Strategy for demand side management effectiveness assessment via a stochastic risk-based bidding approach in a multi-energy microgrid containing combined cooling, heat and power and photovoltaic units

Nosratabadi, Seyyed Mostafa; Moshizi, Hadi Najafizadeh; Guerrero, Josep M.

Published in:
IET Renewable Power Generation

DOI (link to publication from Publisher):
10.1049/rpg2.12482

Publication date:
2022

Document Version
Publisher's PDF, also known as Version of record

IET-Wiley Virtual Symposium on Renewable Energy 2022

Digital and flexible control and operation of transmission and distribution grids for renewable power systems.

September 13 2022

Research conducted at institutions in Germany has led to exciting advances in the areas of renewable energy. This free virtual symposium supported by two of the IET's flagship open access journals *IET Renewable Power Generation (RPG)* and *IET Generation, Transmission & Distribution (GTD)* will be free to attend. It will provide a forum for researchers based in Germany to highlight their research and will celebrate the capacity for renewable energy research to engineer a better world.

Session Topics Include:

- Power Flow Control for efficient Transmission Grids
- Digitalization of Power Systems
- Flexibility in Power Systems
- Smart Distribution Grids

Register free today

Received: 27 September 2021 | Revised: 16 March 2022 | Accepted: 10 April 2022

IET Renewable Power Generation

DOI: 10.1049/rpg2.12482

The Institution of Engineering and Technology WILEY

ORIGINAL RESEARCH

Strategy for demand side management effectiveness assessment via a stochastic risk-based bidding approach in a multi-energy microgrid containing combined cooling, heat and power and photovoltaic units

Seyyed Mostafa Nosratabadi[1] | Hadi Najafizadeh Moshizi[1] | Josep M. Guerrero[2]

[1]Department of Electrical Engineering, Sirjan University of Technology, Sirjan, Iran

[2]Center for Research on Microgrids (CROM), Department of Energy Technology, Aalborg University, Aalborg East, Denmark

Correspondence
Seyyed Mostafa Nosratabadi, Department of Electrical Engineering, Sirjan University of Technology, Sirjan 78137-33385, Iran.
Email: sm.nosratabadi@sirjantech.ac.ir

Abstract

This paper proposes an efficient risk-based infrastructure management approach for a multi-energy microgrid to assess the effectiveness of demand-side management (DSM) through a stochastic strategy. The studied microgrid consists of photovoltaic and combined cooling, heat and power as the energy generation units and load aggregator with the aim of DSM. Based on this structure, day-ahead operational scheduling is investigated for the microgrid in different scenarios in both summer and winter seasons. The risk consideration is also performed in the bidding procedure dealing with different scenarios and variable prices and probabilities. In this study, the conditional value at risk index is considered to assess the amount of risk and is also studied from two perspectives. In the first case, the level of risk acceptable to the investor, the load aggregator, is selected, and its impact on the day-ahead scheduling is examined. In the second case, the effect of different levels of risk-taking and their importance on the scheduling procedure are examined. The main purpose is to show the shortcomings of the traditional DSM method when load management is done for private companies with a certain level of risk and prepare the ground for future studies to solve them.

1 | INTRODUCTION

1.1 | General motivation

In recent years, a significant increase in energy demand and environmental concerns such as air pollution, the long-term effect of hydroelectric units, and nuclear pollution have led to new technologies such as renewable and co-generation resources. For instance, the photovoltaic (PV) power plants and combined cooling, heat & power (CCHP) units are some of the most efficient generators in this way. The original concept of CCHP systems introduces a multi-purpose system that can supply the consumer's electric power, heat, and cold demands. In this new system formation, the bilateral contract between the CCHP and the main grid creates a new set of challenges in the power system's management. This concept introduces new strategies in power system managements that have not been considered in traditional approaches. New strategies such as demand-side management and peak shaving have significantly improved the power system's capability to integrate renewable energy sources. Considerable attention to these new concept has introduced a new field of research known as 'Intelligent Energy Networks' or 'IENs' [1].

The CCHP in microgrids is mainly classified into two main groups. The first one is known as large-scale CCHP applications and the second one known as distributed CCHP units [2]. The distributed CCHP units have considerable benefits, such as higher fuel efficiency and lower emission rates than the typical centralized power plants, making them an extremely appealing solution for institutional, residential, and small industrial sectors. However, these advantages will all go to waste if the operation of these units is not optimized correctly. The independent system operator (ISO) typically does this optimization, but with rapid movement of power system toward deregulation, this task has been assigned to the distribution system operator (DSO). One of the important and efficient solutions to solve the mentioned problems is utilizing the multi-energy microgrid concept. This type of microgrid is a multi-energy system that is included in a set of energy carriers and resources that are aggregated and some proposes are supplying the loads, gaining the profit, minimization of the costs, etc. [3].

1.2 | Literature review

To solve some challenges, many types of research have been performed in recent years. For example, in [4] a minimum distance operation strategy is proposed, which can lead to a better matching performance for CCHP system compared with following electrical loads (FELs), following thermal loads (FTLs), and following hybrid loads (FHLs). Some other research focusing on incentive policies is reference [5], which has proposed two incentive policies consisting of the feed-in tariff and carbon emission trading. In this research, the effects of the policies on the performance of CCHP systems running in office and residential buildings under five different operation strategies are compared, and analyzed. With these incentive policies and government's encouragements, a new concept known as integrated CCHP systems has been introduced. One of the essential strategies introduced in recent years is demand side management (DSM) [6, 7] that has been used widely in CCHP operation management topics [8]. In [9], a fuzzy risk-explicit interval parameter programming approach is proposed for multiple energy supply and demand management in the microgrid system under uncertainties. The programming approach has integrated risk-explicit interval linear programming with fuzzy theorem in a general framework. In addition, in [10] a risk-based performance is proposed for CCHP integrated with renewable sources, in which the uncertainty in price has been considered and to cope with this the information gap decision theory is employed.

A three-stage stochastic management framework is proposed in [11] to solve the optimal day-ahead scheduling and minimizing the operational cost of grid-connected microgrid. In the first stage, possible scenarios for solar and wind power generation profiles are created to address the uncertainty problem and the second stage deals with the microgrid configuration, operational constraints, and assigning DSM load participation data to be incorporated with the objective function. In [12], a multi-time scale dynamic robust optimal scheduling strategy is proposed for the coordinated operation of CCHP microgrid, which includes two time scales: the day-ahead scheduling scale and the intraday adjustment scale. The scheduling decision-making variables and the interaction power with power grid are obtained by considering the regulation cost in the worst-case scenario. In the intraday scheduling operation scale, the rolling optimization strategy is applied to obtain intraday optimal power allocation by minimizing the scheduling cost. In order to achieve economic optimization and peak-load reduction of the CCHP microgrids model, a multi-objective optimal scheduling model for CCHP microgrids integrated with renewable energy, energy storage system, and incentive-based demand response is proposed in [13]. The results in this reference show that the CCHP microgrids are effective in reducing pollutant gas emissions and reducing the cost of treating them. Reference [14] proposes a CCHP-power-to-gas microgrid system and a data-driven set-based robust optimization model considering the uncertainties of wind power and multiple demand response programs have been presented, which consists of two stages: day-ahead dispatching stage and real-time adjusting stage. An optimum design and energy management of various distributed energy resources is investigated in a hybrid microgrid system in [15] with the examination of electrical, heating, and cooling demand. This reference has suggested an optimal approach to design and operate a microgrid incorporating with battery energy storage, thermal energy storage, photovoltaic arrays, fuel cell, and boiler with minimization of the total operational cost of the hybrid microgrid.

