Chapter 5
Optimal Short-Term Scheduling of Photovoltaic Powered Multi-chiller Plants in the Presence of Demand Response Programs

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5.1 Motivation

During the extremely hot weather or sudden transient heat waves, air-conditioning systems are the most common energy consumers in the different residential, commercial, industrial, and administrative buildings especially in the tropical regions. As obvious from Fig. 5.1, currently 30% of total electrical demand is assigned to cooling air-conditioning applications.

In the meantime, use of solar radiations as primary energy resource in a multi-chiller plant not only increases the economic savings in using non-renewable petroleum products and mitigates pollutant emission productions of electric chillers, but also supplies the heating demand of solar assisted absorption chillers and reduces total electricity requirements of central air-conditioners significantly.

5.2 Literature Review

In the literature, some scholars have focused on optimal performance investigation of multi-chiller plants using different evolutionary algorithms. In this context, an improved ripple bee swarm optimization algorithm is proposed in [1, 2] to obtain the economic chiller loading points. Using the features of biological communities, some movement models are developed to minimize total energy requirements of cooling towers and pumps within the feasible solution space. References [3–6] solved the economic chiller dispatching problem using the particle swarm optimization

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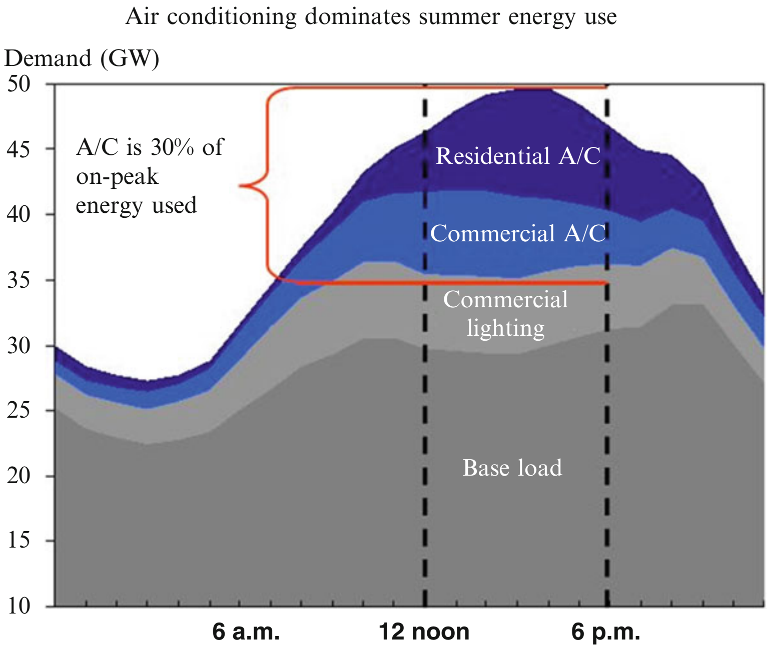

Fig. 5.1 Typical electrical loads during extremely hot summer days

technique. A day-ahead optimal chiller dispatching problem is solved by Powell et al. [7] and implemented on a benchmark district cooling system with and without considering a thermal energy storage. In [8], differential cuckoo search algorithm (DCSA) [9] based on obligate brood-parasitic behavior of some cuckoo species is introduced to optimize the chiller loading design problem. Reference [10] simplifies the complicated evolution process of the genetic algorithm (GA) for solving optimal chiller loading using the evolution strategy (ES). Other search approaches such as GA [11–14], simulated annealing (SA) [15, 16], differential evolution (DE) [17], gradient method (GM) [18], Lagrangian method [19], empirical model [20], artificial neural network (ANN) [21–25], firefly algorithm [26] have also been proposed in the literature.

5.3 Problem Formulation

5.3.1 Multiple-Chiller Plant

As illustrated in Fig. 5.2, a multi-chiller plant consists of two or more chillers connected in parallel or series piping to a distribution system [7, 17].

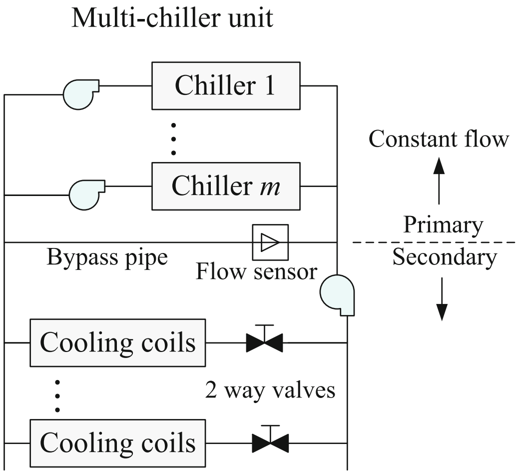

Fig. 5.2 Schematic presentation of a typical CCHP system

In the short-term economic dispatch of the multi-chiller plant, the total electrical power consumed by the centrifugal chillers can be calculated as Eq. (5.1):

$$P_t^{\mathrm{ch}} = \sum_{i=1}^{N} U_i^t \times \left(\alpha_i + \beta_i \times \mathrm{PLR}_i^t + \gamma_i \times \mathrm{PLR}_i^{t2} + \zeta_i \times \mathrm{PLR}_i^{t3}\right) \qquad (5.1)$$

where N is the number of chillers; U_i^t is a binary decision variable that will be equal to 1, if ith chiller is on; otherwise it will be 0; α_i, β_i, γ_i, ζ_i are the coefficients related to the operating characteristic of chiller i; PLR_i^t is the partial load ratio (PLR) of chiller i at time horizon t that is defined as relation (5.2).

