumed as a target function, taking into account demand response of cooling and uncertainty demand. Also, the effect of cooling demand response on two robust and deterministic strategies has been investigated. Achieved results depict, risk-averse method through robust method is robust against cooling requirement uncertainty, contrasting to risk-neutral method through deterministic approach. In addition, the cost of supplying energy of multi-chiller systems from solar systems is reduced by using the demand response program in both of mentioned methods.

1. Introduction

Multi chiller systems are often used as air conditioning systems in commercial, residential and office areas, which application of this system in tropical regions is higher than other areas [1]. With the aim of reducing greenhouse gas releases and minimizing energy consumption of multi-chiller systems, solar systems are used in multi-chill systems [2–5]. In order to accurately estimate the energy consumption of multi-chiller systems and reduce energy consumption, uncertainty of cooling demand is considered in multi-chiller systems [6]. In previous studies, researchers have done various studies using different evolutionary algorithms for optimizing power consumption in multi chiller systems and determining the partial load ratio of each chiller. A number of algorithms used in this field are: an improved ripple bee swarm optimization algorithm [7,8], particle swarm optimization [9–15], simulated annealing [16,17], differential evolution [18], genetic algorithm [19–22], multi-phase genetic algorithm [23], artificial neural network [24–28], firefly algorithm [29], gradient method [30], Lagrangian method [31], empirical model [32], differential cuckoo search approach [33] based on improved cuckoo search [34].

It should be noted that in the mentioned research, the uncertainty of cooling demand in optimal loading of multi chiller system was

* Corresponding author.
E-mail address: ehsan@sejong.ac.kr (E. Gholamalizadeh).

https://doi.org/10.1016/j.applthermaleng.2018.12.121
Received 5 July 2018; Received in revised form 3 December 2018; Accepted 22 December 2018
Available online 24 December 2018
1359-4311/

Nomenclature:

Index

i	index of chiller
t	index of hour

Number

I	number of chillers
T	numbers of hours
N_{pv}	number of photovoltaic panels

Parameters

α_i, β_i, γ_i, ζ_i	coefficients related to the operating characteristic of chiller i
Q_i^n	the nominal capacity of chiller i
CL_t^0	the cooling demand at hour t
λ_t	upstream grid price
η	conversion coefficient of a photovoltaic panel
S	array area of a photovoltaic module
Φ_t	solar irradiance at time t
T_t^a	ambient temperature at time t
P_t^{pv}	procurement power from solar photovoltaic system
$DR_{\max}$	maximum value of load participation in DRP
$inc_{\max}$	maximum value of load increase in DRP

Variables

TPC_{24-h}	total procurement cost in 24 hours
P_t^{grid}	procurement power from upstream grid at time t
$P_{i,t}$	power consumption of chiller i at time t
$PLR_{i,t}$	partial load ratio (PLR) of chiller i at time t
$Q_{i,t}$	cooling load of chiller i at time t
U_i^t	a binary decision variable that will be equal to 1, if i^{th} chiller is on; otherwise it will be 0
CL_t	cooling demand after implementation of DRP at time t
DR_t	percentage of participation in DRPs at time t
ldr_t	shifted demand at time t
CL_t^{inc}	increased demand at time t
inc_t	amount of load increase at time t
$\alpha^{(0)}$	parameter of algorithm which is generated between [0.5, 1]
γ	parameter of algorithm which is generated between [0, 1]
μ	parameter of algorithm which is generated between 0.95
$\beta^{(1)}$	parameter of algorithm which is generated between 0.7

neglected. But in this study, in order to plan and accurately determine the energy consumption of multi chiller systems, using a robust optimization strategy, uncertainty in cooling demand is considered. Furthermore, the solar system is also utilized to supply the system's required energy in addition to the upstream network. With the aim of reducing the cost of purchasing energy from solar systems in multi-chiller systems, cooling demand management techniques are used, which improves the voltage profile and achieves this desired target. The risk-averse strategy has been used to optimize the system performance in this study. In the following, a summary of the innovations and participation of the paper is provided.

Initially, a robust optimization method is proposed for modeling uncertainty. Then, in order to supply system energy, solar system is used in addition to upstream network. Risk-averse strategy is also considered as a robust optimization. Using the aforementioned methods, precise planning is proposed to determine the energy consumption of the multi chiller system, and finally, cooling demand management is suggested to reduce cost of energy supply from solar systems.

The paper structure is: In Section 2, the mathematical model of optimal chiller loading is presented considering the management of cooling demand and in the presence of solar system as a source of energy supply. The optimization model for cooling demand uncertainty in the multi chiller system is formulated in Section 3. In Section 4, numerical results have been compared with the definitive method and the strong optimization method in the presence of cooling demand management and in the absence of it. In Section 4, numerical results obtained from the deterministic method and the robust optimization method in the presence of cooling demand management and in the absence of it have been compared to each other. At the end, the conclusion of the study is stated in Section 5.

2. Formulization of deterministic based optimization problem

In this paper, objective function is presented in Eq. (1) which is total energy procurement cost of solar photovoltaic based multi-chiller system in the presence of cooling demand response program (DRP). The mathematical model of the objective function is presented in Eq. (1). Eq. (1) is minimized with equal and unequal limitations.

$$\text{Min} \quad TPC_{24-h} = \sum_{t=1}^{T} \lambda_t P_t^{grid} \tag{1}$$

The amount of power required by the multi-chiller system with the total power provided by the network and the solar system must be equal to that expressed in Eq. (2) with an equal constraint.

$$P_t^{grid} + N_{pv} P_t^{pv} = \sum_{i=1}^{I} P_{i,t} \tag{2}$$

The energy consumption for each chiller is proportional to partial load ratio, which is expressed using the polynomial Eq. (3), [35,36]. Cooling load of each chiller unit divided by nominal load per unit of chiller is equal to partial load ratio that given in Eq. (4). The partial load ratio is in interval [0.3, 1], and it is equal to 1 when chiller operates at a nominal capacity, and the lowest acceptable value of PRL is 0.3 based on manufacture offer. Finally, constraint (6) shows balance equation which the total cooling loads of chillers supplied the cooling demand in each hour.

$$P_{i,t} = U_i^t \times \{\alpha_i + \beta_i \times PLR_{i,t} + \gamma_i \times PLR_{i,t}^2 + \zeta_i \times PLR_{i,t}^3\} \tag{3}$$

$$PLR_{i,t} = \frac{Q_{i,t}}{Q_i^n} \tag{4}$$

$$U_i^t \times 0.3 \leqslant PLR_{i,t} \leqslant U_i^t \times 1 \quad \rightarrow \quad U_i^t \times 0.3 \times Q_i^n \leqslant Q_{i,t} \leqslant U_i^t \times Q_i^n \tag{5}$$

$$\sum_{i=1}^{I} Q_{i,t} = CL^t \tag{6}$$

It should be mentioned that optimal scheduling of solar photovoltaic based multi-chiller system in the presence of time-of-use rate of cooling demand response program is considered in this paper. The cost of purchasing energy from the solar system is computed using Eq. (7) [37].

$$P_t^{pv} = \eta\, S\, \Phi_t [1 - 0.005 \times (T_t^a - 25)] \tag{7}$$

In demand response program, industrial, residential and commercial consumers, part of the demand for a multi-chiller system in proportion to the cost of purchasing energy will be shifted from peak-time to off-peak time. Demand response program is categorized into two incentive and time-based groups of program. Time-based program performance is based on time consumed, so that consumers transfer their time consuming energy from expensive interval to low-cost interval with the aim of minimizing energy buying price. In Figure 1, the time-of-use rate of DRP is plotted. According to Figure 1, the area under the line (dashed area) is not a member of the demand response program, the upper area of the line, which refers to peak and medium-peak times, transfers the load from this area to the low-consumption area (off-peak time). Eqs. (8)–(10) refer to the equal constraints of the DRP model (Eqs. (8) and (9) represent the cooling demand constraints), and Eqs. (11)–(13) refer to the unequal constraints of the DRP model.

