Demand Response and Flexible Management to Improve Microgrids Energy Efficiency with a High Share of Renewable Resources

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Abstract

Energy and social welfare management of smart buildings have been influenced by cooling systems. Although the combination of cooling systems in the smart grid has stimulated serious discussions over the last decade, its execution and control with more penetration of renewable energy have not been directly tackled. Hence, the present paper is designed to explore the suitability of implementing a novel controller for a cooling system in smart grid settings and high shares of renewable energies. The controller operates from a local control entity by responding to a set of inside nominated points and outside signals, such as access to renewable energy sources and customer welfare. Not only it reduces the purchasing power from the distribution grid with the help of optimization processes, but also minimizes the overall cost and size of the microgrid. Managing the cooling system simultaneously increases the reliability of the microgrid. As a result, the smart cooling system and renewable energy operate in unity, thus providing separate and mutual benefits for the whole system. The results presented in this study support that the proposed cooling system controller is capable of planning a microgrid system.

Keywords: Demand response; renewable resources; microgrid; smart building; active controller; optimization.

Nomenclature

$P_{surplus}$	Surplus power
$P_{surplus,avg}$	Daily average of the extra power signal
$\sigma_{surplus,real}$	The output energy flows
$T_{desired}$	The reference of preferred temperature (°C)
T_{act}	The reference of actual temperature (°C)
T_{min}	Minimum actual temperature (°C)
T_{max}	Maximum actual temperature (°C)

$Ramp_{high}$	Increasing rate between $T_{desired}$ and T_{max} (°C^{-1})
$Ramp_{low}$	Decreasing rate between $T_{desired}$ and T_{min} (°C^{-1})
σ_{min}	Standard variation of extra power at T_{min}
σ_{max}	Standard variation of extra power at T_{max}
P_{WT}	Generation of wind turbine
P_{PV}	Generation of photovoltaic power plant
P_{base}	Electrical consumption of microgrid
$\mathrm{Q_{AC}}$	Heat transport from the air conditioner
$\mathrm{Q_{loss}}$	Heat loss to the inside and outside environment
ρ_{air}	Density of air
V_{room}	Domestic area volume
$\mathrm{Q_{Latent}}$	Latent load (W)
CMH	Infiltration airflow
U	Thermal conduction coefficient (W/m^{2}C)
A	Structured surface (m^2)
ΔT	Air temperature divergence indoors and outdoors (°C)
$Pbase(i)$	Base load
$Pcooling(i)$	Load of the cooling system

1- Introduction

Some power system operation methods manage the power generation based on the estimated network load. In rare cases the loads are directly regulated, for instance when generation is not sufficient during peak days, the load would be reduced via demand-side management algorithms. In general, the power generation is distributed to follow the demand. Evidently, as additional renewable energy is added to the grid it becomes less and less easy to match the network load. There is a lack of certainty when it comes to wind and solar power resources in microgrid. By generating power intermittently, supplies are neither predictable nor possible to schedule.

The generation of power by means of solar sources varies because of changes in weather. The wind energy generation profile also changes day by day showing rapid alterations. As additional un-dispatchable renewable power generation is included, it will become ever more difficult for fast ramping; also load following and controllability of power generation. Smart grids have the advantage of utilizing the direct control of loads. In this situation, loads can be made more dispatchable in order to compensate for generation when it becomes less dispatchable. Dispatched demand and demand-side management are alike since they both involve turning loads on and off. However, there is a difference between the ways which they are applied. Demand response is used rarely and generally for load curtailment objectives through periods of peak load, while demand dispatch is planned to be applied strongly at every period to contribute keen on services that improve the action of the power system. It is referred to as demand dispatch, since in real-time loads are dispatched. Power balance can be achieved by turning the load on or off, producing the similar outcome as rising or decreasing the generation. The demand dispatch scheme aims to create generation-following loads. Currently, the majority of grid dispatches generation utilizes this strategy.

Considering all facilities and electric appliances in a building, the cooling system consumes a significant share of the total energy [1]. Therefore, a major contribution to maintain the power balance of the building is achieved by designing proper demand dispatch of the cooling system.

In order to carry out the study, solar and wind power generation, fuel cell and electrolyzer with cooling systems are incorporated in the simulated microgrid. The reason for considering cooling systems is that they are flexible loads raising the possibility of following renewable energy generation, allowing the increase of the penetration of renewable energy with minimizing the overall price of the microgrid. Some inhabited electricity consumption arrangement problem by different electrical devices in smart grid has been described by [2]. A multi-residential electricity load scheduling problem with multi-class appliances in the smart grid is studied. Through an optimization problem, the sum of the overall satisfaction levels of residences is maximized. The objective function is defined as the sum of utilities of the residential customers minus the total cost for energy consumption . However, the rapid responses of energy management system in the grid emergency are not involved in this study.

The cooling system can control the set temperature [3]. Controlling the cooling system only in the demand response time does not account for the economic benefits obtained from other times [4]. Further, a disadvantage is that the thermal model is simple and not like the actual temperature change shape [5]. Strategies to minimize both the demand cost and energy cost are different. Previous studies have adopted necessary strategies, but the overall process was difficult to understand [6,7].

In [8] it has been offered a consumer comfort model under the thought of consumer waiting times, which is a nonconvex problem. Recently, in [9], a coupon incentive scheme was proposed to persuade small scale customers in reducing the load in peak price period.

It is advised in [10] to utilize a new algorithm for intelligent load control and load curtailment to minimize energy not supplied in impulsive load variation of grid and decrease the peak-to-average relation. The presented work by [11] offers an effective attractive method contain communication-based demand response and a consumer-pleasant inclining block tariff that consider consumers' profits and consumption profiles.

On the other hand, in [12]–[15], multi-objective optimization of microgrids in which economic, environmental and demand response issues are considered has been evaluated. In [12], a smart park microgrid which consider photovoltaic panels. The obtained study in [13] develops a complete organization and investigation of demand response's obstacles and enablers in a smart grid framework. In [14], a stochastic programming method is planned to optimize the performance of an intelligent microgrid to minimize operation prices and emissions by renewable resources In [15] the result of a novel scheme architecture and control algorithm that is able to apply together battery storage and control the temperature of thermal domestic devices is presented.

However, they have attempted to model the residential energy demands by means of pre-specified behavioral rules. While there are some uncertainties in load demand, weather conditions and energy storage's state of charge. Therefore, researchers have recently achieved to formulate optimization problem of residential A/C control. For instance, in their ongoing investigations, they have tried to limit the combination of thermal discomfort and energy consumption under variable electricity price [17]–[20].

Kondziella et al. [21] aim to classify the technical approaches that have been used in elasticity demand studies. Ref [22] describes a DR development model for the new housing society incorporates the present conditions and the future styles of DR agenda. Ref [23] concentrates on the two-way communication linking distribution grid and several inhabited customers, and every consumer is considered as a smart house energy management structure. In [24] an original incorporated form of demand in the presence of energy efficiency programs in addition to DR plans has been designated.

In [25] presents a DR method for energy management in a hierarchical power market that believes both the service provider's income and customers' expenses. A novel model to determine a digit to decide the number of chillers/pumps to be shut down, also how to adjust a load of retained equipment systematically through demand response procedures is described by [26]. A method is expanded by [27] to carry out the demand response for domestics in smart grids, which consider PV generation and energy storage.