$$\mathrm{PLR}_i^t = \frac{\text{Cooling load of chiller } i \text{ at time } t}{\text{Power consumption of chiller } i \text{ at time } t} \qquad (5.2)$$

Subject to:

Power balance criterion which can be stated by Eq. (5.3):

$$\sum_{i=1}^{N} \left(U_i^t \times \mathrm{PLR}_i^t \times \mathrm{RT}_i\right) = \mathrm{CL}_t; \quad \forall t = 1, 2, \ldots, T \qquad (5.3)$$

where RT_i is the Capacity of chiller i; CL_t is the Total cooling demand at time t.

5.3.2 Solar Photovoltaic Cells

In the last decade, use of solar collectors such as flat plat collectors and evacuated tube collectors for thermally driven solar cooling systems and photovoltaic cells to generate electricity for vapor compressing in air-conditioners is rapidly gaining popularity due to nearly-zero carbon footprints. This chapter aims to present optimal short-term dispatching of solar photovoltaic based multi-chiller plants in the presence of time-of-use cooling-demand response programs. Use of solar irradiance as primary energy source during extremely-hot summer days not only mitigate total carbon footprints, but also reduces total energy consumptions of electrical chillers from fossil fuels based non-renewable energy sources, specially by applying peak clipping and valley filling demand response strategies on cooling demand. The power output of a photovoltaic module can be calculated from Eq. (5.4) [27].

$$P_t^{\mathrm{pv}} = \eta S \Phi_t \left[1 - 0.005 \times \left(T_t^a - 25\right)\right] \tag{5.4}$$

where P_t^{pv} is the Power output of a photovoltaic panel; η is the Conversion coefficient of a photovoltaic panel; S is the Array area of a photovoltaic module; Φ_t is the Solar irradiance; T_t^a is the Ambient temperature at time t.

5.3.3 Demand Response Programs

Demand response programs (DRPs) are defined as effective and practical solution to change electrical energy utilization of consumers with respect to their usual power consumption pattern [28]. The US Department of Energy (DOE) defined DRPs as the capability of changing power consumption pattern of industrial, residential, and commercial consumers considering changes in electrical energy price or incentive payments [29]. Application of DRPs to electrical energy systems takes advantages of modifying of market clearing price (MCP) [30], avoiding raising of power market price over production cost as well as improving the performance of the markets [31]. Moreover, employing DRPs is effective in helping the system reliability by decreasing the rate of forced outages of the system [31]. In addition, the industrial loads can rival in power market by incorporating demands in the market. DRPs are mainly classified into time-based programs and incentive-based programs, where the first category involves the programs based on power market pricing and the second one aims to participate in the programs through financial incentives. Applying time-of-use DRPs, end-users shift their electricity consumptions from on-peak high-price hours to off-peak low-price periods. Time-of-use DRPs are illustrated in Fig. 5.3. The dashed section of demand profile doesn't participate in DRPs, while the other one shifts a part of electricity load from mid-peak or on-peak time intervals to off-peak hours.

$$\mathrm{CL}_t = \mathrm{CL}_t^0 \left(1 - \mathrm{DR}_t\right) + \mathrm{ldr}_t \tag{5.5}$$

$$\mathrm{CL}_t^0 - \mathrm{CL}_t = \mathrm{ldr}_t = \mathrm{DR}_t \times \mathrm{CL}_t^0 \tag{5.6}$$

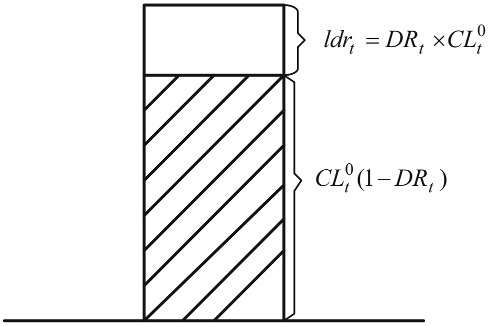

Fig. 5.3 Participation of cooling demand in time-of-use DRP

$$\sum_{t=1}^{T} \mathrm{ldr}_t = \sum_{t=1}^{T} \mathrm{DR}_t \times \mathrm{CL}_t^0 \tag{5.7}$$

$$\mathrm{CL}_t^{\mathrm{inc}} \leq \mathrm{inc}_t \times \mathrm{CL}_t^0 \tag{5.8}$$

$$\mathrm{DR}_t \leq \mathrm{DR}_{\max} \tag{5.9}$$

$$\mathrm{inc}_t \leq \mathrm{inc}_{\max} \tag{5.10}$$

where CL_t^0 is the Initial demand which participates in time-of-use DRPs; CL_t is the Cooling demand after implementation of DRPs at time horizon t; DR_t is the Percentage of participation in DRPs at time t; ldr_t is the Shifted demand at time t; $\mathrm{CL}_t^{\mathrm{inc}}$ is the Increased demand at time t; inc_t is the Amount of load increase at time t; $\mathrm{DR}_{\max}$ is the Maximum value of load participation in DRP; $\mathrm{inc}_{\max}$ is the Maximum value of load increase.