Reference [16] focuses on the operation of CCHP-based microgrid coupled with hybrid chiller, multi-energy storage, solar and wind power, etc., under the chance-constrained programming approach by considering the mutual relationship between carriers. While modelling consumption and wind and solar energies fluctuations, the proposed approach analyzes the violation of the balance constraint for each carrier and subjects it to guarantee the corresponding confidence level. In [17], robust self-scheduling of a virtual energy hub for participating in the energy and reserve markets is presented. The thermal reserve market is proposed to maintain the real-time thermal power balance and compensate for the effects of thermal demand uncertainty. Reference [18] presents a novel stochastic model from a microgrid operator perspective for energy and reserve scheduling considering risk management strategy. It is assumed that the system operator can procure energy from various sources, including local generating units and demand-side resources to serve the customers. The objective is to determine the optimal scheduling with considering risk aversion and system frequency security to maximize the expected profit of operator. The downside risk constraints technique is employed in [19] to manage and minimize the risk associated with various uncertainties in the studied sample CCHP-based microgrid under environmental and economic constraints and the effect of the real-time pricing rate of the demand response program has been studied. In [20], a risk-constrained stochastic framework is presented for joint energy and reserve scheduling of a resilient microgrid considering demand side management. The optimization problem is formulated to schedule the system operation in both normal and islanding modes by addressing the prevailing uncertainties of islanding duration as well as prediction errors of loads, renewable power generation, and electricity price.

1.3 | Contributions of the paper

To the best of knowledge and the literature review performed, no other works and studies have been conducted on the proposed area and considering the impact of risk on the day-ahead operational scheduling of a multi-energy microgrid. So, the main contributions of this paper can be presented as follows:

- *To propose a new stochastic approach for day-ahead scheduling of a multi-energy microgrid*

Although previous studies have focused on day-ahead planning for multi-energy systems and the effect of decentralized management approaches, they mostly used deterministic methods. Therefore, they overlooked the fact that different scenarios could greatly affect this planning. In this study, a suitable formulation is presented to analyze this problem in a stochastic manner that the impact of scenarios on the generation of renewable units, seasonal changes and ambient temperature, transaction prices between main network and microgrid components, especially CCHP and LA, is included. The proposed model makes it possible to plan far more efficiently than the deterministic study because deterministic studies usually only consider the worst-case scenarios. In contrast, the presented stochastic analysis accounts for the probability of each scenario and plans accordingly.

- *To integrate risk measures in the proposed scheduling approach.*

Whenever there is talk of probability in the decision-making process, the discussion of risk is inevitable. Especially in this study, since this trend is examined from a private unit (i.e. LA) perspective, the importance of risk will be doubled. The CVaR index has been used here among different risk measure indices due to its coherence and ability to express it as a linear equation. Using this criterion makes it possible to consider the opinion of non-technical investors in the analysis and planning process. Investors' preferences can significantly impact the choice of sources or their weighting so that total investment at risk is minimized, which is a highly desirable factor for a private sector.

- *To integrate probabilistic model for the PV power plant in the CCHP-based microgrid.*

Given the emerging energy crisis as well as growing concerns about climate change, the integration of renewable resources such as PV units and cogeneration resources like CCHP systems is inevitable. Therefore, in this paper, the PV and CCHP units are probabilistically modelled and added to the framework. Based on different scenarios' probability, their major impact on the LA transactions and consequently the amount of risk imposed on the LA have been investigated by these cases.

- *To investigate the effect of risk measures on demand side management (DSM).*

One strategy that has shown significant impact in recent studies, in both the technical and economic sectors, is load management, a strategy that governments often propose as incentive schemes to help heavy loads shift to off-peak hours. In this paper, it is shown that due to the impartible uncertainties of the energy market, the traditional model of DSM will fall short in a system structure in which the interest of the private sector like LA is different from the main grid. Therefore, in some cases, this strategy not only does not help the system technically but also puts it in a possible worse situation. Obviously, this will also affect the LA risk criteria because it will act as a tool for LA to increase the safe margin of its investment. It can minimize the risk and maximize profits with passive financial savings through incentive schemes and cooperation with private sources. This paper shows how the LA achieves an optimal profit using DSM in some scenarios, while in some other scenarios, this avoids it altogether.

- *To investigate the effect of DSM on amount of risk and day-ahead scheduling.*

Just as load shifting by the LA changes the amount of capital at risk in this unit, in a mutual way, the amount of risk that the private investor is willing to accept can affect load shifting plans by the LA. This paper shows how different scenarios with different risk levels could change decisions drastically.

1.4 | Organization of the paper

The rest of the paper is organized as follows. Section 2 introduces the system structure and operations mode of the multi-energy microgrid. The scheduling model has been presented for different parts of the system and demand response constraints in Section 3. In Section 4, the risk measures and their integration in stochastic programming problem have been explained. In Section 5, the proposed model has been implemented in a hypothesis multi-energy microgrid in the summer and winter seasons and the effect of risk measures has been investigated. Finally, the conclusions of the results and implementation of the proposed model are presented in Section 6.

2 | SYSTEM STRUCTURE AND OPERATION MODE

2.1 | Multi-energy microgrid structure

In this paper, a multi-energy microgrid is considered a hub connected to the main grid. This system consists of PV power plant, CCHP unit, and load aggregator (LA), which supplies electricity, heating, and cooling demands. The structure and operation mode of the microgrid with components are shown in Figure 1.

The CCHP owner cooperates with the LA through bilateral transaction and with PV power plant; they constitute a multi-energy microgrid jointly. The LA in the residential area gains the right to manage loads of residential demands and it provides energy services through signing long-term contracts. As an independent operator, the LA needs to forecast the loads