In [28] an original informational systematic demand response management method for an inhabited customer with a goal to decrease the peak load is presented. In [29], a realistic pricing method is planned to persuade various customers to contribute to demand response by supplying them with a list of price plans. Ref [30] presents a new control algorithm for joint demand response management and thermal comfort optimization in microgrids equipped with renewable energy sources and energy storage units. Ref [31] proposes a simulation-based optimization method for the scheme of an energy management system in grid-connected photovoltaic-equipped microgrids with heterogeneous occupancy schedule. Ref [32] presents an original control algorithm for joint energy demand and thermal comfort optimization in photovoltaic-equipped interconnected microgrids. Ref [33] presents a home energy management model consisting of microgrid framework and demand side management (DSM) technique. To reduce peak load, peak to average, and energy cost, households' loads were shifted on the basis of price-based tariff such as flexible and time of use tariff.

In Ref [34], an integrated planning model was developed to investigate the techno-economic performances of a high renewable energy-based standalone microgrid. Ref [35] presents a suite of demand response constraints that capture more-realistic demand response operational limitations including uptimes and downtimes, numbers of starts per day, allowable power limits, and required recovery periods. Ref [36] presents novel methods for Demand Response programs in order to deal with operational uncertainties, such as wind energy and energy price of upstream network, within the framework of a smart microgrid. Ref [37] proposes a novel energy management system for an isolated structure of networked microgrids. In Ref [38], an innovative model is provided as a strategic management. It is intended to optimise the operation in smart homes consisting of generation units such as a wind turbine, solar panels, storages, and un/controllable loads. The contribution of Ref [39] is to propose a way to facilitate and assess renewable sources' integration into manufacturing systems, by exploring an optimization model that obtains a production schedule adapted to match the onsite renewable energy supply, with energy storage systems and the power grid as backups.

Ref [40] recommends chaotic fast convergence evolutionary programming rooted in Tent equation to solve hydrothermal generation scheduling incorporating pumped-storage-hydraulic unit with demand side management considering uncertainty and outage of renewable energy sources. Ref [41] proposes a hierarchical demand response scheme, which is based on a new two-level market mechanism that results in a win-win situation for both parties. Ref [42] proposes the demand-side power procurement problem to optimally reduce consumer's energy cost. The motivation stems from pressing issues on an increase of energy cost in an industrial section. In Ref [43], a peer-to-peer energy trading platform among residential houses is proposed to coordinate demand response schemes and level of potential generation/consumption disturbances in the hour-ahead intraday context.

According to the previous literature review, the main novelties of the proposed paper are:

- A new method is developed for demand-side management in smart grids considering high penetration of intermittent renewable energy generation sources;
- Making the house demand flexible to follow the variable power output of renewable generation resources and matching the response behavior of generation and consumption in smart grids with high penetration of intermittent renewable generation sources;

- Long term planning of smart grids considering high penetration of intermittent renewable energy generation sources and taking into account the demand side management of smart buildings.

2- The Active controller

One of the methods of controlling ventilation loads is using active controllers. Active controllers set the thermal load based on the set-point of consumer and the external signal in such a way that consumers' welfare is not disturbed, and the consumption is reduced at the needed time. In this paper, the external signal is considered as the difference between the generation of renewable energy resources and the MG's loads. In fact, these types of controllers transform the amount of consumer thermal comfort into a mathematical model and compare it with the external signal to decide whether to warm or cool the place [15, 27].

The power consumption of the cooling system is adjusted according to the environment's temperature so that the room's temperature reaches to this point, which is known as the actual temperature. This adjustment should be made in such a way that firstly it does not disturb consumer's comfort, secondly, it reduces consumption when the difference between the production of renewable energy resources and the MG consumption is low. A home energy management system can be used to implement this method [15, 27].

In a microgrid, local control determines the surplus of power, $P_{surplus,}$ which is transmitted to all active controllers through a communication system. The surplus power is the outcome of difference between renewable production and demand. Home Energy Management (HEM) system receives the surplus power signal, while the information is distributed among the active controller in the building. The accessibility of renewable resources in a specific period is indicated by the surplus power signal [15, 27].

Together with the surplus power signal; the daily average of the extra power signal, $P_{surplus,avg}$, and a daily standard deviation of extra power, $\sigma_{surplus,real}$ are relayed to the active controllers. Including all three signals, the basis is provided to evaluate the power signals among the past 24 hours. An active controller is required in place for the domestic demand to make a response to the received signals [15, 27]. Although active controllers could manage more end-user demands, a cooling system has been selected for further investigation of residential appliances. Here, the implemented cooling system's active controller employs the daily standard deviation of extra power, $\sigma_{surplus,real}$ considering the below parameters:

The block diagram of the active controller is shown in Fig. 1

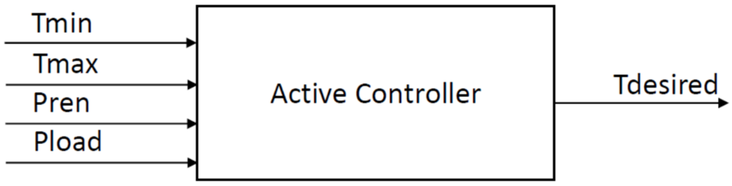

Figure1. The block diagram of the active controller

Where P_{REN} is the generation of renewable energy resources and P_{load} is the microgrid's loads.

2.1. The Cooling model

$$P_{surplus}(t) = P_{REN}(t) - P_{base}(t) \tag{1}$$

$$P_{REN}(t) = P_{WT}(t) + P_{PV} \tag{2}$$

Where, P_{WT} is considered as the generation of wind turbine, P_{PV} is the generation of photovoltaic power plant, and P_{base} shows the consumption of MG.

In this study, $P_{surplus,}$ and $P_{surplus,avg}$ are replaced by $\sigma_{surplus,real}$.

$$\sigma_{surplus,real} = \frac{P_{surplus} - P_{surplus,avg}}{P_{surplus,avg}} \tag{3}$$

$$P_{surplus,avg} = \frac{\sum_{i=1}^{24} P_{surplus,i}}{24} \tag{4}$$

The controller receives additional information from extra power signal, $P_{surplus}$, and, $P_{surplus,avg}$. Whenever the extra power signal is equivalent to $P_{surplus,avg}$, the active controller sets T_{act}, *to* $T_{desired}$. However, when $P_{surplus}$ and $P_{surplus,avg}$ are not equal, T_{act} is moved away from the $T_{desired}$. As long as $P_{surplus}$ is lower than $P_{surplus,avg}$, the controller places the T_{act}, higher than $T_{desired}$. The maximum allowable temperature does not go beyond T_{max}. Provided that $P_{surplus}$ rises above $P_{surplus,avg}$, the controller places T_{act} lower than T_{min}. ΔT represents the difference between $T_{desired}$ and T_{act}. A positive value for ΔT ($\Delta T>0$) signifies higher T_{act} compared to $T_{desired}$. While $P_{surplus}$ is lower than $P_{surplus,avg}$, the $T_{desired}$ increases conversely. Another parameter that has significant effect on the active controller is $\sigma_{surplus,real}$. It depends on the available $P_{surplus}$ and $P_{surplus,avg}$. Fig.2 illustrates the active controller performance which presents the relation between $\sigma_{surplus,real}$ and the temperature reference values.