5.3.4 Objective Function and Constraints

In this chapter, total electricity procurement cost of a multi-chiller plant over the study horizon should be minimized as follows:

$$\mathrm{Min} \sum_{t=1}^{T} \lambda_t P_t^{\mathrm{grid}} \tag{5.11}$$

Subject to:

- Electrical power balance constraint

$$\begin{aligned} & P_t^{\text{grid}} + N_{\text{pv}} P_t^{\text{pv}} = P_t^{\text{ch}}; \quad \forall t = 1, 2, \ldots, T \\ & \text{Constraints (5.1)–(5.10)} \end{aligned} \tag{5.12}$$

where P_t^{grid} is the Purchased electrical power from upstream grid; N_{pv} is the Number of photovoltaic panels.

5.4 Illustrative Examples

5.4.1 Plant 1 with Six Chillers

In this section, four cases are studied for optimal dispatching of multi-chiller plants 1 and 2 in the presence of solar photovoltaic panels and demand response programs as follows:

- Case 1: Without PVs and DRPs
- Case 2: With DRPs
- Case 3: With PVs
- Case 4: With PVs and DRPs

The problem is modeled as a mixed integer nonlinear program (MINLP) and solved using SBB solver under general algebraic mathematical system (GAMS) environment [32]. Figures 5.4 and 5.5 depict total cooling demand of a semiconductor factory located at Hsinchu Scientific Garden (Taiwan) [11] and hourly electricity

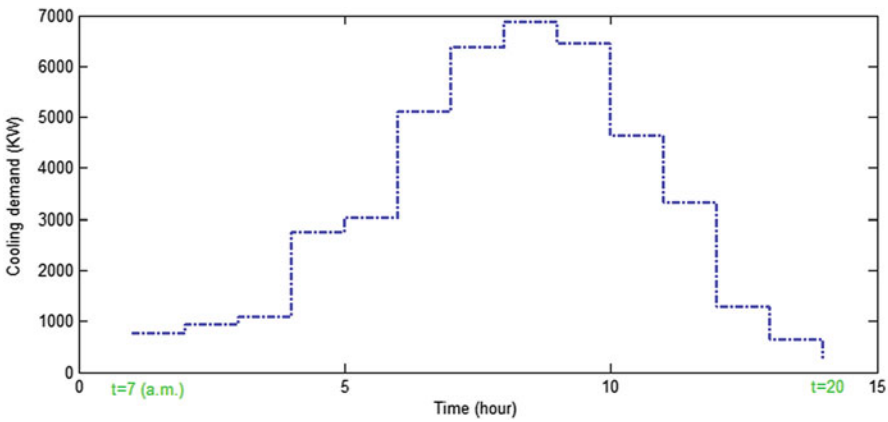

Fig. 5.4 Cooling demand of a semiconductor factory located at Hsinchu Scientific Garden (Taiwan) [11]

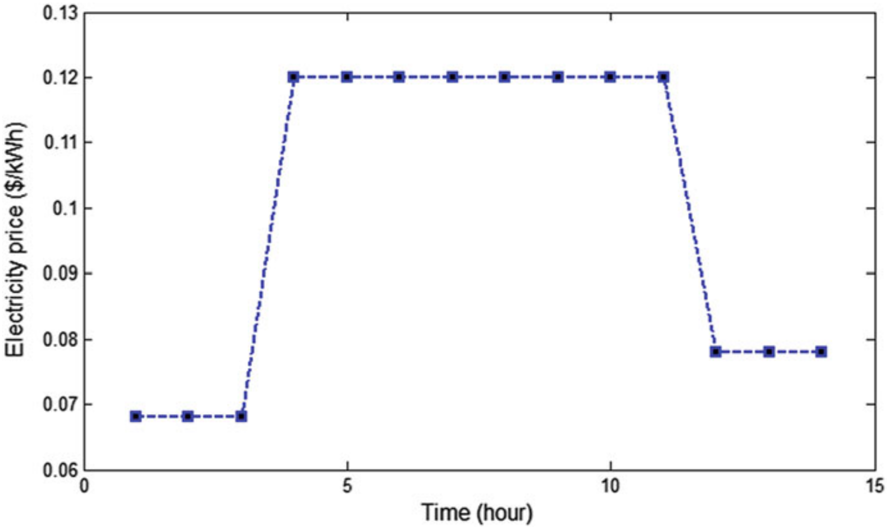

Fig. 5.5 Hourly electricity rates over the study horizon from $t = 7^{\text{a.m.}}$ to $t = 20$