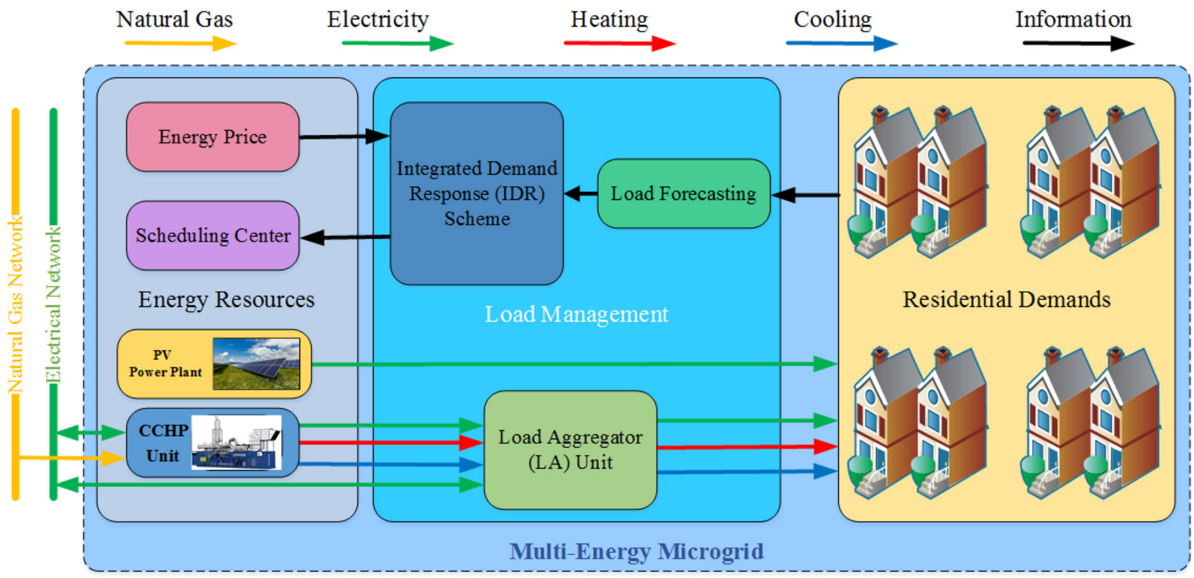

FIGURE 1 Structure and operation mode of the microgrid with components

accurately and provide the integrated demand response (IDR) program using advanced technologies. It has to implement an energy purchase scheme based on the energy price provided by the system to maximize the benefits. In the following subsections, a brief explanation for PV power plant, LA operator, and CCHP unit part has been prepared:

- ***Photovoltaic power plant***

Since the photovoltaic power plant is one of the fastest-growing renewable energy resources in recent years, so this unit is considered within the microgrid structure. The mathematical model used for the PV unit is expressed by (1) [21]:

$$
\begin{aligned}
P_{bi}(G_{bi}) &= P_{\mathrm{sn}}\left(\frac{G_{bi}^{2}}{G_{\mathrm{std}}.R_{\mathrm{c}}}\right),\ 0 \le G_{bi} < R_{\mathrm{c}} \\
&= P_{\mathrm{sn}}\left(\frac{G_{bi}}{G_{\mathrm{std}}}\right),\ R_{\mathrm{c}} \le G_{bi} < G_{\mathrm{std}} \qquad (1)\\
&= P_{\mathrm{sn}},\ G_{bi} > G_{\mathrm{std}}
\end{aligned}
$$

where P_{bi} shows the radiation to energy conversion function for solar radiation band i of the SCG (solar cell generator) [MW], G_{bi} represents the forecasted solar radiation at band i ($\frac{W}{m^2}$), G_{std} with the usual value of 1000 [$\frac{\mathrm{W}}{\mathrm{m}^2}$] is considered as standard environment solar radiation, R_{c} shows a constant radiation point set usually as 150 [$\frac{\mathrm{W}}{\mathrm{m}^2}$], and at last P_{sn} expresses the equivalent rated capacity of the SCG [MW] [22].

Due to the random nature of solar radiation caused by seasonal and environmental phenomena, a probabilistic model constructed from historical data and Equation (1) is used in the proposed microgrid. Figures 2 and 3 show the probability of different scenarios in summer and winter, respectively, and Figure 4 illustrates the power generated at those scenarios.

- ***LA operator***

The LA operator in a residential area is responsible for the DSM through load shifting, buy-, and sell-scheme. This unit provides purchasing scheme utilization based on thermal and electrical load prediction to maximize the daily profit. In this scheduling process, LA uses the FEL and FTL strategies at the same time to make sure that demand side be fed utterly. The LA shares day-ahead plan with these units based on a bilateral contract with CCHP unit and main grid [23].

- ***CCHP unit***

The CCHP unit plans the day-ahead generation scheme to maximize the daily profit based on the LA-reported scheme and the main grid market price provided by the market agent. The CCHP unit same as the LA unit employs the FTL and FEL strategies in the IDR program. Thermal energy produced by the CCHP unit is restricted in a specific range distance around the demand due to the high losses of transmission. This critical problem will mainly affect the price of such units. In such circumstances, bilateral transaction mode is practical and efficient for CCHP through microgrids.

2.2 | Operation mode

The operation mode of the multi-energy microgrid is mainly affected by two main factors that can be summarized as follows:

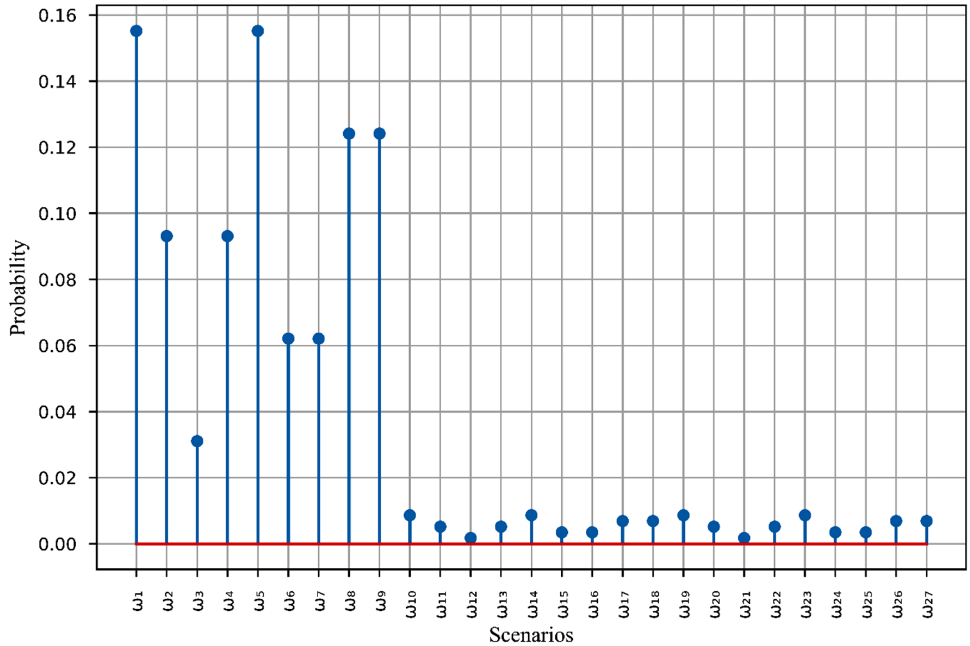

FIGURE 2 Probability of different scenarios in summer

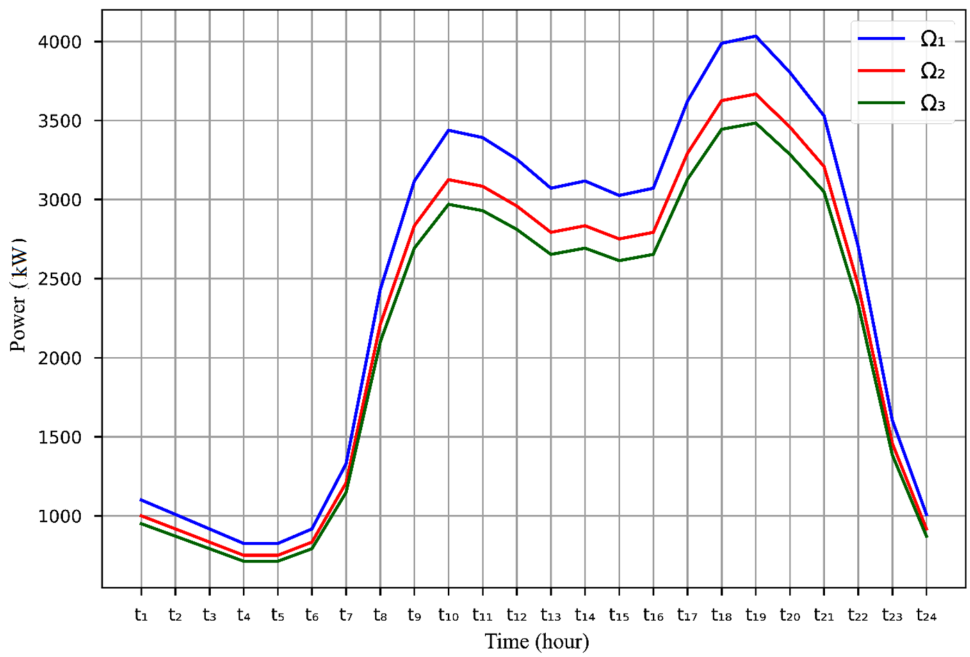

FIGURE 3 Probability of different scenarios in winter

- ***Energy prices of the CCHP system***

The CCHP system needs an efficient pricing strategy due to the complicated relationship between the electricity, heating, and cooling produced that can reflect this complication accurately. At the same time, this pricing strategy should provide a sufficient profit margin for the CCHP system. Furthermore, since LA and CCHP have a bilateral contract, this strategy should also be acceptable by the LA agent.

- ***IDR program of the LA***

The LA runs an IDR program commensurate to the predicted demand that allows it to utilize the full characteristics of the electricity, heating, and cooling loads. An IDR program is

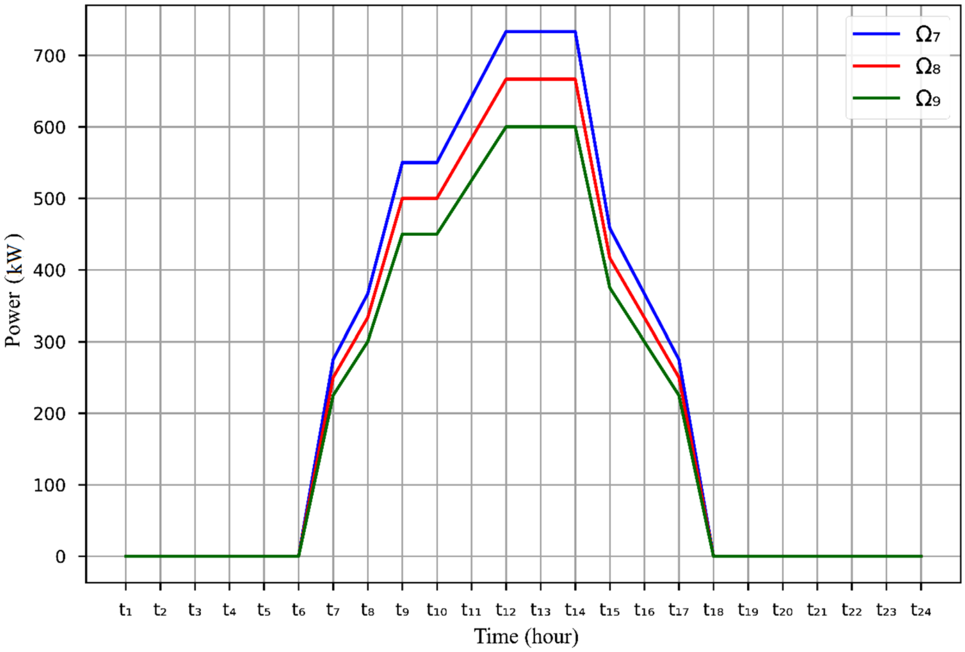

FIGURE 4 Photovoltaic power in different scenarios

valid if it can manage the combination of electrical and thermal loads (heating and cooling) in such a way so as to meet the LA profit margin. Also, the IDR program allows LA to engage the consumer in load management as a key goal of modern DR [24].

3 | PROPOSED MULTI-ENERGY SCHEDULING MODEL

As discussed earlier, the LA has the main management role, and the CCHP agent has to decide on a day-ahead schedule based on the information provided by the LA. So, in other terms, the problem can be seen as a two agent-two stage optimization problem. The first agent is the LA that defines the goal as maximum profit, and the second agent is the CCHP management that should minimize the generation cost and at the same time responds to the LA's demands. In this paper, the problem is considered in a stochastic format and also the risk associated with the LA trades is considered. So, based on this assumption the profit of the LA can be expressed by (2) as follows:

$$\text{Profit}_{\text{LA}} = (1-\beta)\left\{\sum_{\omega}\phi(\omega)\left[\text{Profit}_{\text{Grid}}(\omega) - \text{Cost}^{\text{Buy}}_{\text{CCHP}}(\omega) - \text{Cost}_{\text{Comp}}(\omega)\right]\right\} + \beta\left\{\nu - \left(\frac{1}{1-Con}\right).\sum_{\omega}\phi(\omega)S(\omega)\right\} \quad (2)$$

The LA profit is defined as the difference between the profit made from trading with the main grid and the cost associated with buying from CCHP and compensating for the load shift. The second part in (2) is responsible for the risk measure. As will be mentioned in Section 4, the β is the weighting factor that LA should choose based on the amount of risk that is willing to accept, and Con expresses the level of confidence that LA has in the investment. It will be shown that the answer is not a deterministic and it highly depends on the preferences of the LA. The LA profit is performed through the trades with the main grid which could be modelled by (3):

$$\text{Profit}_{\text{Grid}} = \sum_{t=1}^{t=24} \Pr^{\text{Sell}}_{\text{Grid,LA}}(\omega).\left(P^{\text{Sell}}_{\text{Grid,LA}}(t,\omega) + P_{\text{res}}(t,\omega)\right) - \sum_{t=1}^{24} \Pr^{\text{Buy}}_{\text{Grid,LA}}(t,\omega).P^{\text{Buy}}_{\text{Grid,LA}}(t,\omega), \quad \forall\omega\in\Omega \quad (3)$$

Equation (3) is made out of two terms, in which the first one shows LA's sources of income and the second one models the cost of electricity that LA has to buy in order to meet the demand. The electricity sold to the main grid consists of two parts, the first part is the electricity that LA collects by shifting loads, and the second part is electricity generated by the PV unit.

Since the price that LA sells this electricity follows the market price, so the risk evaluation is necessary.