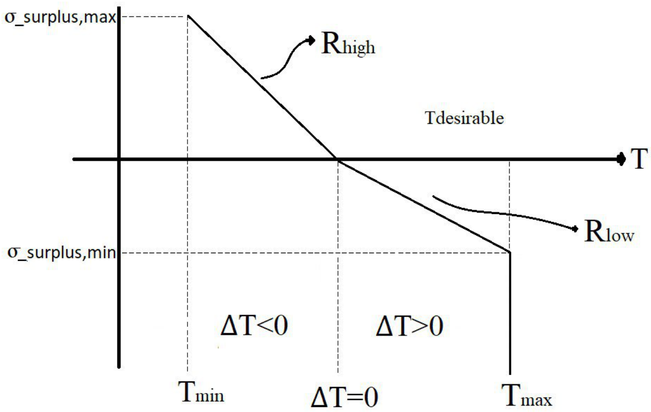

Figure2. Active controller performance for a specific cooling system

Figure 2 shows the relation between $\sigma_{surplus,real}$ and set-point of active controller. The main purpose of this figure is the temperature adjustability.

It is clearly obtained from Fig.2,that R_{low} and R_{high} may get different values, pointing out various consumers preferences in response to heating and cooling habitual. In other words, end-users may have the tendency to increase the house temperature above $T_{desired}$, thus far be resistant to allow decreasing temperature below the heating temperature reference. Also, it is not necessary for T_{min} *and* T_{max} to be symmetric around $T_{desired}$.

Equation (5) calculates the actual temperature reference of the active controller which is subject to the constraints of equation (6). Equations (7-8) determine R_{low}, R_{high}.

$$T_{act} = T_{desirable} + \Delta T \tag{5}$$

$$T_{min} - T_{desirable} \leq \Delta T \leq T_{max} - T_{desirable} \tag{6}$$

$$R_{high} = \frac{\sigma_{surplus,max}}{T_{min} - T_{desirable}} \qquad if\ \sigma_{surplus,real} > 0 \tag{7}$$

$$R_{low} = \frac{\sigma_{surplus,min}}{T_{max} - T_{desirable}} \qquad if\ \sigma_{surplus,real} < 0 \tag{8}$$

In order to calculate ΔT, it requires ascertaining whether $P_{surplus}$ is higher or lower than $P_{surplus,avg}$ to begin with. This could be worked out by assigning $\sigma_{surplus,real}$ (equation 3). For an inhabited application, positive values indicate that the $P_{surplus}$ is lower than the $P_{surplus,avg}$ and negative ones indicate that it is higher. The value of ΔT where $\sigma_{surplus,real}$>0 is given by equation (9) and $\sigma_{surplus,real}$ <0 is specified by equation (10), supposing zero value $\sigma_{surplus,real}$ no ΔT is generated.

$$\Delta T = \frac{\sigma_{surplus,real}}{R_{high}} \qquad \sigma_{surplus,real} > 0 \tag{9}$$

$$\Delta T = \frac{\sigma_{surplus,real}}{R_{low}} \qquad \sigma_{surplus,real} < 0 \tag{10}$$

Merging equations (5), (9), and (10), equations (11) and (12) are obtained which are nevertheless subject to the constraints determined by equation (6). Provided that $P_{surplus} > P_{surplus,avg}$, yields a $\sigma_{surplus,real}$>0, the T_{act} is born by equation (11) furthermore, if $P_{surplus} < P_{surplus,avg}$, yields a $\sigma_{surplus,real}$<0, and is computed by equation (12).

$$T_{act} = T_{desirable} + \frac{\sigma_{surplus,real}}{R_{high}} \qquad \sigma_{surplus,real} > 0 \tag{11}$$

$$T_{act} = T_{desirable} + \frac{\sigma_{surplus,real}}{R_{low}} \qquad \sigma_{surplus,real} < 0 \tag{12}$$

It is important to note that based on Figure 2 and equations (11) and (12) no absolute $P_{surplus}$ or temperature reference values are available. The T_{act} is tuned based on $\sigma_{surplus,real}$ and internal reference values by the active controller. It is essential for the device to have the flexibility and be capable of operating at different $P_{surplus}$ levels.

3. Determining the cooling system power consumption

Regarding the technique explained in Section 2, the variation of indoor temperature, which should be provided by the cooling system, is computed as follows:

$$\Delta T_i' = T_{real_i} - T_{real_{i-1}} \tag{13}$$

Equation (14) must be satisfied to guarantee that the deviation of the pointed temperature is a proper value.

$$Q_{AC_i} - Q_{loss} = -m.c_{air}.\Delta T_i' \tag{14}$$

That $\mathrm{Q_{AC}}$ is the heat transport from the air conditioner. $\mathrm{Q_{loss}}$ is the heat loss to the inside and outside environment throughout the barrier, glass and roof area and summation of inside demands. Equation (14) is reworked as bellow:

$$Q_{AC_i} - Q_{loss} = -\rho_{air}.V_{room}.c_{air}.\Delta T_i' \tag{15}$$

Where ρ_{air} is the density of air and V_{room} is the domestic area volume.

In many cases, the cooling system’s efficiency is related by the Seasonal Energy Efficiency Ratio (SEER). [44].

Equation (15) could be defined as below:

$$P_{AC_i} \times t \times SEER - Q_{loss_i} = -\rho_{air}.V_{room}.c_{air}.\Delta T_i' \tag{16}$$

$$P_{AC_{min}} \leq P_{AC_i} \leq P_{AC_{max}} \quad (17)$$

3.1. Heat loss for the cooling system

for the purpose of evaluating the cooling demand, the parameters below should be taken into account [7]:

- Heat gain from external loads: sun, exterior walls, roof, glasses,
- Heat gain from internal loads: ventilation or infiltration, interior partitions, equipment, light fixtures and residents.

Cooling consumption load is comprised of radiation, conduction, convection, and interior demands. Cooling data is used as a substitute for heating to calculate conduction load. The air infiltrated latent load by the formula below [7] and responsible load as heating, make up the convection load.

$$Q_{Latent} = CMH \times 0.82 \times \Delta W \quad (18)$$

Where Q_{Latent}latent load (W), *CMH* (Cubic Meter per Hour) is infiltration airflow (m^3/hour). Transferred thermal demand is computed by equation (19) [7]:

$$Q_{Conduction} = U \times A \times \Delta T \quad (19)$$

Where *U* is the thermal conduction coefficient (W/m^2C), A is the structured surface (m^2) and ΔT is the Air temperature divergence indoors and outdoors (°C).