$$CL_t = CL_t^0(1 - DR_t) + ldr_t \tag{8}$$

$$CL_t^0 - CL_t = ldr_t = DR_t \times CL_t^0 \tag{9}$$

$$\sum_{t=1}^{T} ldr_t = \sum_{t=1}^{T} DR_t \times CL_t^0 \tag{10}$$

$$CL_t^{inc} \leqslant inc_t \times CL_t^0 \tag{11}$$

$$DR_t \leqslant DR_{\max} \tag{12}$$

$$inc_t \leqslant inc_{\max} \tag{13}$$

3. Mathematical model of robust optimization method

In this section, a robust optimization method has been developed to model uncertainty variable with the aim of risk management. One of the advantages of this approach is low cost and economical in compared with other methods. In this study, cooling demand was considered as an uncertainty parameter and a robust optimization method was used to model this parameter. Eqs. (1)–(13), which relate to optimizing the problem of purchasing energy from multi chiller systems from solar systems with the consideration of the demand response program, are formulated in the standard form in the following:

3.1. Accelerated particle swarm optimization

Accelerated particle swarm optimization (APSO) method [9], is an improved PSO and it is similarly a computational method which is imitated from animal behavior such as ant colonies, bird flocks, fish schools and extra. Accelerated PSO in general comprised from three key stages as follow:

1- In first step, particle (agents) begin from a primary random location inside exploration region under relative limits. Amount of objective function of particles are calculated by primary points and models of practical problem. Then, the best point of primary particles can be achieved using regaining the particle which obtained best objective amount.
2- In this phase, particles position update in every iteration based on present position of particles and position of best agent in primary agents. The agents shifted based on three factors covering of present position, optimal position among agents and a random element.
3- Lastly, repetition quits once some defined conditions are gained and ultimate best answer could be determined which obtained in final iteration.

Position of agents in accelerated PSO algorithm can be rewritten as follows:

$$x^{(i+1,j)} = (1 - \beta) * x^{(i,j)} + \beta * g^{(i,*)} + \alpha(i) * r^{(i,j)} \tag{14}$$

where, the position of optimal solution in iteration i is indicated by $g^{(i,*)}$; the attraction variants of accelerated PSO is determined by β, and the convergence variables of this algorithm is shown with α which can be calculated in each repetition by:

$$\alpha^{(i)} = \alpha^{(0)} * \gamma^i \tag{15}$$

According to [10,11], $\alpha^{(0)}$ and γ take value in interval [0.5, 1] and [0, 1], respectively. Amounts of this parameters are assumed 0.9 and 0.8 in this work for intelligent sizing.

3.2. Chaotic mapping (CM) method

Clearly, amount of β influences convergence of accelerated PSO. If β amount be equal to one in a step, the convergence of agents will stay invariant much as present Gbest isn't actual global optimal solution. In contrary, if this value be equal to zero, mechanism may cause to light alterations. So, this parameter should be well adjusted. Mostly, in criteria accelerated PSO amount of β assumed to be 0.5 [12]. Despite that practice has proposed it could be effective, the answers are yet varying lightly as optimum are being achieved. Hence, for generation a few 'accidents', dynamic amount for β is required in iterations. This dynamic value could aid the agents to jump out of the regional optimum convergence. In order to set this parameter in various iterations, the chaotic mapping is suggested in this work. Four kinds of CM methods are presented in this work to edit accelerated PSO containing: Gauss/mouse map, singer map, sinusoidal map as well as logistic map. Accelerated PSO using suggested CM methods are appraised as fittest four out of twelve nominations for resolving criteria mechanism testing functions (covering of Griewank, Ackley and Sphere functions) [38].

Each CM method outlined in following:

(a) Gauss/mouse map

This mapping is expressed by following relations:

$$\beta^{(i+1)} = \begin{cases} 0\beta(i) = 0 \\ \frac{1}{\beta^{(i)}} mod(1) \quad otherwise \end{cases} \tag{16}$$

In this formula, residual of unit of number by 1 is denoted by mod (1); primary amount $\beta(1)$ is assumed 0.7 in simulations. The edited CAPSO using Gauss/mouse map is determined by CAPSO-1 in this work.

(b) Singer map

Outline of singer map which is 1-D system is represented as follows [38]:

$$\beta^{(i+1)} = \mu * (7.86 * \beta^{(i)} - 23.31 * (\beta^{(i)})^2 + 28.75 * (\beta^{(i)})^3 - 13.302875 * (\beta^{(i)})^4) \tag{17}$$

In Eq. (17), value of μ and primary value of $\beta^{(1)}$ are considered to be 0.95 and 0.7, respectively. The edited CAPSO using singer map is indicated by CAPSO-2 in this work.

(c) Sinusoidal map

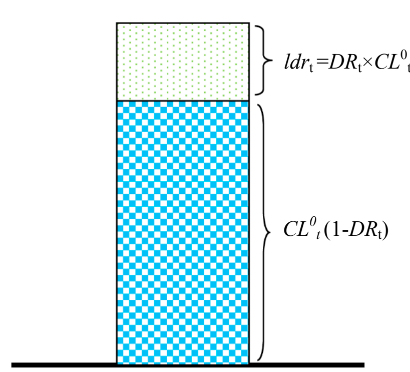

Fig. 1. Cooling demand considering demand response program.

Table 1
Parameters of PV panels [37].

N_{pv}	η	S
400	0.187	2.5

Table 2
Chiller data for six units [20].

Chiller	α_i	β_i	γ_i	ζ_i	Chiller capacity (RT)
1	399.345	−122.12	770.46	0	1280
2	287.116	80.04	700.48	0	1280
3	−120.505	1525.99	−502.14	0	1280
4	−19.121	898.76	−98.15	0	1280
5	−95.029	1202.39	−352.16	0	1280
6	191.750	224.86	524.4	0	1280

Outline of this mapping is expressed in below [38]:

$$\beta^{(i+1)} = \sin(\pi * \beta^{(i)}) \tag{18}$$

In which, starting amount of $\beta^{(1)}$ is assumed 0.7 in this work. The edited CAPSO using sinusoidal map is indicated by CAPSO-3 in this work.

(d) Logistic map

Logistic map [33] is mapped with below equation. This formula represents non-linear dynamic of biological population confirming chaotic treatment.

$$\beta^{(i+1)} = a * \beta^{(i)} * (1 - \beta^{(i)}) \tag{19}$$

In this equation, primary amount of $\beta^{(1)}$ and a are respectively assumed 0.7 and 4. The edited CAPSO using logistic map in this work is called CAPSO-4.

Eqs. (20)–(23) shows criteria form for presented power supplement optimization of PV based multi chiller with DRP in (1)–(14).

$$Min \quad \sum_{t=1}^{T} \sum_{i=1}^{I} c_{i,t}.\ x_{i,t} \tag{20}$$

Subject to:

$$a_{i,t}.\ x_{i,t} \leqslant b_{i,t} \quad ; \quad \forall\ i,\ t \tag{21}$$

$$x_{i,t} \geqslant 0 \quad ; \quad \forall\ i,\ t \tag{22}$$

$$x_{i,t} \in \{0,\ 1\}\ for\ some\ i,\ t \tag{23}$$

In the above equation, the decision parameters and factor of the objective function are defined by $x_{i,t}$ and $C_{i,t}$, respectively. Decision parameter factor in limitation and the factor at right hand side of limitation are represented by $a_{i,t}$ and $b_{i,t}$, respectively. Although parameter $b_{i,t}$ indicates the uncertainty of the cooling demand, but its range is clear and known that is in the range $[b_{i,t} - \widetilde{b}_{i,t},\ b_{i,t} + \widetilde{b}_{i,t}]$, it should be noted that $\widetilde{b}_{i,t}$ represents the deviation from the prediction value of the factor $b_{i,t}$ and $\widetilde{b}_{i,t} \geqslant 0$.

To achieve the comprehensive formula of robust optimization and uncertainty modeling, a new parameter, Γ_i is set to be selected in range 0–1. The desired conservatism level is controlled with this parameter which the robustness of proposed model is obtained against the uncertainty parameter.