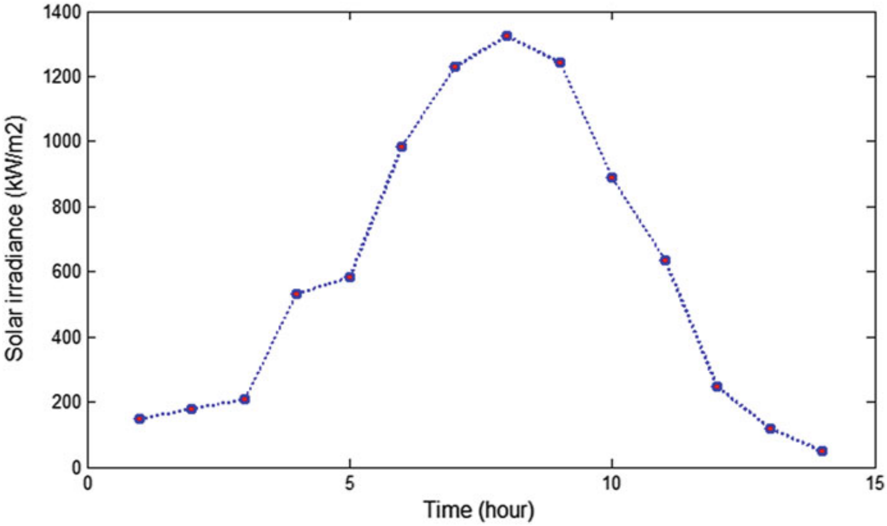

Fig. 5.6 Solar irradiance during a sample extremely-hot summer day

rates [33, 34], respectively. In addition, Figs. 5.6, 5.7, and 5.8 illustrate the variations of solar irradiance, ambient temperature, and power output of PV panels during a sample extremely-hot summer day from $t = 7^{\text{a.m.}}$ to $t = 20$ [35]. Tables 5.1 and 5.2, respectively, present all coefficients related to PV panels and operating characteristic of six chillers plant 1 which participate in supplying the cooling demand.

Table 5.3 summarizes total electricity requirements of six chillers in their optimum operating points. Considering $DR_{\max} = inc_{\max} = 0.15$, the optimum operating

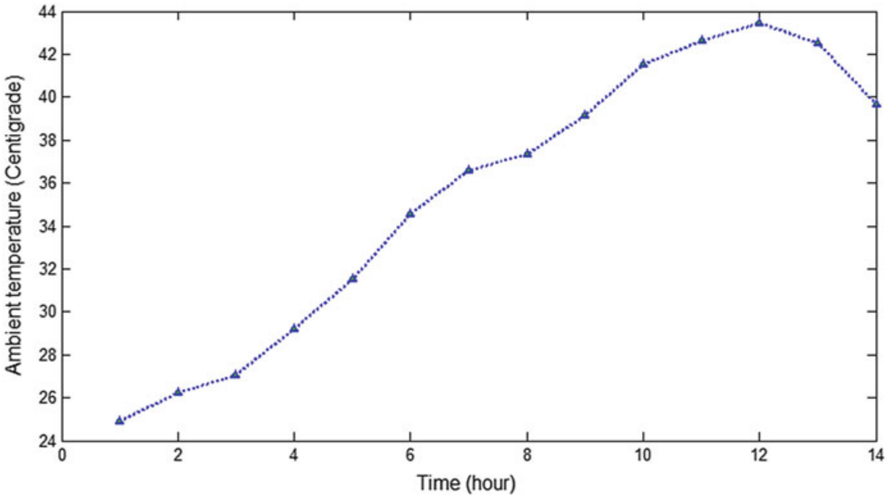

Fig. 5.7 Variations of ambient temperature from $t = 7^{\text{a.m.}}$ to $t = 20$

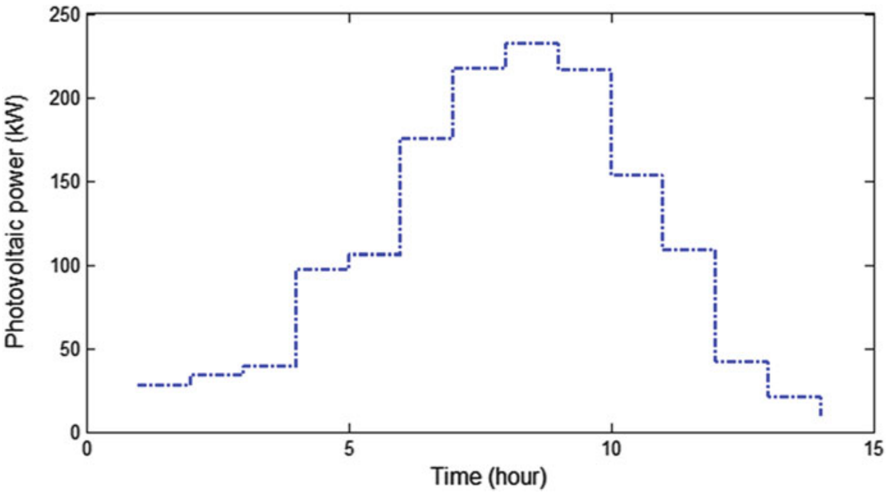

Fig. 5.8 Power output of photovoltaic panels from $t = 7^{\text{a.m.}}$ to $t = 20$

Table 5.1 Parameters of PV panels [27]

N_{pv}	η	S
400	0.187	2.5

points of these chillers in cases 2 and 4 vary as reported in Table 5.4. Moreover, the variations of cooling load in four cases before and after implementation of time-of-use DRPs are shown in Fig. 5.9.