This profit function is limited to a set of constraints expressed in (4). The first two constraints show the limitation in the amount of electricity that LA can trade with the main grid and the third constraint ensures that LA is only allowed to sell/buy, to/from the main grid at a specific time and scenario.

$$\begin{cases} 0 \le P^{\mathrm{Buy}}_{\mathrm{Grid,LA}}(t,\omega) \le \varepsilon^{\mathrm{Buy}}_{\mathrm{Grid,LA}}.P^{\mathrm{Max}}_{\mathrm{Grid,LA}}, \forall t,\omega \in T,\Omega \\ 0 \le P^{\mathrm{Sell}}_{\mathrm{Grid,LA}}(t,\omega) \le \varepsilon^{\mathrm{Sell}}_{\mathrm{Grid,LA}}.P^{\mathrm{Max}}_{\mathrm{Grid,LA}}, \forall t,\omega \in T,\Omega \\ \varepsilon^{\mathrm{Buy}}_{\mathrm{Grid,LA}}(t,\omega) + \varepsilon^{\mathrm{Sell}}_{\mathrm{Grid,LA}}(t,\omega) = 1, \forall t,\omega \in T,\Omega \\ \varepsilon^{\mathrm{Buy}}_{\mathrm{Grid,LA}}(t,\omega), \varepsilon^{\mathrm{Sell}}_{\mathrm{Grid,LA}}(t,\omega) \in \{0,1\} \end{cases} \tag{4}$$

One of the main costs that LA should cover is the energy cost bought from the CCHP unit. Since this unit can generate electricity, cooling, and heating on demand, it is necessary to define a proper model that can cover the whole range of its operation. However, such modelling can lead to a complicated formulation which makes the computational burden costs and untraceable complexity. The seasonal changes in energy demand are used for simplification to prevent this. In the summer, most of the energy demand consists of electricity and cooling, and by the winter, the cooling demand is replaced with heating. Therefore, the formulation can be modified based on this information.

$$\mathrm{Cost}^{\mathrm{Buy}}_{\mathrm{CCHP,summer}} = \sum_{t=1}^{24} \Big(\mathrm{Pr}_{\mathrm{el}}.P_{\mathrm{el}}(t,\omega) + \sum_{i=\iota}^{\iota\iota\iota} C^{\mathrm{Cold}}_i.Q^{\mathrm{Cold}}_i(t,\omega)\Big), \forall \omega \in \Omega \tag{5}$$

There are two main parts in this cost function. The first part is the electricity cost and the second part expresses the cooling cost in a three-step pricing strategy. In (5), P_{el} represents the generated and sold power by the CCHP unit. This power changes based on the LA's needs and price fluctuations, and its surplus will be sold directly to the main grid.

$$\begin{cases} Q^{\mathrm{Cold}}(t,\omega) = \sum_{i=\iota}^{\iota\iota\iota} Q^{\mathrm{Cold}}_i(t,\omega) \\ Q^{\mathrm{Cold}}(t,\omega) = \alpha.\eta_{\mathrm{hr}}.P_{\mathrm{el}}(t,\omega) + \sum_{i=1}^{\iota\iota} \psi^{\mathrm{Cold}}_i \\ Q^{\mathrm{Cold}}(t,\omega) = \psi^{\mathrm{Cold}}_{\iota\iota\iota} + Q^{\mathrm{Cold}}_{\iota\iota\iota}(t,\omega) - \kappa_{\mathrm{ec}}.P_{\mathrm{el}}(t,\omega) \\ \varepsilon_{\mathrm{el}}(t,\omega).P^{\mathrm{Min}}_{\mathrm{gt}} \le P_{\mathrm{el}}(t,\omega) + \left(\dfrac{Q^{\mathrm{Cold}}_{\mathrm{II}}(t,\omega)}{\kappa_{\mathrm{ec}} + \alpha.\eta_{\mathrm{hr}}.\kappa_{\mathrm{ac}}}\right) \le \varepsilon_{\mathrm{el}}(t,\omega).P^{\mathrm{Max}}_{\mathrm{gt}} \\ \psi^{\mathrm{Cold}}_{\mathrm{I}}(t,\omega) + K.\varepsilon^{\mathrm{Cold}}_{\mathrm{I}}(t,\omega) \ge 0 & , \forall t,\omega \in T,\Omega \\ \psi^{\mathrm{Cold}}_{\mathrm{II}}(t,\omega) \le (\varepsilon^{\mathrm{Cold}}_{\mathrm{II}}(t,\omega) + \varepsilon^{\mathrm{Cold}}_{\mathrm{III}}(t,\omega)).K \\ Q^{\mathrm{Cold}}_{\mathrm{III}}(t,\omega) \le \varepsilon^{\mathrm{Cold}}_{\mathrm{III}}(t,\omega).K \\ \varepsilon^{\mathrm{Cold}}_{\mathrm{III}}(t,\omega).(\kappa_{\mathrm{ec}} + \alpha.\eta_{\mathrm{hr}}.\kappa_{\mathrm{ac}}).P^{\mathrm{Max}}_{\mathrm{gt}} \le \psi^{\mathrm{Cold}}_{\mathrm{III}}(t,\omega) \\ \quad \le (\kappa_{\mathrm{ec}} + \alpha.\eta_{\mathrm{hr}}.\kappa_{\mathrm{ac}}).P^{\mathrm{Max}}_{\mathrm{gt}} \\ Q^{\mathrm{Cold}}_{\iota\iota}(t,\omega) = \psi^{\mathrm{Cold}}_{\mathrm{II}}(t,\omega) - Q^{\mathrm{Cold}}_{\iota\iota\iota}(t,\omega) \\ \varepsilon^{\mathrm{Cold}}_{\mathrm{I}}(t,\omega) + \varepsilon^{\mathrm{Cold}}_{\mathrm{II}}(t,\omega) + \varepsilon^{\mathrm{Cold}}_{\mathrm{III}}(t,\omega) = 1 \\ \varepsilon^{\mathrm{Cold}}_{\mathrm{I}}(t,\omega), \varepsilon^{\mathrm{Cold}}_{\mathrm{II}}(t,\omega), \varepsilon^{\mathrm{Cold}}_{\mathrm{III}}(t,\omega) \in \{0,1\}, \end{cases} \tag{6}$$

The constraints associated with this model are defined in (6), where $\psi^{Cold}_{I}.\psi^{Cold}_{II}.\psi^{Cold}_{III}$ are auxiliary variables to determine the steps of the cooling demand, K is a positive number that is sufficiently large, and $\varepsilon^{Cold}_{I}.\varepsilon^{Cold}_{II}.\varepsilon^{Cold}_{III}$ are binary variables that determine the cooling demand in different times and scenarios. For example, $\varepsilon^{Cold}_{I}(t_1.\omega_1) = 1$ means that the cooling demand at $(t_1.\omega_1)$ is in the first step.