The thermal conduction coefficient (*U*) is computed as presented below:

$$U = \frac{1}{\sum R_i} \quad (20)$$

$$R_i = \frac{x_i}{k_i} \quad (21)$$

Convection demand could be determined as below [7]:

$$Q_{Convection} = 0.335 \times CMH \times \Delta T \quad (22)$$

That 0.335 is the sensible thermal factor, *CMH* is the airflow infiltration rate (m^3/hour) and ΔT is the Air temperature variation between indoors and outdoors (°C). Thus, Q_{loss} is given as:

$$Q_{loss} = Q_{Latent} + Q_{Conduction} + Q_{Convection} \quad (23)$$

Figure 3 provides a flowchart of the recommended method.

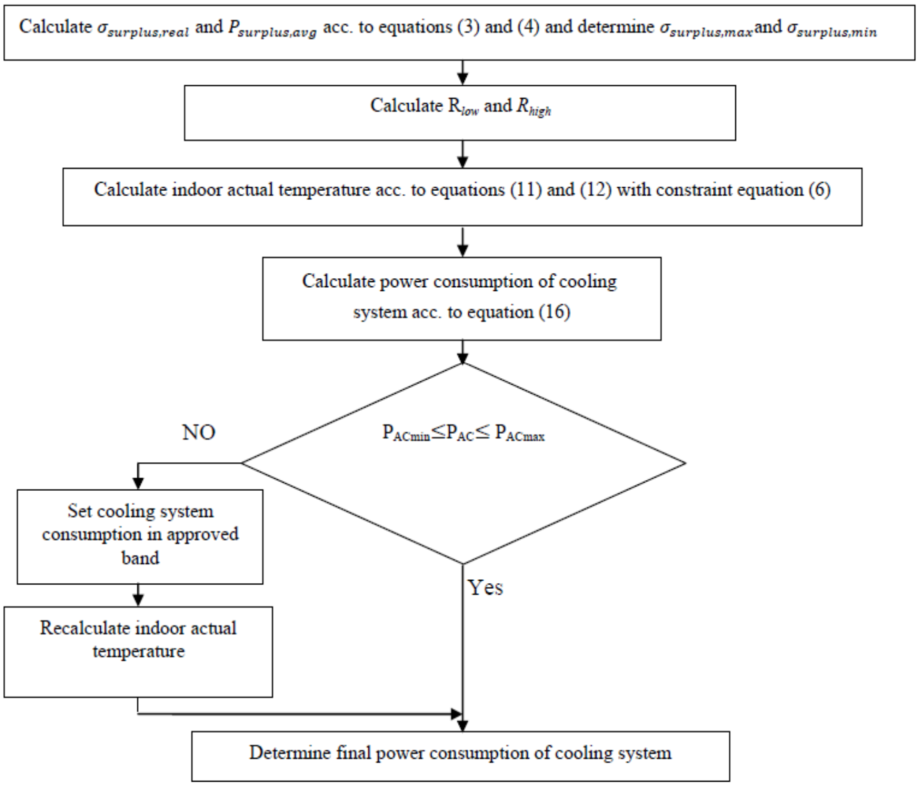

Figure3. Flowchart of the proposed method

4. Simulation results

Thus far, the peak demand of the microgrid is considered 500kW i.e. the total demand regardless of the cooling load. The amount of every wind power generation system and the rest of the unit i.e. Photovoltaic, Fuel cell, electrolyzer, and hydrogen tank are 7.5kW and 1kW in that order. The optimal sizing of the components which form the microgrid is established by the proper management of cooling loads. Indoor cooling is provided by means of air conditioning. It has been attempted, in this study, to manage the cooling loads on the basis of an intermittent renewable generation with wind, solar, microgrid load, the outdoor temperature and the preferred indoor temperature of the end-users. The main aim has been to look into the influence of the cooling managing system on the optimal sizing of microgrid elements, the reliability of demands and the overall cost of the microgrid. More detail of economic data is shown in Table 1 [45-48].

Table 1. The economic data of each component.

	Wind	PV	Fuel Cell	Electrolyzer	Hydrogen Tank
Capital cost($)	1850	1300	1500	500	250
Replacement cost($)	1400	600	800	55	40
Operation and Maintenance cost($/kw/year)	85	40	150	50	45

In Figure 3, first, $P_{surplus,avg}$ and σsurplus,real are calculated based on Eq. 3 and Eq. 4, then R_{high} and R_{low} are calculated by Eq. 7 and Eq.8. The real temperature is determined by Eq. 11 and Eq. 12 considering constraint in Eq. 6. At the next step, the power consumption of cooling system is calculated by Eq. 16. The minimum and maximum acceptable power of cooling system are checked, and if this limit is not met, the power of cooling system is defined in permissible range. For example, if the power is higher than $P_{AC\max}$, it will be set on $P_{AC\max}$, and the real temperature will be recalculated.

Optimal sizing of the microgrid components can be achieved by determining the following parameters as inputs to the program:

- Microgrid components: solar and wind resources.
- Energy storage components.
- Wind and solar production's specification
- Outside temperature
- Desired temperature: T_{max} and T_{min}
- Energy purchasing price: from and into the distribution grid.
- Hourly load curve.
- A typical air conditioner's lowest and highest power usage
- The essential information for Particle Swarm Optimization (PSO).
- Mentioned building's features: walls, windows, etc.

In the simulation process, a transformer with 90% efficiency and 100kVA capacity is considered. The tariffs on electricity in this paper are based on case studies in Iran. The electrical energy rates are presented in table 2.

Table2. The electrical tariffs for inhabited properties in Iran within the consumption range of over 30kW and under 30kW

	Middle load	Peak load	Off-peak load
Hour	07:00-19:00	19:00-23:00	23:00-07:00
$/kWh (the power more than 30kW)	0.034	0.068	0.017
$/kWh (the power less than 30kW)	0.044	0.088	0.022

The assumed house size for a cooling system's load control method to be implemented and installed was 160m^2 with 10m×16m in dimensions. Side walls may have accrued the heat interchange i.e. (50m^2+50m^2+28m^2+28m^2). The k factor of the window equals to 0.05 (w/m.k) according to the computation. The walls are 30cm in thickness. Therefore, two hundred cooling systems were estimated to be used in the simulated microgrid to keep the inside temperature around 23°C, and the power consumption is displayed in figures 4 and 5. As can be seen in Figures 5 and 6, when the outside temperatures rise, the energy consumption increases as well.