Eqs. (20)–(23) relate to the robust optimization problem by considering the uncertainty parameter is formulated in the standard form Eqs. (24)–(32)

$$Min \quad \sum_{t=1}^{T} \sum_{i=1}^{I} c_{i,t}.\ x_{i,t} \tag{24}$$

Subject to:

$$a_{i,t}.\ x_{i,t} \leqslant b_{i,t} + z_i.\ \Gamma_i + q_{i,t}\ ;\ \forall\ i,\ t \tag{25}$$

$$z_i.\ \Gamma_i + q_{i,t} \geqslant \widetilde{b}_{i,t}.\ y_t\ ;\ \forall\ i,\ t \tag{26}$$

$$q_{i,t} \geqslant 0 \tag{27}$$

$$y_t \geqslant 0 \tag{28}$$

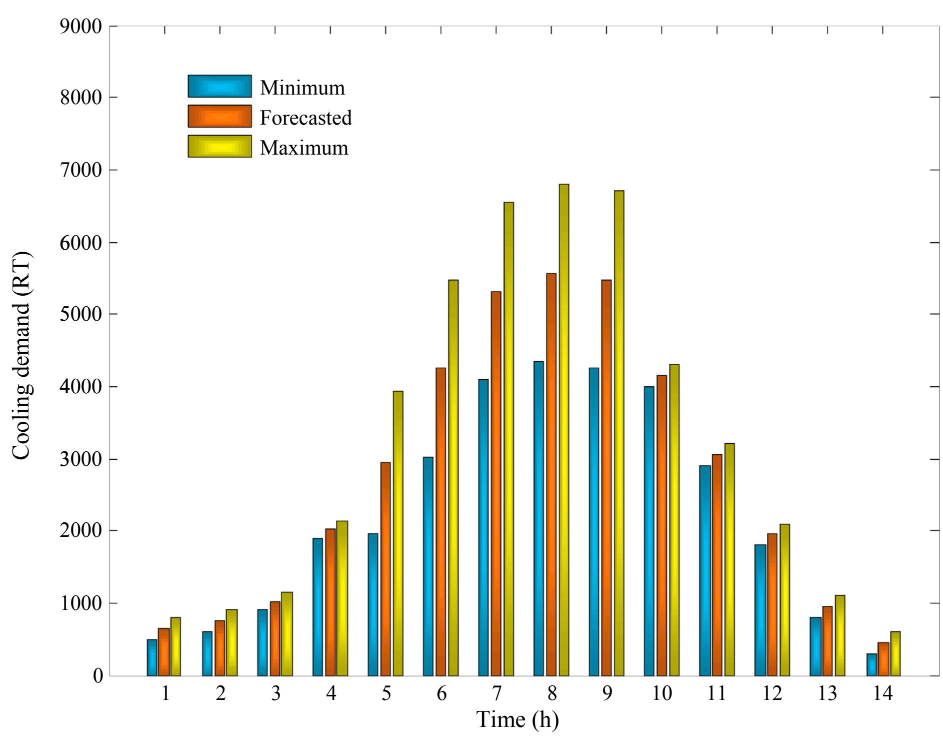

Fig. 2. Cooling demand [20].

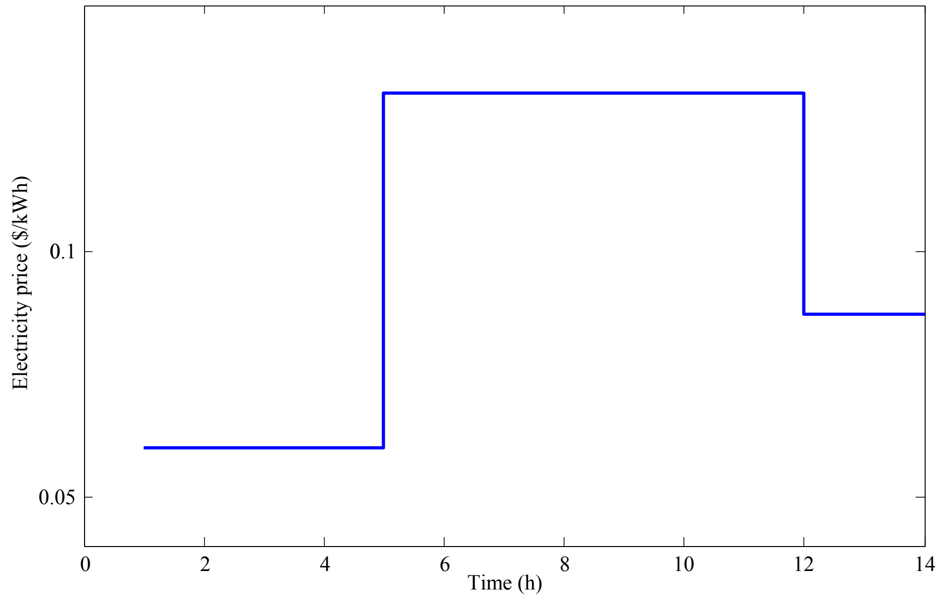

Fig. 3. Hourly electricity price from $t=7^{\text{a.m.}}$ to $t=20$.

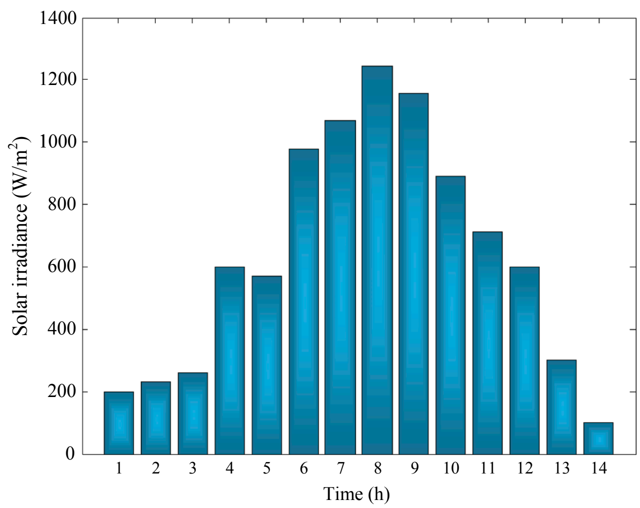

Fig. 4. Solar irradiance.

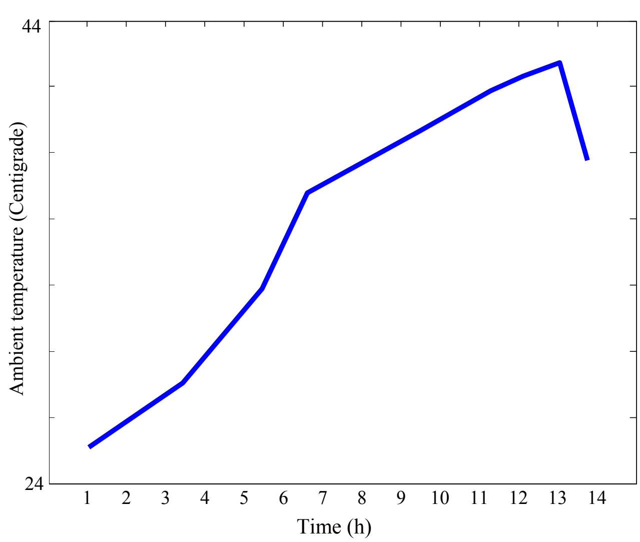

Fig. 5. Ambient temperature from $t=7^{\text{a.m.}}$ to $t=20$.