The cost function shown in (5) will be reformed as (7) based on the fact that most of the energy demand in winter consists of electricity and heating.

$$\mathrm{Cost}^{\mathrm{Buy}}_{\mathrm{CCHP,winter}} = \sum_{t=1}^{24} \Big(\mathrm{Pr}_{\mathrm{e}}.P_{\mathrm{el}}(t,\omega) + \sum_{i=I}^{II} C^{i}_{\mathrm{h}}.Q^{i}_{\mathrm{hl}}(t,\omega)\Big), \forall \omega \in \Omega \tag{7}$$

This function also consists of two main terms. The first term is the electricity cost, and the second term is the heating demand cost. It is important to mention that in this model, the price of electricity for CCHP is considered constant for both summer and winter. In this function, $C^{I}_{b}.C^{II}_{b}$ are the heating prices at the first and second steps, respectively. As same as constraints that were established for summer, the constraints for the winter version are represented by (8):

$$\begin{cases} Q_{\mathrm{hl}}(t,\omega) = \sum_{i=I}^{II} Q^{i}_{\mathrm{hl}} \\ Q_{\mathrm{hl}}(t,\omega) - \alpha.\eta_{\mathrm{hr}}.P_{\mathrm{el}}(t,\omega) = \psi_{\mathrm{hl}}(t,\omega) + Q^{\mathrm{II}}_{\mathrm{hl}}(t,\omega) \\ \varepsilon_{\mathrm{el}}(t,\omega).P^{\mathrm{Min}}_{\mathrm{gt}} \le P_{\mathrm{el}}(t,\omega) \le \varepsilon_{\mathrm{el}}(t,\omega).P^{\mathrm{Max}}_{\mathrm{gt}} \\ -\varepsilon^{\mathrm{I}}_{\mathrm{hl}}(t,\omega).K \le \psi_{\mathrm{hl}}(t,\omega) \le 0 & , \forall t,\omega \in T,\Omega \\ 0 \le Q^{\mathrm{II}}_{\mathrm{hl}}(t,\omega) \le \varepsilon^{\mathrm{II}}_{\mathrm{hl}}.K \\ \varepsilon^{\mathrm{I}}_{\mathrm{hl}}(t,\omega) + \varepsilon^{\mathrm{II}}_{\mathrm{hl}}(t,\omega) = 1 \\ \varepsilon^{\mathrm{I}}_{\mathrm{hl}}(t,\omega), \varepsilon^{\mathrm{II}}_{\mathrm{hl}}(t,\omega) \in \{0,1\} \end{cases} \tag{8}$$

where ψ_{hl} is an auxiliary variable to determine the steps of the heat demand, K is a positive sufficiently large number, and $\varepsilon_{\mathrm{el}}$ is a binary variable that determines whether LA needs to buy electrical power from CCHP or not. Also, $\varepsilon^{\mathrm{I}}_{\mathrm{hl}}.\varepsilon^{\mathrm{II}}_{\mathrm{hl}}$ are binary variables that determine the LA needs for purchasing the heating energy from CCHP and at which step it should do so. One important note here is that purchasing the electrical power from CCHP is an optional choice for LA but based on the sixth part of (8), this is not the case for heating/cooling energy. This is because that the CCHP should compete with the main grid by the electrical power price but because there is no competition in the cooling and heating market, CCHP is the only option that LA is facing with it.

Another cost that LA should consider is the compensation cost which is a direct function of the IDR program. The compensation cost is the cost of shifting the load out from where the consumer wants it to be. In other words, it is the cost of the incentive plan that LA proposes to consumers to encourage them to participate in the DR program. This cost is modelled by (9):

$$\text{Cost}_{\text{Comp}}(t,\omega) = U_e.\sum_{t=1}^{24} P_{\text{el}}^{\text{out}}(t,\omega),\ \forall\omega\in\Omega \tag{9}$$

where U_e is the compensation factor and $P_{\text{el}}^{\text{Out}}$ is the electrical load that is shifted out. The compensation factor is defined based on the worst-case scenario meaning the minimum and maximum price differences. This factor works as a tool for LA to first incentivize customers to participate in the DR program and secondly assure the customers that they got the best deal possible. It can be also used as a strong leverage point over LA's competitors and give them the slight advantage in the market. As mentioned earlier, the compensation cost is a direct function of shifted power, so it is required to explain the program behind the IDR. This program includes two main parts, the first part addresses the electrical-loads shifting and the second part models the flexible heating/cooling supply:

- The electrical load of the end-users comprises three main parts. The first part is the fixed load; this part of the load is constant and there is no control over it from the management perspective. The second part is the shiftable load and could be adjusted based on the LAs desire or incentive plans that are proposed. The last part is the random load that is not plannable. So, based on these three parts, the electrical-load shifting could be modelled as (10):

$$\begin{cases} P_{\text{el}}(t,\omega)+|P_{\text{Grid,LA}}^{\text{Buy}}(t,\omega)|-|P_{\text{Grid,LA}}^{\text{Sell}}(t,\omega)| = \\ \qquad P_{\text{Demand}}(t,\omega)+P_{\text{el}}^{\text{In}}(t,\omega)-P_{\text{el}}^{\text{Out}}(t,\omega) \\ P_{\text{Demand}}(t,\omega)=P_{\text{el}}^{\text{fix}}(t,\omega)+P_{\text{el}}^{\text{random}}(t,\omega)+P_{\text{el}}^{\text{Shiftable}}(\text{t},\omega) \\ 0\le P_{\text{el}}^{\text{In}}(t,\omega)\le \varepsilon_{\text{el}}^{\text{In}}(t,\omega).P_{\text{el}}^{\text{In,Max}} \\ 0\le P_{\text{el}}^{\text{Out}}(t,\omega)\le \varepsilon_{\text{el}}^{\text{Out}}(t,\omega).P_{\text{el}}^{\text{Out,Max}} \\ \sum_{t=1}^{24} P_{\text{el}}^{\text{In}}(t,\omega)=\sum_{t=1}^{24} P_{\text{el}}^{\text{Out}}(t,\omega) \\ \varepsilon_{\text{el}}^{\text{In}}(t,\omega)+\varepsilon_{\text{el}}^{\text{Out}}(t,\omega)=1 \\ \varepsilon_{\text{el}}^{\text{In}}(t,\omega),\varepsilon_{\text{el}}^{\text{Out}}(t,\omega)\in\{0,1\} \end{cases},\ \forall t,\omega\in T,\Omega \tag{10}$$

where the first two constraints express the balance in electrical power and different parts of electrical demand. The third and fourth constraints show the limitation of load shifting. The fifth constraint makes sure that the amount of power shifted out in a specific scenario always is equal to the power that shifted in. Finally, the sixth constraint expresses that the power only could shift out or in at a determined time and scenario, and it cannot happen simultaneously.

- The second part of the IDR program is the flexible heating/cooling supply. By using the thermodynamic model proposed for the residential buildings [23], it is considered that the indoor temperature should stay within the comfortable range. So, based on this assumption:

$$T_{\text{in}}(t,\omega)\in[T_{\text{In}}^{\text{Min}},T_{\text{In}}^{\text{Max}}],\forall t,\omega\in T,\Omega \tag{11}$$

where $T_{\text{In}}^{\text{Min}}.T_{\text{In}}^{\text{Max}}$ are the indoor minimum and maximum comfortable ranges, respectively. To reach the goal of maintaining the temperature at the desired value, its fluctuations are the main concern. By modelling them using (12), the heating and cooling demands are related to the temperature demands.

$$\begin{cases} \zeta_{\text{Air}}^{+}(t,\omega)=\dfrac{T_{\text{In}}^{\text{Max}}-T_{\text{In}}^{\text{Opt}}}{|T_{\text{In}}^{\text{Opt}}-T_{\text{Out}}(t,\omega)|} \\ \zeta_{\text{Air}}^{-}(t,\omega)=\dfrac{T_{\text{In}}^{\text{Min}}-T_{\text{In}}^{\text{Opt}}}{|T_{\text{In}}^{\text{Opt}}-T_{\text{Out}}(t,\omega)|} \end{cases},\forall t,\omega\in T,\Omega \tag{12}$$

Therefore, for a given forecasted outdoor temperature and optimal indoor temperature, the relative value of the scope of fluctuations for $Q_{\text{air}}(t.\omega)$ can be obtained.