Table 5.2 Chiller data for six units [11]

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

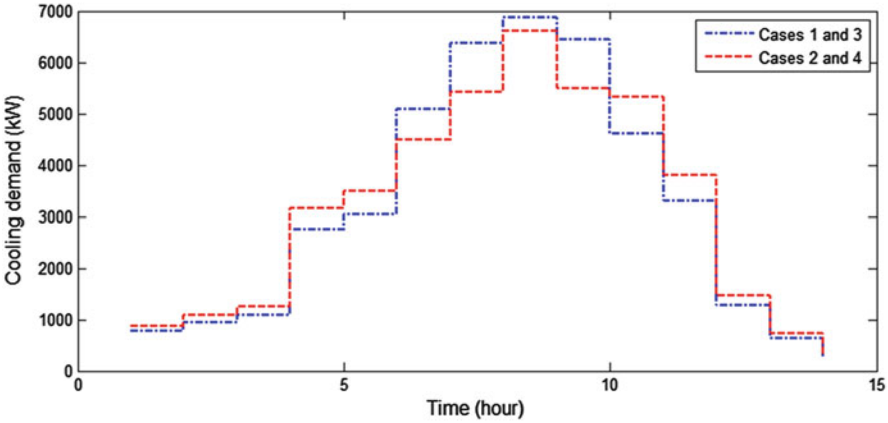

Fig. 5.9 Variations of cooling demand before and after participation in time-of-use DRPs

As obvious from Fig. 5.9, time-of-use DRPs shift the cooling demand from on-peak hours to other mid-peak and off-peak periods. Moreover, total energy procurement cost of this multi-chiller plant in four cases with and without participation of PVs and DRPs can be reported as Table 5.5. As expected, using the photovoltaic panels and implementing the time-of-use DRPs on cooling demand reduces total energy cost of multiple-chiller plants.

5.4.2 Plant 2 with Four Chillers

In this subsection, same cases are studied on another multi-chiller plant with four units. The operating characteristics of four centrifugal chillers and total cooling demand of a benchmark hotel building located in Ahvaz, Iran have, respectively, been shown in Table 5.6 and Fig. 5.10. Solar radiations, ambient air temperature, and electrical power generated by 400 photovoltaic cells during a severe-hot summer day in Ahvaz, Iran are shown in Figs. 5.11, 5.12, and 5.13, respectively.

Table 5.7 summarizes total electricity requirements of four chillers in their optimum operating points. Considering $DR_{max} = inc_{max} = 0.2$, the optimum

Table 5.3 Economic loading points of six chillers in cases 1 and 3

CL^t (kW)	Chiller	PLR_i^t	CL^t (kW)	Chiller	PLR_i^t
$t = 7^{\text{a.m.}}$	1	0.937	$t = 14$	1	0.794
762 (kW)	2	0.463	6858 (kW)	2	0.729
	3	0.081		3	1
	4	0.021		4	1
	5	0.081		5	1
	6	0.412		6	0.836
$t = 8^{\text{a.m.}}$	1	0.939	$t = 15$	1	0.703
933 (kW)	2	0.451	6445.8 (kW)	2	0.629
	3	0.081		3	1
	4	0.021		4	1
	5	0.081		5	1
	6	0.545	6		0.703
$t = 9^{\text{a.m.}}$	1	0.941	$t = 16$	1	0.720
1080 (kW)	2	0.375	4618.6 (kW)	2	0.713
	3	0.081		3	0.081
	4	0.048		4	1
	5	0.081		5	1
	6	0.634		6	0.814
$t = 10^{\text{a.m.}}$	1	0.720	$t = 17$	1	0.720
2752.5 (kW)	2	0.640	3304.5 (kW)	2	0.667
	3	0.081		3	0.081
	4	1		4	1
	5	0.416		5	0.081
	6	0.653		6	0.753
$t = 11^{\text{a.m.}}$	1	0.720	$t = 18$	1	0.937
3024.6 (kW)	2	0.640	1275 (kW)	2	0.597
	3	0.363		3	0.081
	4	1		4	0.834
	5	1		5	0.081
	6	0.605		6	0.542
$t = 12^{\text{noon}}$	1	0.665	$t = 19$	1	0.935
5092.9 (kW)	2	0.587	622 (kW)	2	0.406
	3	0.081		3	0.081
	4	1		4	0.021
	5	1		5	0.081
	6	0.646		6	0.303
$t = 13$	1	0.688	$t = 20$	1	0.931
6375.9 (kW)	2	0.613	264.5 (kW)	2	0.485
	3	1		3	0.081
	4	1		4	0.045
	5	1		5	0.081
	6	0.681		6	0.605