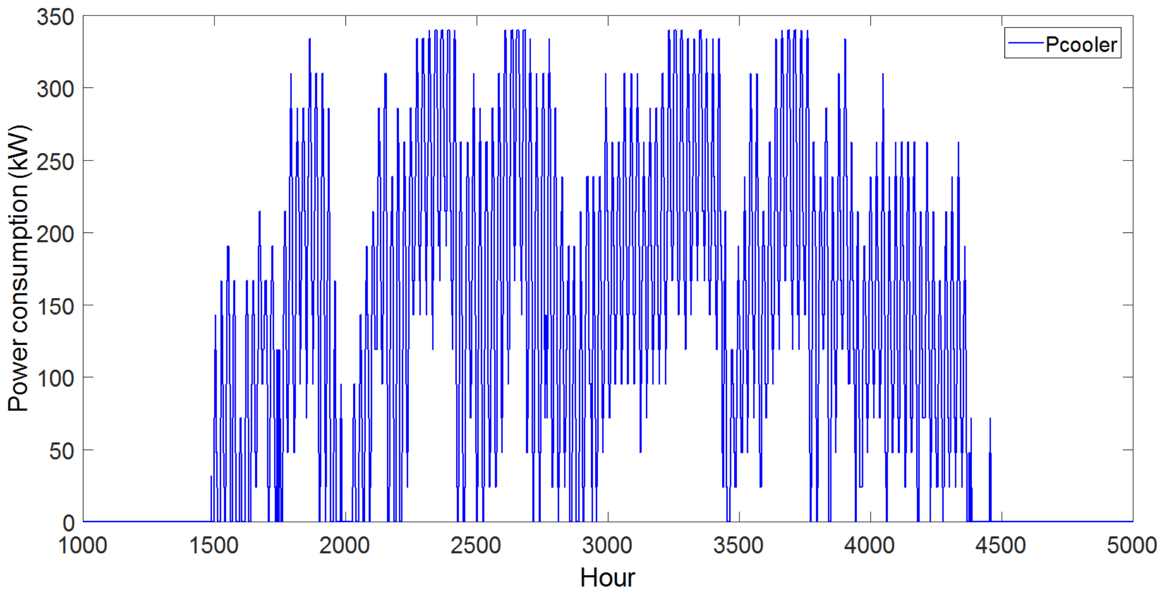

Figure4. Hourly power consumption of cooling systems without control

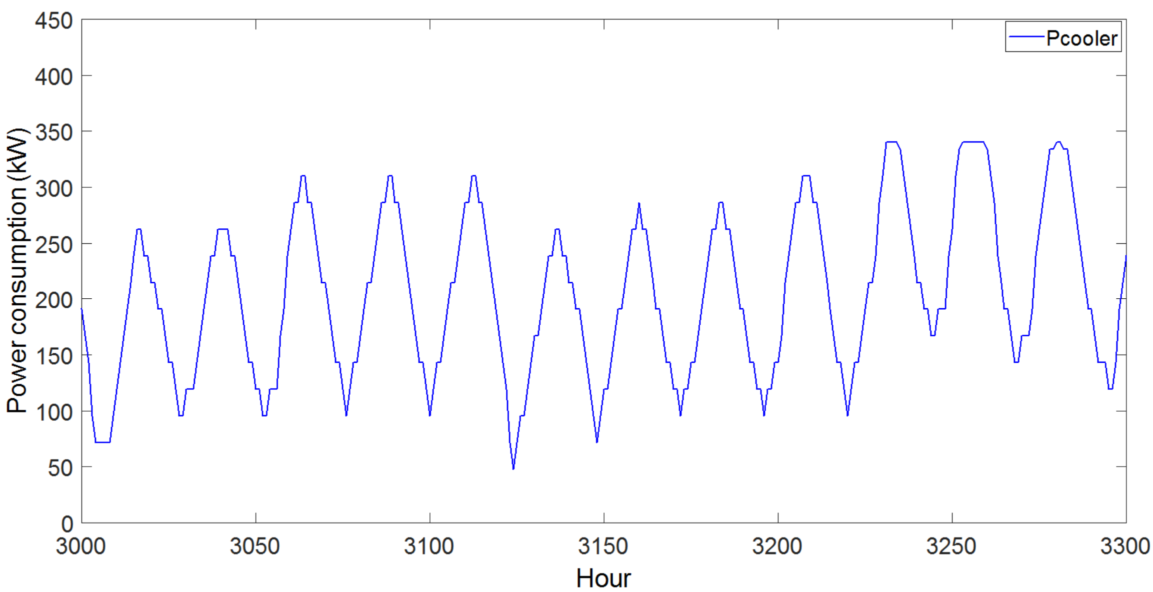

Figure5. Hourly power consumption of cooling systems without control during 10 days

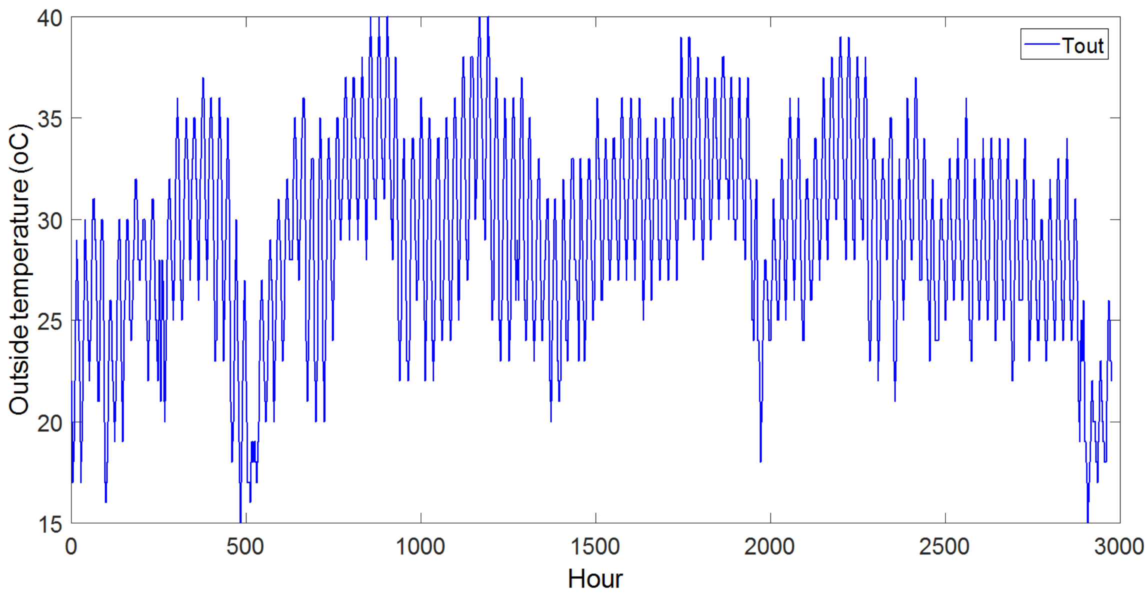

Figure6. The hourly outdoor temperature during 10 days

The optimal number of microgrid components prior to organizing the energy usage of the air conditioning system are given in table 3. Table 4 depicts the optimal quantity and price of buying energy from the distribution grid on the one hand and, the optimal quantity and price of sold energy to the distribution grid on the other, in addition to the optimal price of the microgrid, shed loads, punishment for interrupted loads and microgrid reliability. In this part the impact of cooling load managing on optimal sizing of microgrid components has been considered. Figure 7 shows the comparison between optimal sizing of microgrid components before and after cooling system management.

It is necessary to determine the following parameters before employing the presented control methodology:

- The preferred temperature in warm time of year, i.e., summer: 23°C
- The lowest and highest temperature in hot time of year: 19-26°C

Table3. Optimal price and amount of every component in microgrid in the absence of cooling system management.