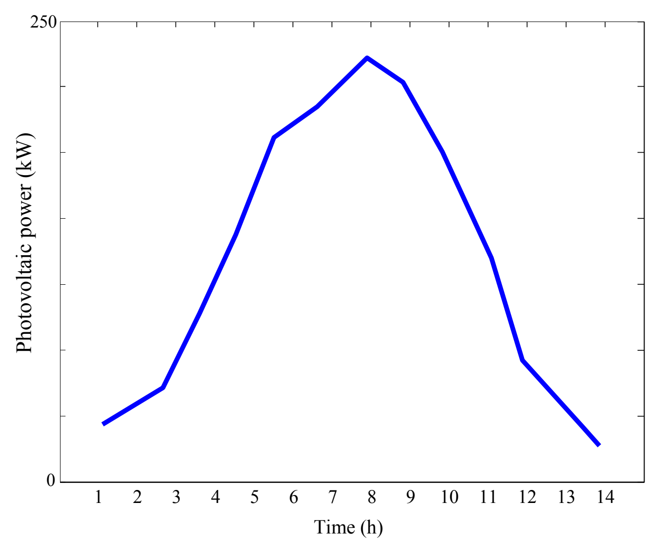

Fig. 6. Power output of photovoltaic panels from $t=7^{\text{a.m.}}$ to $t=20$.

$$z_i \geqslant 0 \tag{29}$$

$$1 \leqslant y_t \tag{30}$$

$$x_{i,t} \geqslant 0 \quad ; \quad \forall\, i,\, t \tag{31}$$

$$x_{i,t} \in \{0,\, 1\}\ \textit{for some}\ i,\, t \tag{32}$$

In Eqs. (24)–(32), the decision parameters are represented by $x_{i,t}$, $q_{i,t}$, y_t, z_i. In order to simplify and achieve the linear model of the problem, deviation of uncertainty parameter (while y_t is an auxiliary parameter) is obtained by using two dual parameters z_i, $q_{i,t}$ in the standard optimization problem (23)–(20) [39]. In the robust optimization method, when the values of $\widetilde{b}_{i,t}$ are positive, the value of Γ_i is chosen from the interval [0, 1] as risk-averse methodology, and if the value of $\widetilde{b}_{i,t}$ is zero, then the numerical value of Γ_i is considered zero in deterministic method as risk-neutral strategy.

In deterministic optimization method, only uncertainty variable is CL_t which is considered in Eqs. (1)–(13) in the right-hand side limitation. Given that CL_t is an uncertainty parameter, then $\widetilde{CL}_t$ is selected at intervals of [0 and 1], if $\widetilde{Q}_t^L$ is the derivative of the prediction

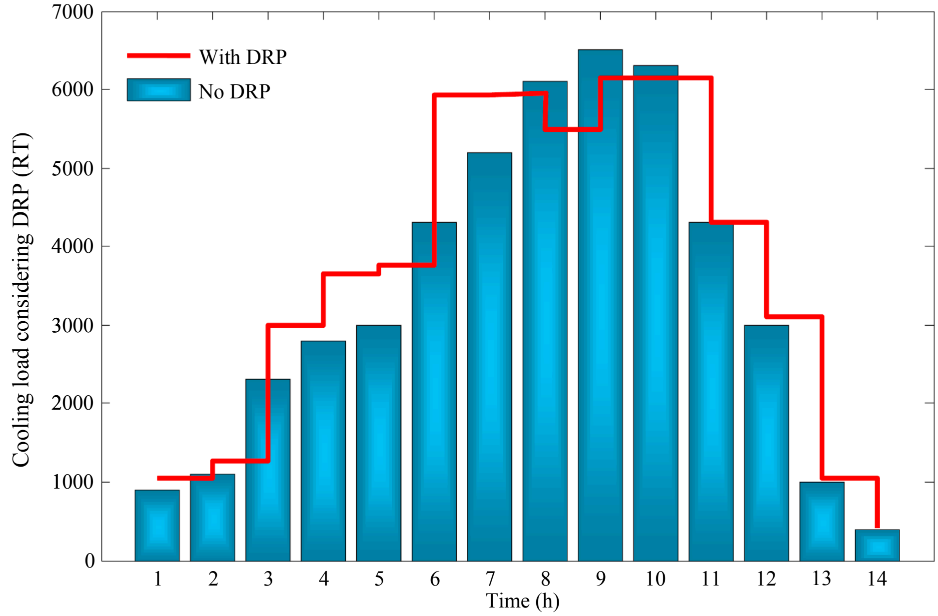

Fig. 7. Cooling demand with and without DRP.

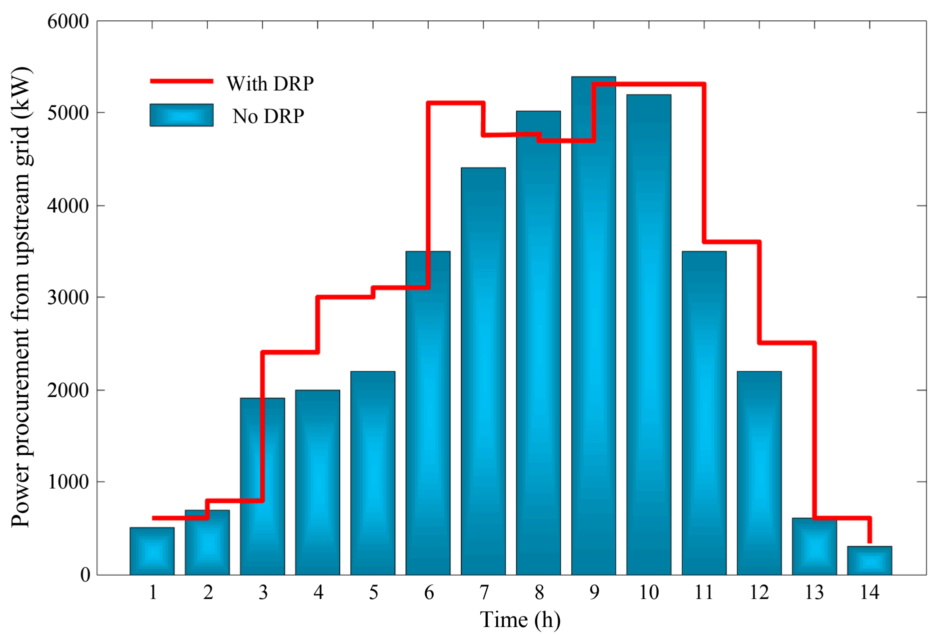

Fig. 8. Power procurement from upstream grid with and without DRP in deterministic strategy.

coefficient Q_t^L and $\widetilde{Q}_t^L > 0$. From the robust optimization Eqs. (24)–(32) there is only one uncertainty parameter used in limitation (6). Therefore, Eqs. (2)–(13), except for Eq. (6), stay unaltered. Finally, Eqs. (24)–(32) are formulated in the form of Eqs. (2)–(13) that are robust optimization model in the presence of uncertainty.

$$\text{Min} \quad TPC_{24-h} = \sum_{t=1}^{T} \lambda_t P_t^{grid} \tag{33}$$

Subject to:

$$\text{Constraints}(2)-(5) \ \text{and} \ (7)-(13) \tag{34}$$

$$\sum_{i=1}^{I} Q_{i,t} = CL_t + z.\,\Gamma + q_t \tag{35}$$

$$z + q_t \geqslant \widetilde{C}L_t.\, y_t \ ; \quad \forall \ t|\widetilde{C}L_t > 0 \tag{36}$$

$$q_t \geqslant 0 \ ; \quad \forall \ t|\widetilde{C}L_t > 0 \tag{37}$$

$$y_t \geqslant 0 \tag{38}$$

$$z \geqslant 0 \tag{39}$$

$$1 \leqslant y_t \tag{40}$$

It should be noted that in the robust optimization based problem formulation (33)–(40), Γ takes values in the interval [0, 1] in robust