Table 5.4 Economic loading points of six chillers in cases 2 and 4

CL^t (kW)	Chiller	PLR_i^t	CL^t (kW)	Chiller	PLR_i^t
$t = 7^{\text{a.m.}}$ 876.3 (kW)	1	0.951	$t = 14$ 6597.784 (kW)	1	0.737
	2	0.504		2	0.666
	3	0.081		3	1
	4	0.021		4	1
	5	0.081		5	1
	6	0.501		6	0.752
$t = 8^{\text{a.m.}}$ 1072.95 (kW)	1	0.952	$t = 15$ 5478.93 (kW)	1	0.749
	2	0.508		2	0.68
	3	0.081		3	0.081
	4	0.041		4	1
	5	0.081		5	1
	6	0.635		6	0.77
$t = 9^{\text{a.m.}}$ 1242 (kW)	1	0.946	$t = 16$ 5311.39 (kW)	1	0.712
	2	0.559		2	0.639
	3	0.081		3	0.081
	4	0.808		4	1
	5	0.081		5	1
	6	0.561		6	0.716
$t = 10^{\text{a.m.}}$ 3165.375 (kW)	1	0.695	$t = 17$ 3800.175 (kW)	1	0.639
	2	0.424		2	0.559
	3	0.081		3	0.081
	4	0.921		4	1
	5	1		5	0.081
	6	0.47		6	0.609
$t = 11^{\text{a.m.}}$ 3478.29 (kW)	1	0.738	$t = 18$ 1466.25 (kW)	1	0.693
	2	0.38		2	0.52
	3	0.081		3	0.081
	4	1		4	0.983
	5	1		5	0.081
	6	0.636		6	0.535
$t = 12^{\text{noon}}$ 4478.744 (kW)	1	0.72	$t = 19$ 715.3 (kW)	1	0.952
	2	0.666		2	0.547
	3	0.081		3	0.081
	4	1		4	0.021
	5	1		5	0.081
	6	0.752		6	0.375
$t = 13$ 5421.637 (kW)	1	0.737	$t = 20$ 304.175 (kW)	1	0.951
	2	0.666		2	0.215
	3	0.081		3	0.081
	4	1		4	0.076
	5	1		5	0.081
	6	0.752		6	0.605

Table 5.5 Total energy cost of six chillers in four cases

Case study	Energy cost ($)
1	3212.22
2	3138.83
3	3043.40
4	2970.02

Table 5.6 Chiller data for four units of plant 2

Chiller	α_i	β_i	γ_i	ζ_i	Chiller capacity (RT)
1	104.09	166.57	−430.13	512.53	850
2	−67.15	1177.79	−2174.53	1456.53	1200
3	384.71	−779.13	1151.42	−63.2	1630
4	541.63	413.48	−3626.5	4021.41	1850

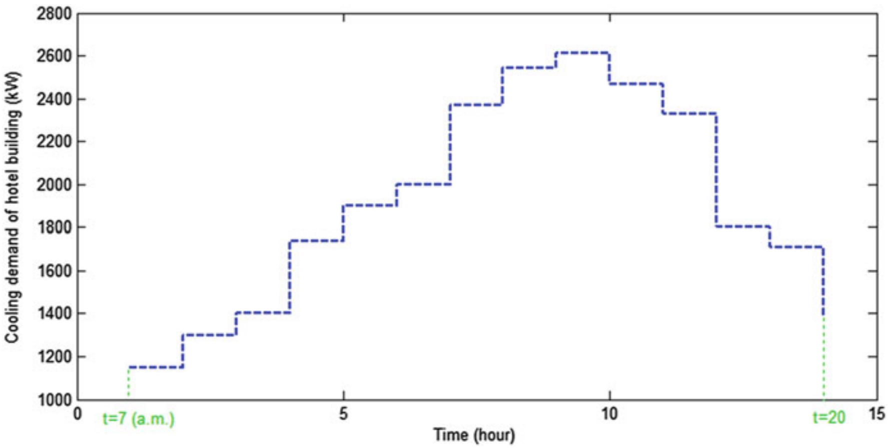

Fig. 5.10 [!t] Cooling demand of a hotel building located in Ahvaz, Iran before participation in time-of-use DRPs

operating points of these chillers in cases 2 and 4 vary as reported in Table 5.8. Moreover, the variations of hotel cooling load in four cases before and after implementation of time-of-use DRPs are shown in Fig. 5.14.

As obvious from Fig. 5.14, time-of-use DRPs shift the cooling demand from on-peak hours to other mid-peak and off-peak periods. Moreover, total energy procurement cost of this multi-chiller plant in four cases with and without participation of PVs and DRPs can be reported as Table 5.9. As expected, using the photovoltaic cells and implementing the time-of-use DRPs on hotel cooling demand reduces total energy cost of multiple-chiller plants.