The constraints of IDR for the heat and cool loads are introduced by (13).

$$\begin{cases} \sum_{t=1}^{24} Q_{\text{Air}}(t,\omega)=\sum_{t=1}^{24} Q_{\text{Air}}^{\text{F}} \\ (1+\zeta_{\text{Air}}^{-}(t,\omega)).Q_{\text{Air}}^{\text{F}}(t,\omega)\le Q_{\text{Air}}(t,\omega) \\ \qquad \le(1+\zeta_{\text{Air}}^{+}(t,\omega)).Q_{\text{Air}}^{\text{F}}(t,\omega) \\ (1-\zeta_{\text{Air}}^{\text{Max}}).Q_{\text{Air}}^{\text{F}}(t,\omega)\le Q_{\text{Air}}(t,\omega) \\ \qquad \le(1+\zeta_{\text{Air}}^{\text{Max}}).Q_{\text{Air}}^{\text{F}}(t,\omega) \end{cases},\forall t,\omega\in T,\Omega \tag{13}$$

where the first constraint ensures that the summation of the heating and cooling supply is equal to the summation of the demand. The second constraint indicates the range of flexibility of $Q_{\text{Air}}(t.\omega)$ and the third constraint limits the adjusting range of $Q_{\text{Air}}(t.\omega)$.

So, based on the explanations mentioned, the heating and cooling load can be represented by (14) and (15) for summer and winter, respectively.

$$\begin{cases} Q_{\text{hl}}(t,\omega)=0 \\ Q^{\text{Cold}}(t,\omega)=Q_{\text{Air}}(t,\omega) \end{cases},\forall t,\omega\in T,\Omega \tag{14}$$

$$\begin{cases} Q_{\text{hl}}(t,\omega)=Q_{\text{Air}}(t,\omega) \\ Q^{\text{Cold}}(t,\omega)=0 \end{cases},\forall t,\omega\in T,\Omega \tag{15}$$

It is worth mentioning that any other source of heating or cooling can be simply added to (14) and (15).

As mentioned before, another agent in the presented model is the CCHP unit which has to plan the day-ahead dispatch in such a way that minimizes the cost and at the same time meets the LA demand. After receiving the purchase plan from the LA, the CCHP agent defines an optimization problem that tries to minimize the total cost and, at the same time, meet the LA demand. The cost function that the CCHP agent must consider is the function introduced by (16).

$$Cost_{\text{CCHP}} = \sum_{\omega} \varphi(\omega).\left[\Pr_{\text{gas}}.\sum_{t=1}^{24}\left(\frac{P_{\text{gt}}(t,\omega)}{\eta_{\text{gt}}} + \frac{Q_{\text{gb}}(t,\omega)}{\eta_{\text{gb}}}\right) + \sum_{t=1}^{24} \Pr_{\text{Grid}}^{\text{Buy}}(t,\omega).P_{\text{CCHP,Grid}}^{\text{Buy}}(t,\omega) + \sum_{t=1}^{24} C_{\text{Grid}}^{\text{Sell}}(\omega).P_{\text{CCHP,Grid}}^{\text{Sell}}(t,\omega)\right] \tag{16}$$

in which this function consists of three main parts. The first one is the natural gas cost which highly depends on the natural gas price and the efficiency of the gas turbine and gas boiler. The second and third parts are the cost of the electricity purchasing from the main grid and selling power to the main grid, respectively.

The constraints of this model can be classified into three main categories: energy flow balance, power limits of the main grid, and power limits of the devices.

The energy flow balance constraints are represented in (17). In this set of constraints, the balance of electrical, heating, and cooling energies will be checked.

$$\begin{cases} P_{\text{gt}}(t,\omega) + P_{\text{Res}}(t,\omega) + P_{\text{CCHP,Grid}}^{\text{Buy}}(t,\omega) = \\ \qquad P_{\text{el}}(t,\omega) + P_{\text{ec}}(t,\omega) + P_{\text{CCHP,Grid}}^{\text{Sell}}(t,\omega) \\ Q_{\text{hr}}(t,\omega) + Q_{\text{gb}}(t,\omega) = Q_{\text{he}}(t,\omega) \\ \qquad +Q_{\text{ac}}(t,\omega) + \Delta Q(t,\omega) \\ Q^{\text{Cold}}(t,\omega) = \kappa_{\text{ec}}.P_{\text{ec}}(t,\omega) + \kappa_{\text{ac}}.P_{\text{ac}}(t,\omega) \\ Q_{\text{gt}}(t,\omega) = \alpha.P_{\text{gt}}(t,\omega) \\ Q_{\text{hr}}(t,\omega) = \eta_{\text{hr}}.Q_{\text{gt}}(t,\omega) \\ Q_{\text{hl}} = \eta_{\text{he}}.Q_{\text{he}}(t,\omega) \end{cases} ,\forall t,\omega \in T,\Omega \tag{17}$$

The power limits of the main grid constraints have been represented by (18). The first and second constraints are the limitations of the exchanged power, and the third and fourth are the states constraints that make sure that at a set time and scenario, the CCHP can trade only in one direction.

$$\begin{cases} 0 \le P_{\text{Grid,CCHP}}^{\text{Buy}}(t,\omega) \le \varepsilon_{\text{Grid,CCHP}}^{\text{Buy,Max}}(t,\omega).P_{\text{Grid,CCHP}}^{\text{Buy,Max}} \\ 0 \le P_{\text{Grid,CCHP}}^{\text{Sell}}(t,\omega) \le \varepsilon_{\text{Grid,CCHP}}^{\text{Sell,Max}}(t,\omega).P_{\text{Grid,CCHP}}^{\text{Sell,Max}} \\ \varepsilon_{\text{Grid,CCHP}}^{\text{Buy,Max}}(t,\omega) + \varepsilon_{\text{Grid,CCHP}}^{\text{Sell,Max}}(t,\omega) = 1 \\ \varepsilon_{\text{Grid,CCHP}}^{\text{Buy,Max}}(t,\omega), \varepsilon_{\text{Grid,CCHP}}^{\text{Sell,Max}}(t,\omega) \in \{0,1\} \end{cases} ,\forall t,\omega \in T,\Omega \tag{18}$$

The constraints expressed in (19) show the limitation of devices that are used in the CCHP. In these equations, x in the first constraint denotes the gas turbines and electrical chillers, and in the second constraint it denotes the gas boiler, absorption chiller, heat exchangers, and radiators. ε_x is the binary variable that shows the state of these devices.