Total cost ($)	Transformer (KVA)	Fuel Cell	Hydrogen tank	Electrolyzer	Wind turbine	Photovoltaic
1.96361×10^{7}	57	522	4397	875	202	598

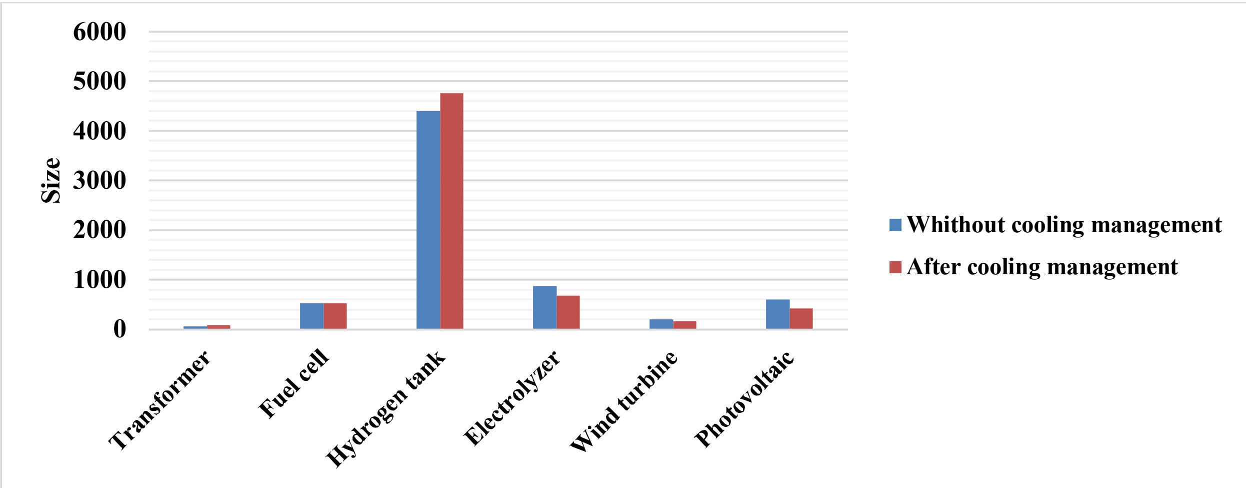

Figure7. Optimal sizing of microgrid components without and with cooling management

Table4. The quantity and price of exchanging energy, interrupted loads and penalty in the absence of cooling system management

ELF	Penalty for Interrupted load ($)	Interrupted load (kWh)	Cost of selling energy ($)	Selling energy (kWh)	Cost of buying energy ($)	Buying energy (kWh)
0.00253	8.4508×10^5	15.3702×10^3	1.052×10^5	1.0716×10^5	2.194×10^4	2.234×10^4

Figures 8-12 show, the divergence between power production of renewable energy and microgrid load, the actual inside and outside temperature in a 10-day period, the controlled power consumption of cooling systems throughout a year and also in a 10-day period.