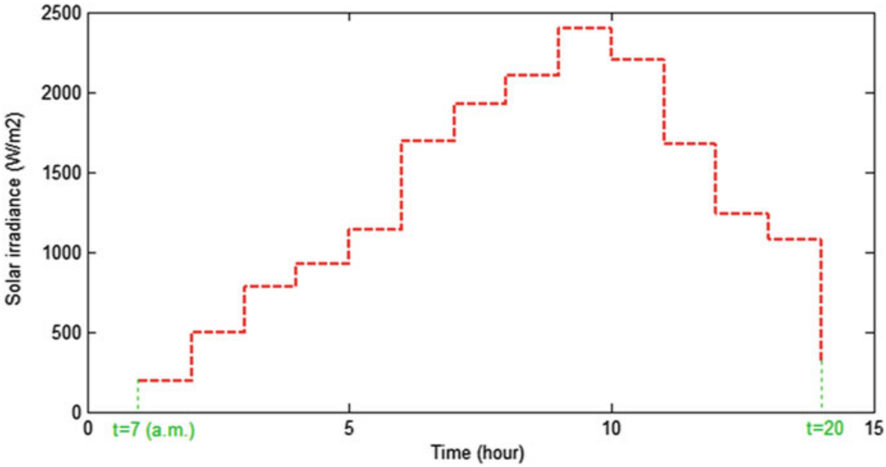

Fig. 5.11 Solar radiations during a severe-hot summer day in Ahvaz, Iran

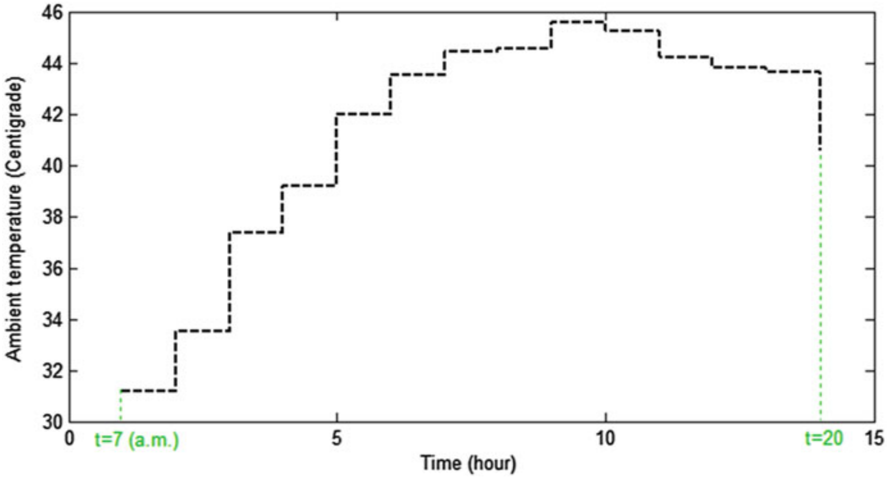

Fig. 5.12 Climatic conditions over a sample summer day in Ahvaz, Iran

5.5 Concluding Remarks

In this chapter, short-term optimal scheduling of solar powered multi-chiller plants was presented. As we know, total cooling demand directly depends on solar irradiations in a way that when solar irradiance increases, the value of building cooling demand in different residential, commercial, and industrial sectors will be increased. Hence, use of solar energy for supplying total electricity requirement of chillers will be a cost-effective way in comparison with other energy resources. This is an interesting result indicating that if solar photovoltaic panels are employed to

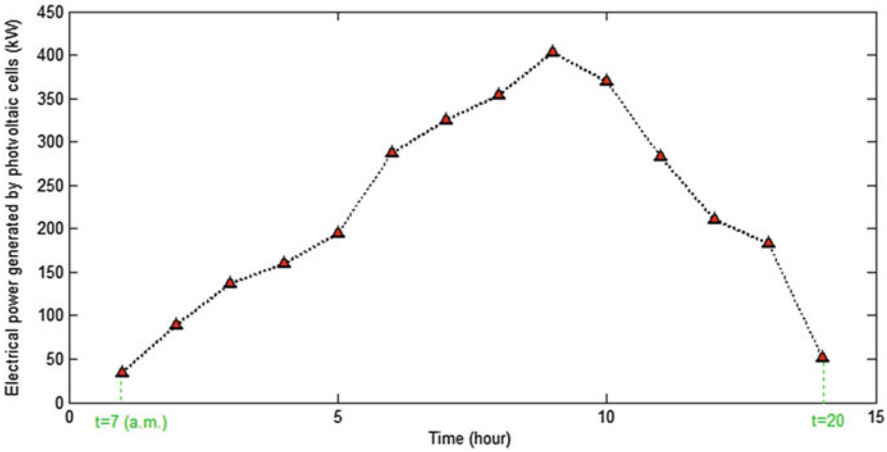

Fig. 5.13 Power output of photovoltaic panels from $t = 7^{\mathrm{a.m.}}$ to $t = 20$