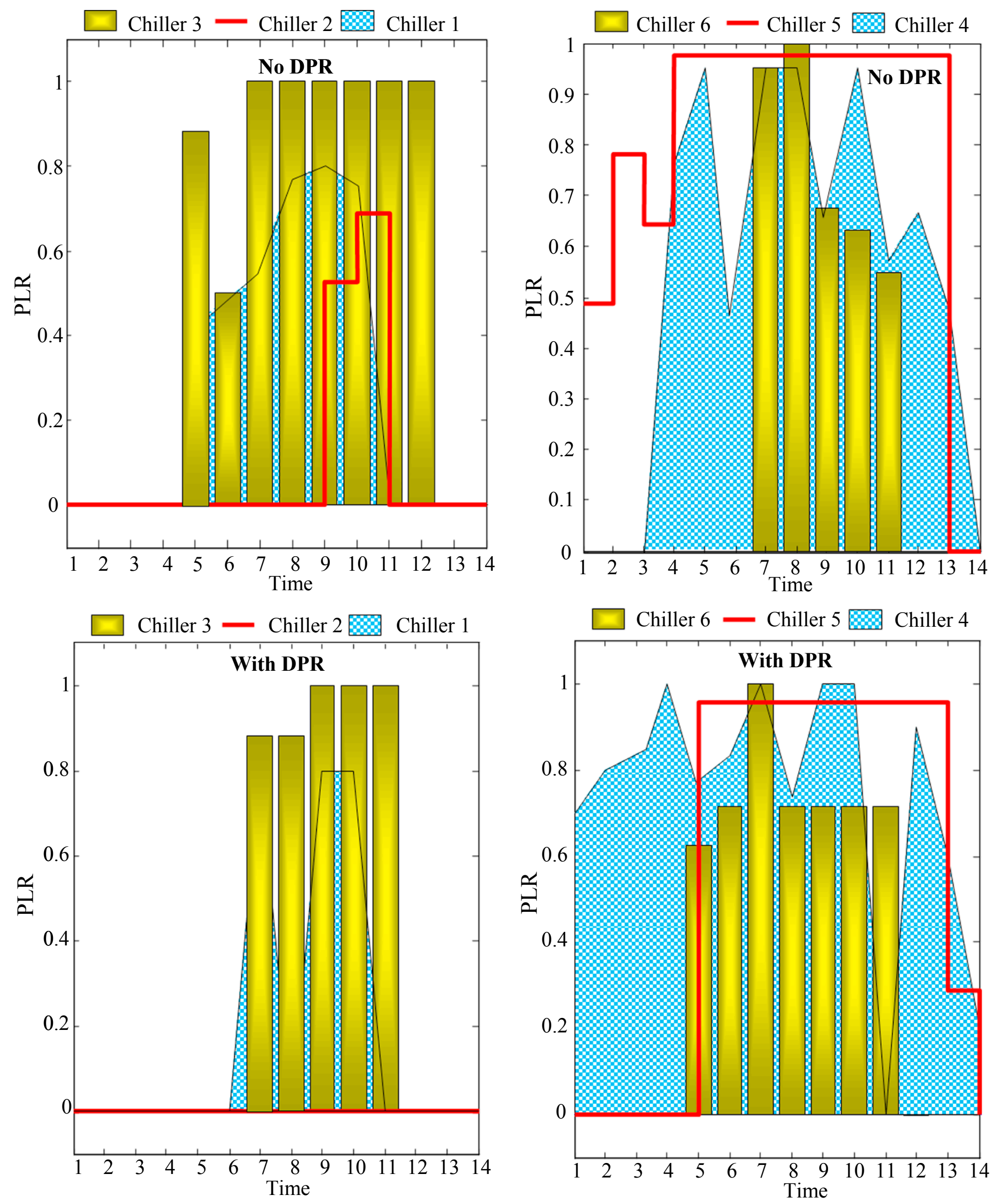

Fig. 9. PLR of the chillers with and without DRP in deterministic strategy.

optimization approach as risk-averse strategy if $\widetilde{C}L_t > 0$ while $\Gamma = 0$ in deterministic approach as risk-neutral strategy if $\widetilde{C}L_t = 0$.

4. Numerical study

In this paper, in order to investigate the effect of demand response program on the robust optimal planning as risk-averse methodology and deterministic approach as risk-neutral strategy in multi-chiller systems and solar system sources, four test cases are considered, which is as follows:

- Test Case 1: Deterministic approach in the absence of DRP.
- Test Case 2: Deterministic approach in the presence of DRP.
- Test Case 3: Robust optimization approach in the absence of DRP.
- Test Case 4: Robust optimization approach in the absence of DRP.

Using proposed model [40], the mixed-integer non-linear programming of the proposed planning in multi chiller system and solar system source is modeled with consideration of demand response program.

4.1. Input data

Related data about photovoltaic source is given in Table 1. In this study, the multi chiller system consists of 6 chiller units; their data are given in Table 2 [41]. The cooling energy demand of a semiconductor factory situated [42–44] is depicted in Fig. 2. Also, energy price for each hour are shown in Fig. 3. On a very hot summer day from 7:00 to 8:00 pm, the amount of solar irradiance, the power output of solar panels and ambient temperatures are shown in Figs. 4–6.

4.2. Results of deterministic method

The definitive results of optimal chiller loading problem in the absence of uncertainty are achieved through solving the robust optimization model Eqs. (27)–(34) as a risk-free strategy ($\Gamma = 0$). Furthermore, these results can be achieved through solving objective function (1) by considering limitations (2)–(13). In deterministic methodology, the total cost of buying power in the presence of demand response program is equal to \$3106.54, and in the absence of uncertainty, is equal to\$3011.32. By examining the results, the cost of buying power is

Applied Thermal Engineering 149 (2019) 1114–1124

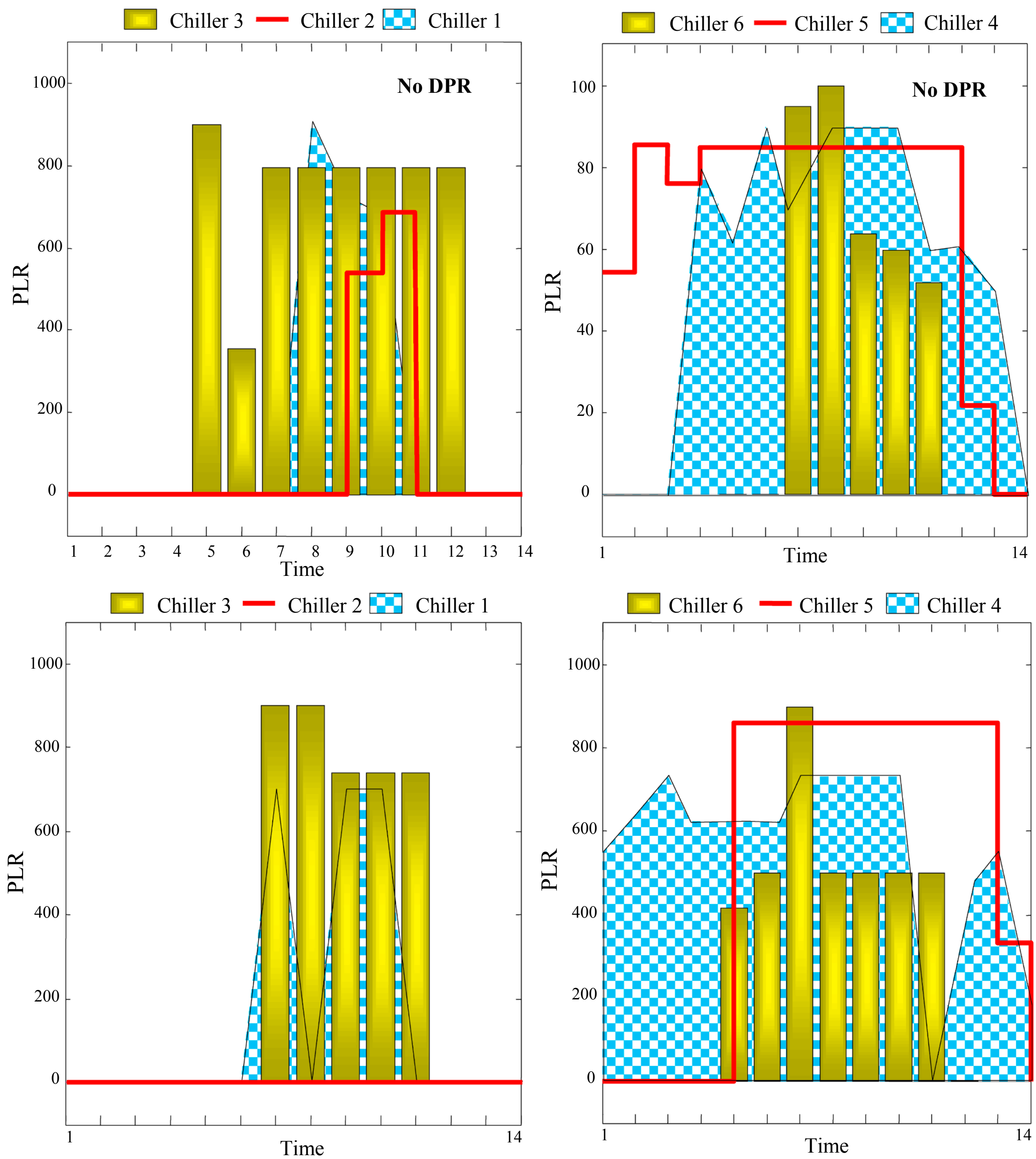

Fig. 10. The consumed power of the chillers with and without DRP in deterministic strategy.

reduced by $95.55 because of exploitation DRP (about 2.97 % decreases in cost). Due to the use of the real time rate method in DRP for optimizing cooling demand, the buying energy cost of the multi-chill system decreases. In Figure 7, the effect of two states of with and without the time-of-use rate of DRP on the cooling demand is shown.