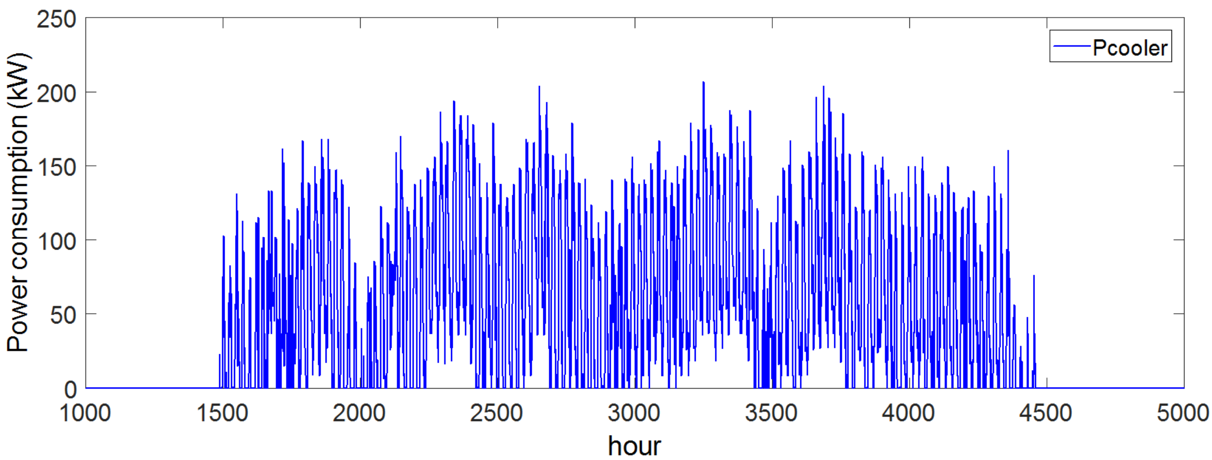

Figure 8. Hourly power consumption of cooling systems with active controller

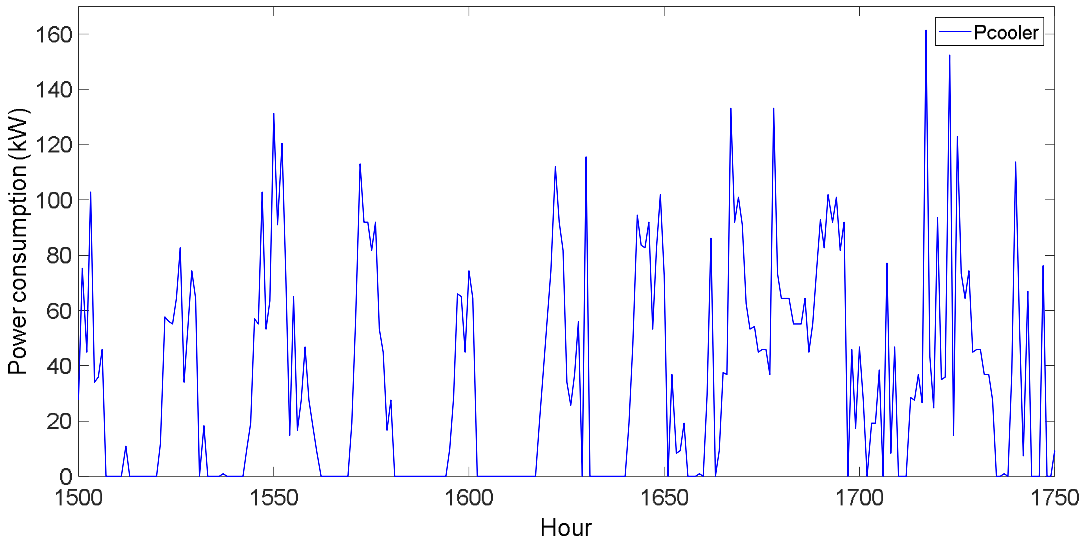

Figure 9. Power consumption of cooling systems with active controller in 10 days

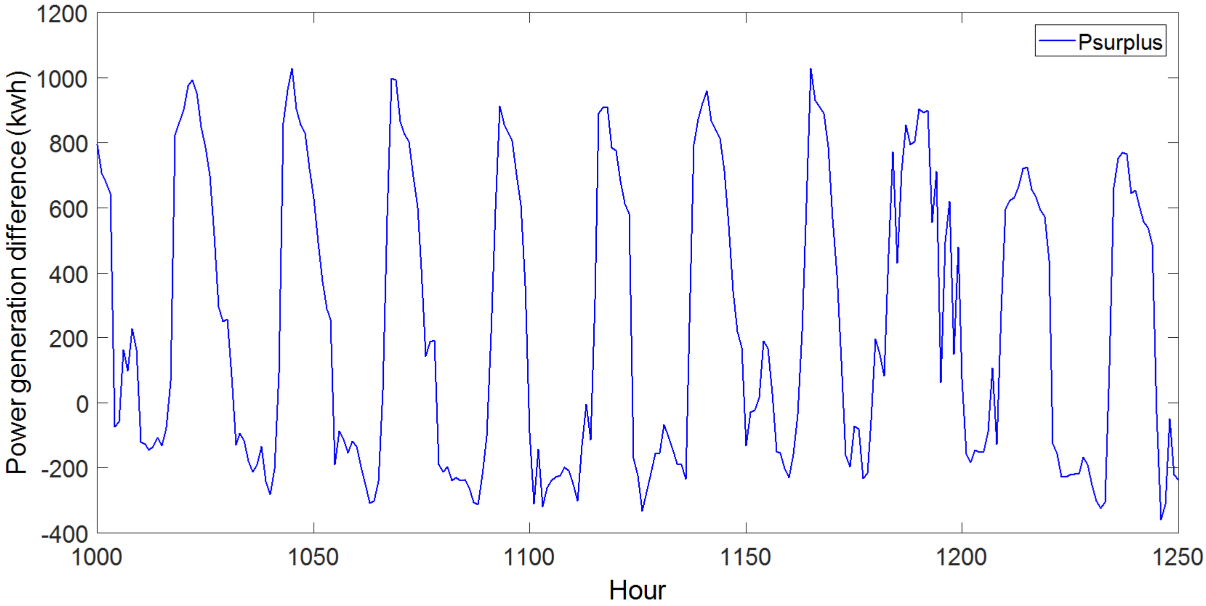

Figure 10. variation between power production of renewable energy and microgrid demand in 10 days

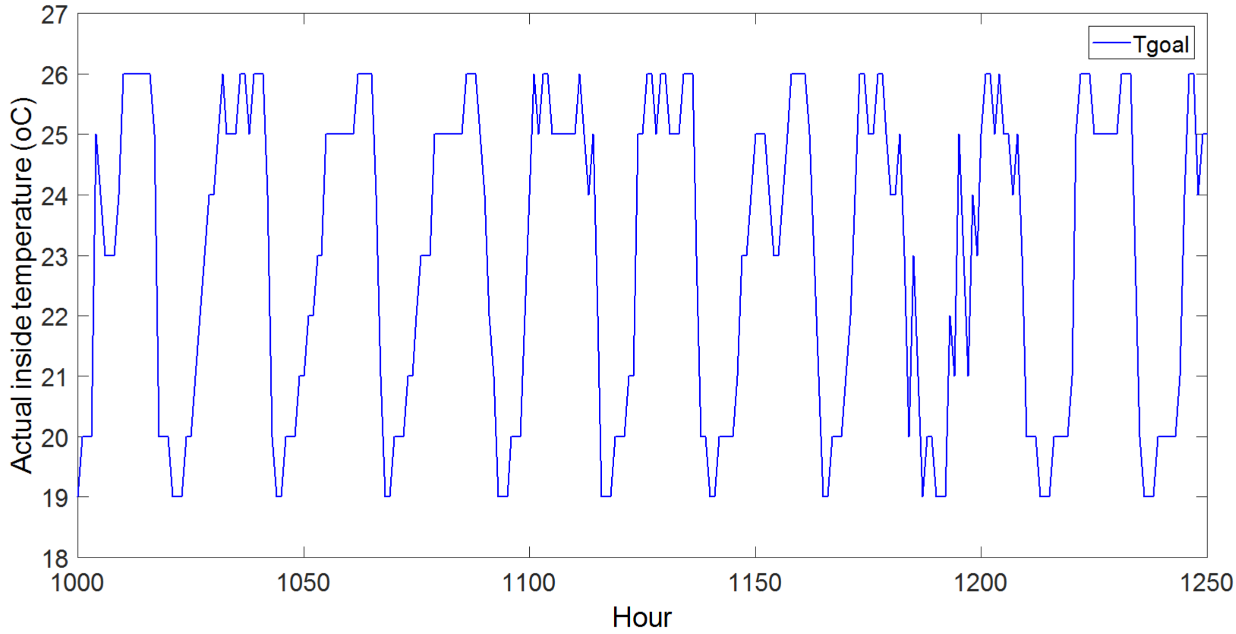

Figure 11. Actual temperature of inside in 10 days

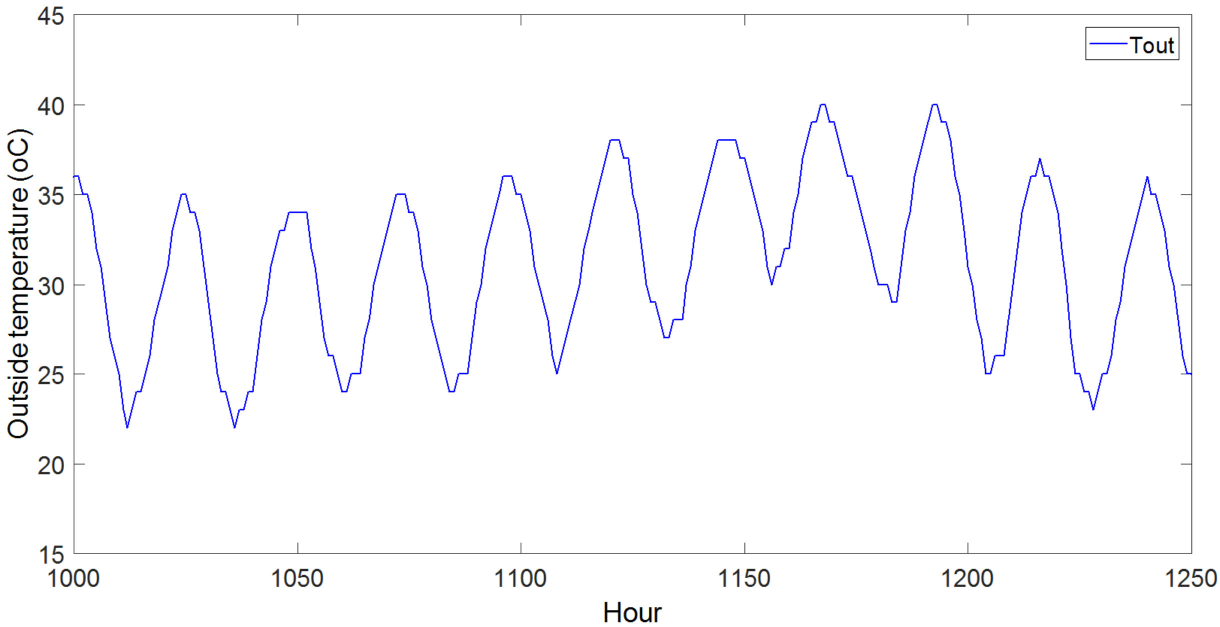

Figure 12. The outside temperature in 10 days

As it is apparent in figures (8-12), the quantity of electricity usage of cooling systems is relative to the extra power and outside temperature. The indoor temperature of the house gets adjusted as stated by the extra power. For instance, the temperature can be lowered when the surplus power is low. Based on the amount of surplus electrical power the inside temperature is adjusted.