Table 5.7 Optimum loading points of four chillers in cases 1 and 3

CL^t (kW)	Chiller	PLR_i^t	CL^t (kW)	Chiller	PLR_i^t
$t = 7^{\mathrm{a.m.}}$	2	0.064	$t = 14$	2	0.906
1150 (kW)	3	0.658	2540 (kW)	3	0.891
$t = 8^{\mathrm{a.m.}}$	2	0.064	$t = 15$	2	0.920
1300 (kW)	3	0.750	2610 (kW)	3	0.924
$t = 9^{\mathrm{a.m.}}$	2	0.064	$t = 16$	2	0.893
1400 (kW)	3	0.812	2470 (kW)	3	0.858
$t = 10^{\mathrm{a.m.}}$	2	0.715	$t = 17$	2	0.864
1740 (kW)	3	0.541	2330 (kW)	3	0.793
$t = 11^{\mathrm{a.m.}}$	2	0.762	$t = 18$	2	0.733
1900 (kW)	3	0.605	1800 (kW)	3	0.564
$t = 12^{\mathrm{noon}}$	2	0.788	$t = 19$	2	0.706
2000 (kW)	3	0.647	1710 (kW)	3	0.529
$t = 13$	2	0.873	$t = 20$	2	0.064
2370 (kW)	3	0.812	1380 (kW)	3	0.799

produce electricity for driving chiller equipment, higher coefficient of performance for chillers will be attained and lower electricity cost will be paid while increasing the amount of cooling demand. Moreover, it is demonstrated that use of photovoltaic panels as renewable based power generation facilities and time-of-use demand response programs for peak clipping reduces total electricity cost significantly.

Table 5.8 Optimum loading points of four chillers in cases 2 and 4

CL^t (kW)	Chiller	PLR_i^t	CL^t (kW)	Chiller	PLR_i^t
$t = 7^{\text{a.m.}}$	2	0.064	$t = 14$	2	0.802
1437.5 (kW)	3	0.799	2036.4 (kW)	3	0.671
$t = 8^{\text{a.m.}}$	2	0.064	$t = 15$	2	0.810
1569.2 (kW)	3	0.910	2036.4 (kW)	3	0.685
$t = 9^{\text{a.m.}}$	2	0.064	$t = 16$	2	0.802
1569.2 (kW)	3	0.932	2036.4 (kW)	3	0.671
$t = 10^{\text{a.m.}}$	2	0.802	$t = 17$	2	0.802
2036.4 (kW)	3	0.671	2036.4 (kW)	3	0.671
$t = 11^{\text{a.m.}}$	2	0.802	$t = 18$	2	0.827
2036.4 (kW)	3	0.671	2250 (kW)	3	0.716
$t = 12^{\text{noon}}$	2	0.802	$t = 19$	2	0.801
2036.4 (kW)	3	0.671	2137.5 (kW)	3	0.669
$t = 13$	2	0.802	$t = 20$	2	0.064
2036.4 (kW)	3	0.671	1445 (kW)	3	0.853

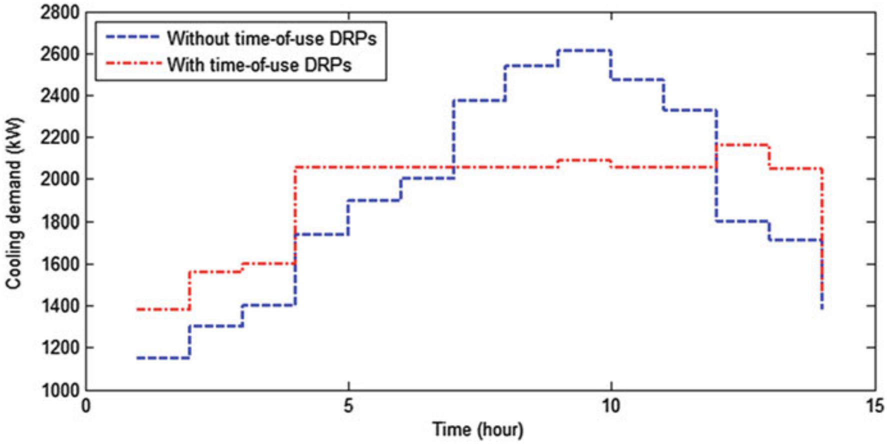

Fig. 5.14 Variations of cooling demand before and after participation in time-of-use DRPs

Table 5.9 Total energy cost of four chillers in four cases

Case study	Energy cost ($)
1	874.82
2	818.15
3	537.36
4	480.70

Nomenclature

$\alpha_i, \beta_i, \gamma_i, \zeta_i$	Coefficients related to the operating characteristic of chiller i
η	Conversion coefficient of a photovoltaic panel

Φ_t	Solar irradiance
CL_t	Cooling demand after implementation of DRPs at time horizon t
CL_t^0	Initial demand which participates in time-of-use DRPs
N	Number of chillers
N_{pv}	Number of photovoltaic panels
P_t^{ch}	Total electrical power consumed by all centrifugal chillers at time t
P_t^{pv}	Power output of a photovoltaic panel
P_t^{grid}	Purchased electrical power from upstream grid
PLR_i^t	Partial load ratio (PLR) of chiller i at time horizon t
RT_i	Capacity of chiller i
S	Array area of a photovoltaic module
U_i^t	A binary decision variable that will be equal to 1, if ith chiller is on; otherwise it will be 0
T_t^a	Ambient temperature at time t

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