According to Fig. 7, it can be stated that the time-of-use rate of DRP method, by transferring cooling demand from high cost to low-cost or middle-cost, can improve cooling demand profiles and reduce costs. The amount of energy purchased from the upstream grid for two states of presence and without the presence of DRP as a definitive strategy is shown in Fig. 8. Similar to the previous process, in terms of purchasing energy from the upstream network, if the time-of-use rate of DRP is used, the cost of purchasing energy will be reduced due to the transfer of purchase time from peak hours to other hours.

In Fig. 9, the changes in Partial load ratio (PLR) load of each unit of chiller in the presence of DRP and without the presence of DRP are depicted using a robust optimization method for daily optimal chiller loading issue. As already stated, in Fig. 9 it is seen that the PLR is limited between the minimum and nominal capacities. Because of using DRP, PLR is decreased. In Fig. 10, the optimum power consumption per unit of chiller is shown in deterministic methodology with and without DRP.

4.3. Robust optimization based results

In Fig. 11, according to Eq. (27) and with respect to the limitation of (28)–(34), the change in the total energy procurement cost for dual use with and without time-of-use rate of DRP has been is investigated by

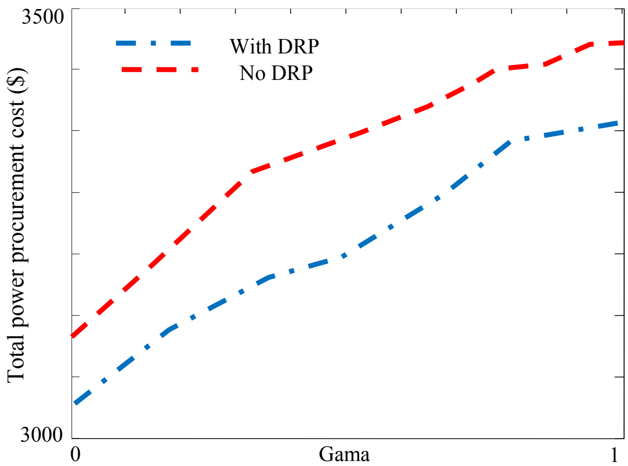

Fig. 11. Robust total power procurement cost versus robust control parameter.

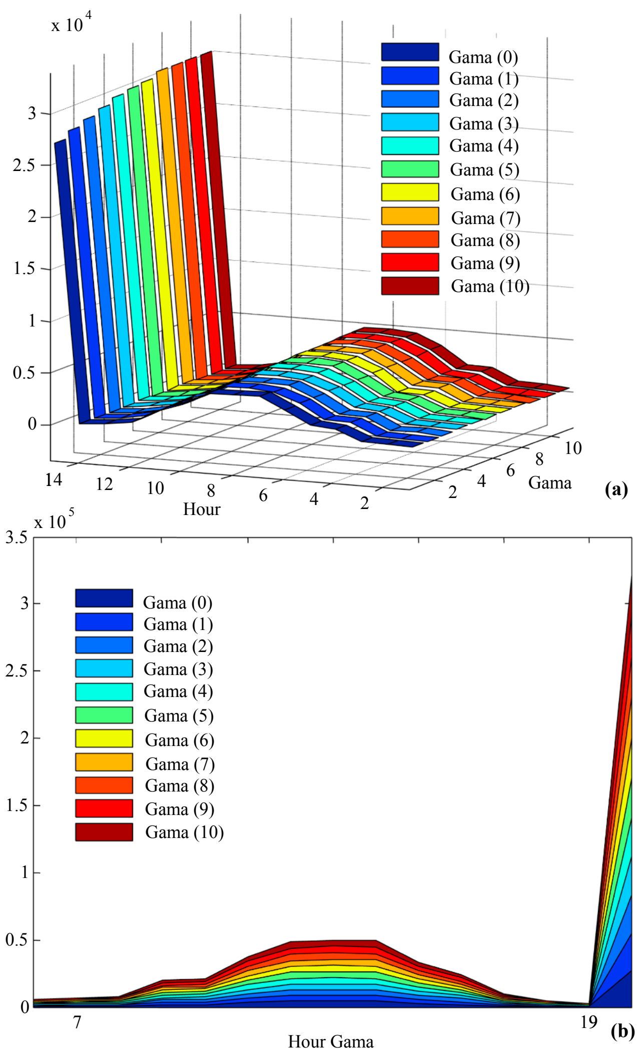

Fig. 12. Robust power procurement from upstream grid versus robust control parameter in case without DRP: (a) ribbon plot, (b) line plot.

changing the gamma values from 0 to 1 in 0.1 step and 11 iterations. By examining Fig. 11, it can be seen that for the first iteration, which is deterministic strategy, the total cost of energy purchases in the presence and absence of DRP is equal to $3106.54 and $3011.32, respectively. If DRP is used in deterministic methodology, the cost of purchasing

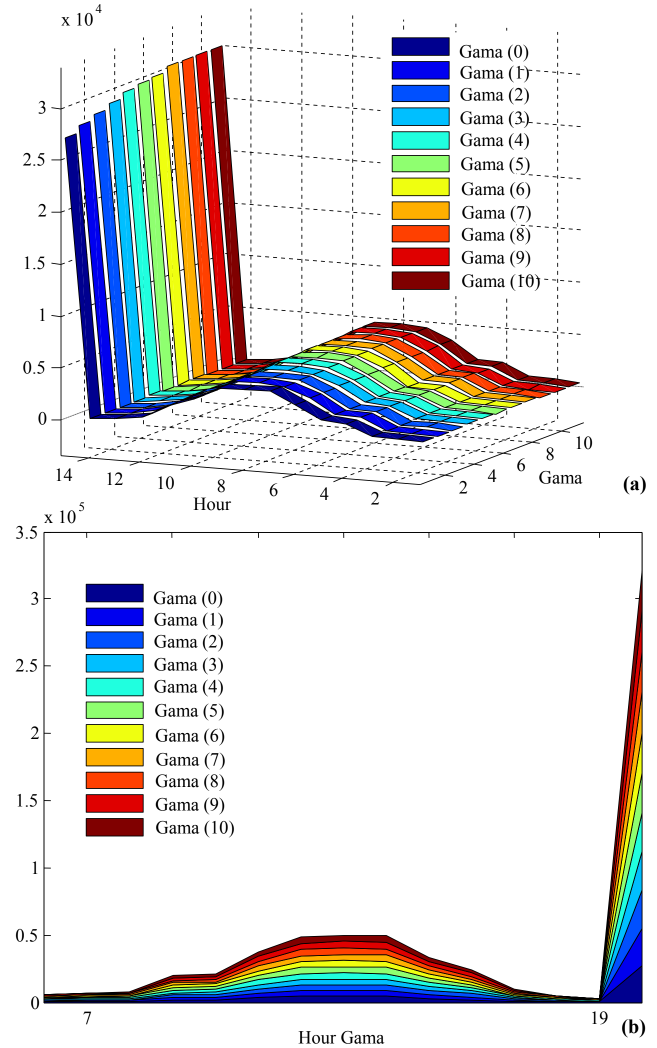

Fig. 13. Robust power procurement from upstream grid versus robust control parameter in case with DRP: (a) ribbon plot, (b) line plot.

energy is reduced by 2.97% ($95.55). When $\Gamma = 1$, the worst conditions are obtained in the robust optimization method. In this case, the total energy purchase in the presence of DRP and in the absence of DRP is equal to $3458.76 and $3367.54, respectively. As expected, in a robust optimization method using DRP, the cost of purchasing energy is reduced by 2.62%, or $91.12. The uncertainty rate is about 20% of the predicted cooling demand, in order to check out the worst-case modeling system. Therefore, in two methods studied in this paper, the total cost of energy purchases in the presence and absence of DRP is raised about 11.28% and 11.63% respectively.