As it can be observed, Table 5 provides the optimal number of microgrid components past organization the usage of cooling systems. Moreover, Table 6 depicts the optimal quantity of exchanged power from/to distribution grid, the loads which were not supplied due to related expenses and microgrid reliability.

Table 5. Optimal price and amount of power consumption in each microgrid unit in the presence of the cooling system management

Total cost ($)	Transformer (KVA)	Fuel Cell	Hydrogen tank	Electrolyzer	Wind Turbine	Photovoltaic
1.8009×10^7	90	521	4764	675	158	422

Tables 3 and 5 have been compared, indicating that the proposed method managed to reduce the size of renewable resources and enlarge the quantity of hydrogen reserved in the tank. The evaluation of tables 4 and 6 shows that the proposed technique has resulted in the lessening of the buying energy from the distribution grid and rising the power sold to the distribution grid, in addition to, lessening load shedding and purchased gas from the grid.

Table 6. The quantity and price of exchanging energy, non-supply loads and punishment in the presence of the cooling system management.

ELF	Penalty for interrupted loads ($)	Interrupted loads (kWh)	Cost of selling energy ($)	selling energy (kWh)	Cost of buying energy ($)	Buying energy (kWh)
0.000161	39765	903	1.386×10^5	1.423×10^5	6.464×10^3	6.62×10^3

In order to verify the effectiveness of the proposed PSO methodology, GA algorithm is also implemented to determine the optimal design of the microgrid. The optimization results are shown in Table 7. It is obvious from Table 7, the total cost and optimal sizing of microgrid components of the PSO algorithm is better than GA algorithm, which depicts that the convergence speed and global search ability of PSO algorithm are better than GA algorithm.

Table 7. Simulation results comparison of PSO and GA algorithms.

	Total cost($)	Fuel Cell	Hydrogen Tank	Electrolyzer	Wind Turbine	Photovoltaic
PSO	1.8009×10^7	521	4764	675	158	422
GA	1.8347×10^7	528	4778	686	162	433

Next, the correlation of the cooling system demand before and after the use of the demand dispatch technique by the energy surplus curve has been studied to confirm the offered cooling system managing technique. The correlation values between $P_{surplus}$, $P_{cooler,Unmannaged}$ and $P_{surplus}$, $P_{cooler,Mannaged}$ are 0.49 and 0.78 correspondingly. The changing rate of the cooling system consumption gets nearer to the changing rate of the extra power generated by renewable energy, so as to expand the ability for higher renewable resource penetration.

Figure 13 shows the cooling system power usage before and after load management and renewable energy generation power surplus. It can be seen that when the surplus power is low (i.e. the load is higher than the renewable energy generation), the consumption is reduced because of the way the controller operates.

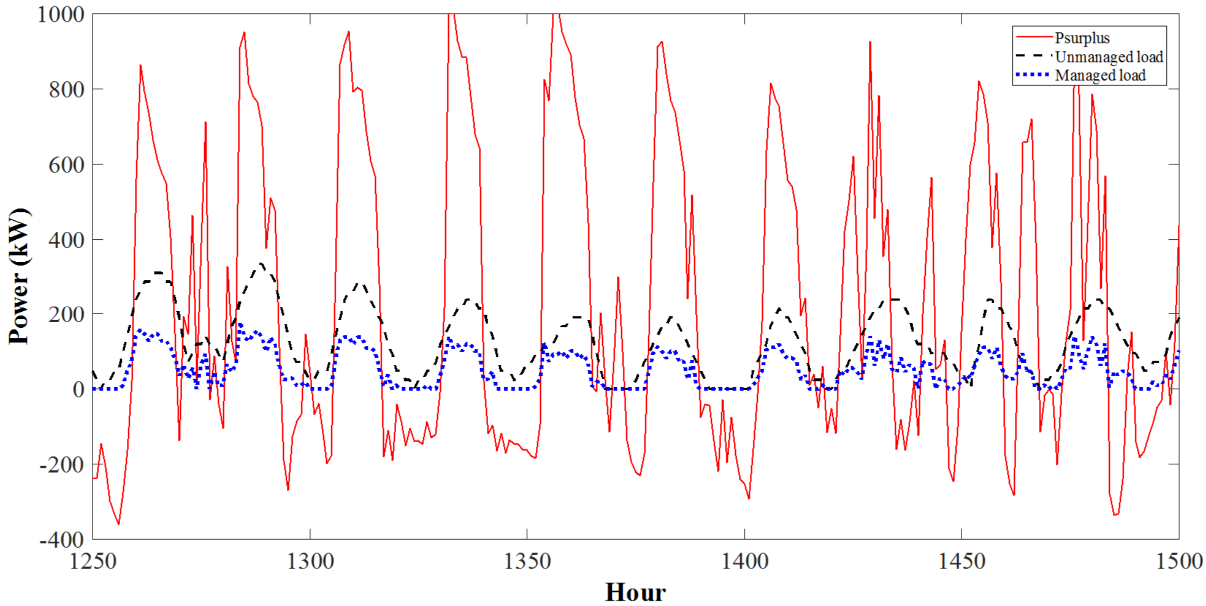

Figure13. The extra power of renewable resources and the cooling system consumption

The whole load is composed of two items:

1. The base load *Pbase(i)* representing total demand inside a microgrid excluding cooling loads.
2. *Pcooling(i)* representing the load of the cooling system.

The measurement was taken at hourly intervals denoted by *i*. It can be gathered that the base load *Pbase(i)* remains steady in the measured period *i*.

$$Pload(i) \;=\; Pbase(i) + \;Pcooling(i)$$

$$Pload_{Old}\ (i) = \ Pbase(i) + Pcooling_{Unmannaged}(i) \qquad (24)$$

$$Pload_{New}\ (i) = \ Pbase(i) + Pcooling_{Mannaged}(i) \qquad (25)$$

Regarding the obtained results, the correlation values between $P_{surplus}$, $P_{load,old}$ and $P_{surplus}$, $P_{load,\ new}$ are 0.5 and 0.72 correspondingly.

Where $\mathrm{Pload}_{\mathrm{old}}$ represents the cooling load value before considering the presented demand dispatch technique and $\mathrm{Pload}_{\mathrm{new}}$denotes the cooling load after being employed. The introduced method develops a positive correlation between demand of microgrid and the extra power by renewable resources.

5. Conclusion

The present investigation intended to introduce an original smart cooling system for household purposes. The purpose was to examine a viable implementation of an active controller. A mixture of inside settings and outside signals from a local control unit actuated the proposed active controller. As a result, the cooling management system was optimized by minimizing the price of the microgrid, minimizing the amount of renewable resources and importing power from the grid. The overall reliability of the microgrid was also improved. The proposed method and its simulation results suggest that managing the consumption of cooling systems would reduce the amount of renewable resources while the quantity of hydrogen in the hydrogen tank would increase. This would successively increase the sold power to the grid and lower the rate of purchased power from the distribution grid, non-supply loads, followed up by a decrease in the whole expense of the smart microgrid. The outcomes confirmed that the intelligent cooling systems and sustainable resources could function effectively combined with their benefits added together.

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