In Figs. 12 and 13, information on purchasing energy from the upstream grid via a robust methodology for two modes with and without DRP is given, respectively. In the presence of DRP and through robust methodology, the total cost of energy purchases based on Fig. 12 data is about 2035.0 kWh and also without regard to DRP and in accordance with Fig. 13 is equal to 2644.0 kWh.

By studying the results, it can be stated that using the DRP method in a deterministic methodology, the total energy supply from upstream network is reduced by 2.16% or 591 kWh and ultimately decreases total buying energy costs.

According to the preceding statements, the worst conditions are obtained taking into account the $\Gamma = 1$; in this case, the cost of purchasing energy from the upper network in the presence of DRP and without the presence of DRP is equal to 30101.3 kWh and 29543.1 kWh

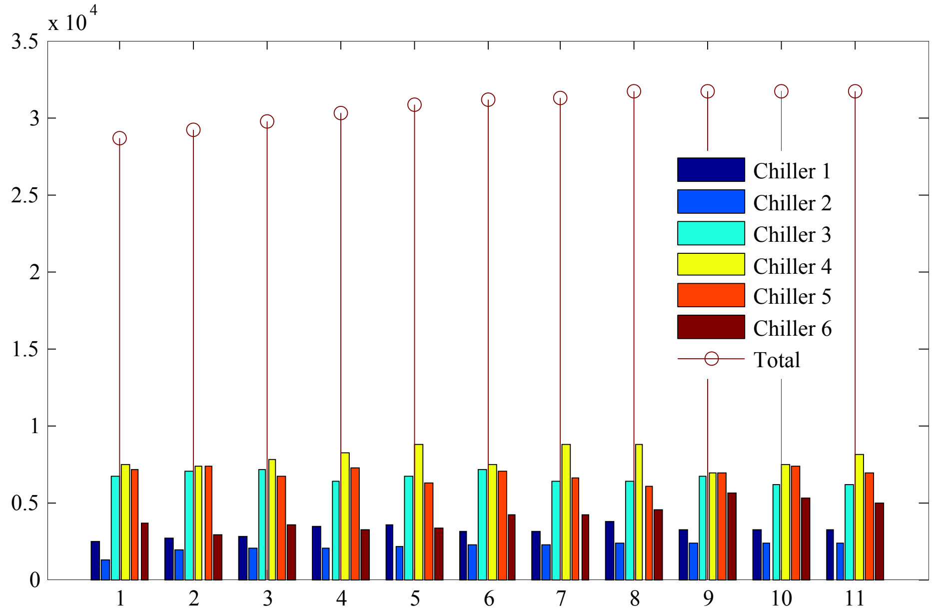

Fig. 14. Robust power consumption of each chiller versus robust control parameter in case without DRP.

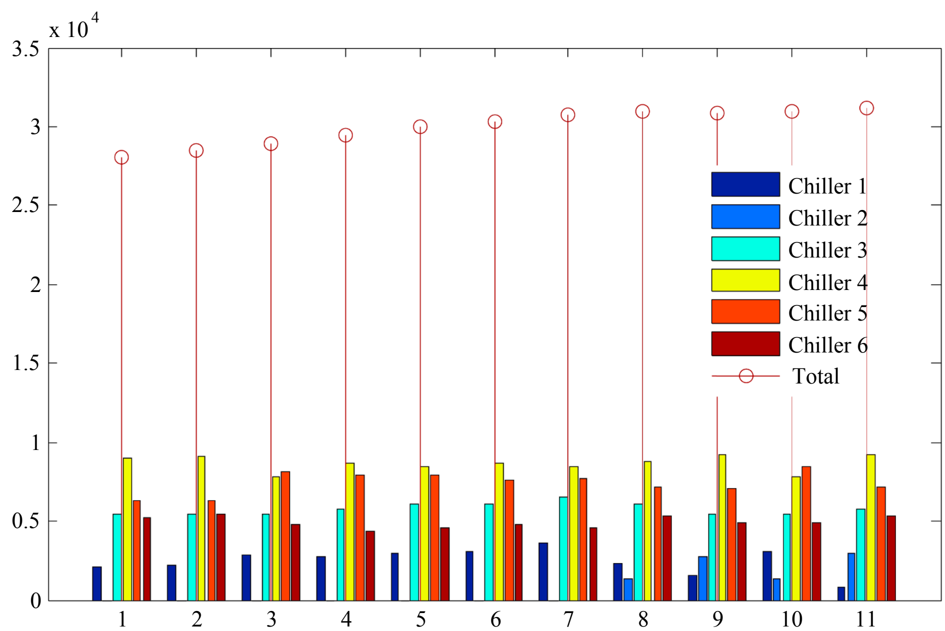

Fig. 15. Robust power consumption of each chiller versus robust control parameter in case without DRP.

,respectively. By using robust methodology and operating DRP in cooling loads, the total cost of buying energy from the upper grid is optimized 1.83% (558.2 kWh). Since uncertainty in cooling demand is considered this paper, so the total cost of buying energy for both strong and deterministic methodology in the presence of DRP and without the presence of DRP has increased about 11.28% and 11.63% , respectively. In Figs. 14 and 15, the results of energy consumption for per unit of chiller are listed using a robust methodology in the presence of time-of-use rate of DRP and without DRP are listed. According to Fig. 14 and 15, the total power consumption in chiller system with and without DRP using robust methodology is equal to 28547.8 kWh and 27956.8 kWh, respectively. By examining the obtained results of deterministic methodology, it can be stated that the total energy consumption of the system under study due to using DRP has decreased by 2.69% (591 kWh), and thus the total cost of buying energy is reduced proportionately. Then, assuming that $\Gamma = 1$, the total energy consumption of the multi chiller system with DRP and without DRP at worst conditions are obtained 31614.1 kWh and 31055.9 kWh. As expected, if DRP is used for cooling load in a robust methodology, the total power consumption of the multi chiller system will be reduced to 1.73% (558.2 kWh). Based on obtained results, power consumption in multi-chiller systems for both robust and deterministic methodology, with considering uncertainty in cooling demand in the presence of DRP and without DRP is raised 10.63% and 11.05 %, respectively.

5. Conclusion

In this paper, using robust methodology and demand response programing, multi-chiller systems operation is investigated by considering the solar system as an additional source of energy supplier.

Using the proposed method, the impact of utilizing robust optimization method as a risk-averse methodology versus deterministic method as a risk-neutral methodology is compared. Also, the benefits of using DRP in planning of multi-chiller systems is reduced in the total cost of purchasing energy with a deterministic model. In order to accurately examine the effect of the proposed method, the worst conditions in a robust strategy with regard to DRP were studied and the results indicate a redution in the total cost of energy purchases. Due to considering uncertainty in cooling demand (about 20% of forecasted cooling demand), the total cost of energy purchases in two robust and deterministic methodologies with DRP and without DRP is raised. Ultimately, due to the use of DRP in the multi-chiller system, the amount of energy consumed decreased, and on the other hand, the because of using solar system the amount of energy purchased from the upper network is reduced, as a result the total cost of purchasing energy is reduced.

Acknowledgement

Supported by the National Key Research and Development Program under grant 2017YFB0802300

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.applthermaleng.2018.12.121.

References

[1] X.Y. Li, L. Yang, X.L. Wang, X.Y. Miao, Y. Yao, Q.Q. Qiang, Investigation on the charging process of a multi-PCM latent heat thermal energy storage unit for use in conventional air-conditioning systems, Energy 1 (150) (2018 May) 591–600.
[2] H.A. Shayanfar, et al., PSO-IIW for combined heat and power economic dispatch, Int. J. Tech. Phys. Prob. Eng. (IJTPE) 4 (11) (2012) 51–55.
[3] Mohammadhossein Saeedi, et al., Robust optimization based optimal chiller loading under cooling demand uncertainty, Appl. Therm. Eng. (2018) In Press, Accepted Manuscript.
[4] Hossein Khodaei, et al., Fuzzy-based heat and power hub models for cost-emission operation of an industrial consumer using compromise programming, Appl. Therm. Eng. 137 (2018) 395–405.
[5] Mohsen Mohammadi, et al., Small-scale building load forecast based on hybrid forecast engine, Neural Process. Lett. 48 (1) (2018) 329–351.
[6] Z. Liu, H. Tan, D. Luo, G. Yu, J. Li, Z. Li, Optimal chiller sequencing control in an office building considering the variation of chiller maximum cooling capacity, Energy Build. 1 (140) (2017 Apr) 430–442.
[7] C.C. Lo, S.H. Tsai, B.S. Lin, Economic dispatch of chiller plant by improved ripple bee swarm optimization algorithm for saving energy, Appl. Therm. Eng. 5 (100) (2016 May) 1140–1148.
[8] T. Niknam, F. Golestaneh, Enhanced bee swarm optimization algorithm for dynamic economic dispatch, IEEE Syst. J. 7 (4) (2013 Dec) 754–762.
[9] Oveis Abedinia, Ali Ghasemi, Nasser Ojaroudi, Improved time varying inertia weight PSO for solved economic load dispatch with subsidies and wind power effects, Complexity 21 (4) (2016) 40–49.
[10] H. Shayeghi, et al., Optimal thermal generating unit commitment with wind power impact: a PSO-IIW procedure, Int. J. Tech. Phys. Probl. Eng. (IJTPE) 4 (2) (2012) 90–97.
[11] A. Askarzadeh, L. dos Santos Coelho, Using two improved particle swarm optimization variants for optimization of daily electrical power consumption in multi-chiller systems, Appl. Therm. Eng. 5 (89) (2015 Oct) 640–646.
[12] A. Ghasemi, et al., PSO-TVAC algorithm for multi objective PSS design in multi-machine power system, Proceedings on the International Conference on Artificial Intelligence (ICAI), The Steering Committee of The World Congress in Computer Science, Computer Engineering and Applied Computing (WorldComp), 2011.
[13] T. Kazama, Thermohydrodynamic lubrication model of a slipper in swashplate type axial piston machines-validation through experimental data, Int. J. Hydromech. 1 (3) (2018) 259–271.
[14] Hua Leng, et al., A new wind power prediction method based on ridgelet transforms, hybrid feature selection and closed-loop forecasting, Adv. Eng. Inf. 36 (2018) 20–30.
[15] Alireza Nouri, et al., Optimal performance of fuel cell-CHP-battery based micro-grid under real-time energy management: An epsilon constraint method and fuzzy satisfying approach, Energy (2018).
[16] Eskandari Nasab, Mohammad, et al., A new multiobjective allocator of capacitor banks and distributed generations using a new investigated differential evolution, Complexity 19 (5) (2014) 40–54.
[17] Roozbeh Morsali, et al., A new multiobjective procedure for solving nonconvex environmental/economic power dispatch, Complexity 20 (2) (2014) 47–62.
[18] Roozbeh Morsali, et al., Solving a novel multiobjective placement problem of recloser and distributed generation sources in simultaneous mode by improved harmony search algorithm, Complexity 21 (1) (2015) 328–339.
[19] O. Abedinia, et al., Optimal tuning of multi-machine power system stabilizer parameters using genetic-algorithm, *Power System Technology (POWERCON), 2010 International Conference on.* IEEE, (2010).
[20] Y.C. Chang, Genetic algorithm based optimal chiller loading for energy conservation, Appl. Therm. Eng. 25 (17–18) (2005 Dec 1) 2800–2815.
[21] Heidar Ali Shayanfar, et al., Design rule-base of fuzzy controller in multimachine power system stabilizer using genetic algorithm, IC-AI (2010).
[22] Y.C. Chang, J.K. Lin, M.H. Chuang, Optimal chiller loading by genetic algorithm for reducing energy consumption, Energy Build. 37 (2) (2005 Feb 1) 147–155.
[23] A. Beghi, L. Cecchinato, M. Rampazzo, A multi-phase genetic algorithm for the efficient management of multi-chiller systems, Energy Convers. Manage. 52 (3) (2011 Mar 1) 1650–1661.
[24] Farzaneh Mirzapour, et al., A new prediction model of battery and wind-solar output in hybrid power system, J. Ambient Intell. Hum. Comput. (2017) 1–11.
[25] Paria Akbary, et al., Extracting appropriate nodal marginal prices for all types of committed reserve, Comput. Econ. (2017) 1–26.
[26] Oveis Abedinia, Nima Amjady, Noradin Ghadimi, Solar energy forecasting based on hybrid neural network and improved metaheuristic algorithm, *Comput. Intell.* 34 (1) (2018) 241–260.
[27] Mohammadhosein Dideban, et al., Optimal location and sizing of shunt capacitors in distribution systems by considering different load scenarios, J. Elect. Eng. Technol. 8 (5) (2013) 1012–1020.
[28] Oveis Abedinia, Nima Amjady, Net demand prediction for power systems by a new neural network-based forecasting engine, Complexity 21 (S2) (2016) 296–308.
[29] O. Abedinia, N. Amjady, Mohammad S. Naderi, Multi-objective environmental/economic dispatch using firefly technique, Environment and Electrical Engineering (EEEIC), 2012 11th International Conference on. IEEE, (2012).
[30] Iman Maleksaeedi, et al., A new two-stage algorithm for solving power flow tracing, Complexity 21 (1) (2015) 187–194.
[31] Hadi Aghazadeh, et al., Robust placement and tuning of UPFC via a new multi-objective scheme-based fuzzy theory, Complexity 21 (1) (2015) 126–137.
[32] H. Manafi, et al., Optimal placement of distributed generations in radial distribution systems using various PSO and DE algorithms, Elektronika ir Elektrotechnika 19 (10) (2013) 53–57.
[33] Melika Hamian, et al., A framework to expedite joint energy-reserve payment cost minimization using a custom-designed method based on mixed integer genetic algorithm, Eng. Appl. Artif. Intell. 72 (2018) 203–212.
[34] Mahdiyeh Eslami, et al., A new formulation to reduce the number of variables and constraints to expedite SCUC in bulky power systems, Proceedings of the national academy of sciences, India section a: physical sciences, 2018, pp. 1–11.
[35] Supervisory Control Strategies and Optimization. ASHRAE Handbook, 1999 (chapter 40).
[36] P. Panwar, P. Michael, Empirical modelling of hydraulic pumps and motors based upon the Latin hypercube sampling method, Int. J. Hydromech. 1 (3) (2018) 272–292.
[37] D.T. Nguyen, L.B. Le, Optimal bidding strategy for microgrids considering renewable energy and building thermal dynamics, IEEE Trans. Smart Grid 5 (4) (2014 Jul) 1608–1620.
[38] Oveis Abedinia, Nima Amjady, Ali Ghasemi, A new metaheuristic algorithm based on shark smell optimization, Complexity 21 (5) (2016) 97–116.
[39] D. Bertsimas, M. Sim, Robust discrete optimization and network flows, Math. Program. 98 (1–3) (2003 Sep 1) 49–71.
[40] O. Abedinia, et al., Optimal congest management based VEPSO an electricity market, Int. J. Tech. Phys. Probl. Eng. 4 (2) (2012) 56–62.
[41] F. Jabari, S. Nojavan, B.M. Ivatloo, Designing and optimizing a novel advanced adiabatic compressed air energy storage and air source heat pump based μ-Combined Cooling, heating and power system, Energy 1 (116) (2016 Dec) 64–77.
[42] Alireza Noruzi, et al., A new method for probabilistic assessments in power systems, combining monte carlo and stochastic-algebraic methods, Complexity 21 (2) (2015) 100–110.
[43] Wei Gao, et al., Different states of multi-block based forecast engine for price and load prediction, Int. J. Electr. Power Energy Syst. 104 (2019) 423–435.
[44] Bagal, Hamid Asadi, et al., Risk-assessment of photovoltaic-wind-battery-grid based large industrial consumer using information gap decision theory, Sol. Energy 169 (2018) 343–352.