$$\begin{cases} \varepsilon_x(t,\omega).P_x^{\text{Min}} \le P_x(t,\omega) \le \varepsilon_x(t,\omega).P_x^{\text{Max}} \\ \varepsilon_x(t,\omega).Q_x^{\text{Min}} \le Q_x(t,\omega) \le \varepsilon_x(t,\omega).Q_x^{\text{Max}} \\ \varepsilon_x(t,\omega) \in \{0,1\} \end{cases} ,\forall t,\omega \in T,\Omega \tag{19}$$

4 | RISK CONTROL IN THE STOCHASTIC PROGRAMMING PROBLEM

The general formulation for a two-stage stochastic problem is as follows [25]:

$$\begin{aligned} &\mathbf{Max}_{x,y(\omega)} c^T x + \sum_{\omega\in\Omega} \Pi(\omega).q^T(\omega).y(\omega) \\ &\mathbf{S.t.} \\ &Ax = b \\ &T(\omega)x + W(\omega).y(\omega) = h(\omega) \\ &x \in X, y(\omega) \in Y, \forall \omega \in \Omega \end{aligned} \tag{20}$$

where x and $y = \{y(\omega) : \forall\omega \in \Omega\}$ are the first- and second-stage decision-making variables. If $f(x,\omega)$ is defined by the following formulation:

$$\begin{aligned} f(x,\omega) &= c^T x + \max_{y(\omega)}\{q^T(\omega).y(\omega) : T(\omega)x + W(\omega).y(\omega) \\ &= h(\omega), y(\omega) \in Y\} \end{aligned} \tag{21}$$

Then the problem can be reformulated as follows:

$$\begin{aligned} &\mathbf{Max}_x \varepsilon_\omega\{f(x,\omega)\} \\ &\mathbf{S.t.} \\ &x \in X, \forall\omega \in \Omega \end{aligned} \tag{22}$$

The objective of this problem is to maximize the expected value of $f(x,\omega)$ which can be the profit of an LA in a specific scheduling horizon.

If the problem is considered in more depth, it can be seen that after decision-making about x and observing the ω scenario, it is time to find the optimal $y(\omega)$ that is acceptable for the second-stage optimization problem. This stage optimization problem can be represented as follows:

$$\begin{aligned} &\mathbf{Max}_{y(\omega)} q^T(\omega).y(\omega) \\ &\mathbf{S.t.} \\ &W(\omega).y(\omega) = h(\omega) - T(\omega).x \\ &y(w) \in Y \end{aligned} \tag{23}$$

Therefore, it is convenient to view $f(x,\omega)$ as the value of a random variable $f(x,.)$ at argument ω. In other words, it means that for a variable like x in X, a group of random variables with the form of $\{f(x,.) : x \in X\}$ will be introduced to the second-stage problem.

The objective of such a problem is to find the best x that corresponds to the best random variable in $\{f(x,.) : x \in X\}$.

Till this point, the formulation proposed for modelling the LA profit is risk neutral. In the following two sections, by defining the concept of risk-averse decision-making and risk measures, this model will be transformed into a risk-based decision-making problem.

4.1 | Risk-averse decision-making

The main disadvantage of neglecting the risk term in this problem is that it is possible to find optimal x and $y(\omega)$ that leads to the maximum expected profit; however, reaching this optimal point is at the expense of having a meager profit in some undesirable scenarios. Therefore, it is advisable to consider a risk management term in a two-stage problem to avoid such situations.

It is important to know that the risk is associated with the amount of profit made; therefore, the term that represents the risk of a specific scenario should be introduced as follows:

For $f(x,\omega), \forall \omega \in \Omega \Rightarrow r_\omega\{f(x,\omega)\} \rightarrow$ also known as Risk-Measure

The Risk-Measure terms can be added to the problem formulation in two ways. Risk-Measure can be incorporated either into the objective function or be added as a set of additional constraints. So with this information, it is tried to rewrite the general formulation of the two-stage problem:

$$\begin{aligned} &\mathbf{Max}_x : \sigma_\omega\{f(x,\omega)\} - \beta . r_\omega\{f(x,\omega)\} \\ &\mathbf{S.t.} \rightarrow x \in X, \beta \in [0,\infty) \end{aligned} \tag{24}$$

where β is a weighting factor that materializes the trade-off between expected profit and risk aversion. Based on this, if $\beta = 0$, the problem becomes a risk-neutral two-stage optimization problem.

It is also possible to consider the risk measure as a constraint in the optimization problem; therefore, in this context, the formulation will be rewritten as follows:

$$\begin{aligned} &\mathbf{Max}_{x,y(\omega)} \sigma_\omega\{f(x,\omega)\} \\ &\mathbf{S.t.} \rightarrow x \in X, r_\omega\{f(x,\omega)\} \le \delta \end{aligned} \tag{25}$$

where δ is the maximum risk that decision-maker is willing to take. Based on this formulation, it can be said that the optimal solution obtained from the problem depends on the value of β/δratio. For a specific β/δ, the optimal expected profit and risk solution will be known as an efficient point. If the operator wants to achieve a greater expected profit or lower risk, he or she should change β or δ. Now, if a set of expected values versus risk is drawn for each weighting factor, it can be ended up with a diagram that is known as the efficient frontier. This frontier helps decision-makers to find the trade-off between risk and expected profit.

4.2 | Risk measures

Risk measures characterize the risk associated with different solutions to a problem and help decision-makers choose the best one. In technical literature, there is a wide range of risk measures that have been used for different applications. In [25], a set of properties such as Transition Invariance, Subadditivity, Positive Homogeneity, and Monotonicity are presented that risk-measures should fulfill to be considered a coherent risk-measure. Some of the most known risk-measures are Variance, Shortfall Probability, Expected Shortage, Value-at-Risk (VaR), and Condition Value-at-Risk (CVaR). Among these measures, Conditional Value at Risk (CVaR), because of its coherence and linear formulation, is chosen to evaluate the risk associated with the proposed problem.

4.2.1 | CVaR

The $\mathbf{CVaR}(\alpha, x)$for a discrete distribution is mathematically defined as

$$\mathbf{CVaR}(\alpha, x) = \mathbf{Max}\left\{\eta - \frac{1}{1-\alpha}\varepsilon_\omega\left\{Max\left\{\eta - f(x,\omega), 0\right\}\right\}\right\}, \quad \forall\, \alpha \in (0,1) \tag{26}$$

The $\mathbf{CVaR}(\alpha, x)$ can be incorporated to the general formulation of the two-stage optimization problem. Therefore, the formulation will be rewritten as follows [25]:

$$\begin{aligned} &\mathbf{Max}_{x,y(\omega),\eta,S(\omega)} (1-\beta)\left(C^T x + \sum_{\omega\in\Omega} \pi(\omega).q^T(\omega).y(\omega)\right) \\ &\quad + \beta\left(\eta - \frac{1}{1-\alpha}\sum_{\omega\in\Omega}\pi(\omega).S(\omega)\right) \\ &\mathbf{S.t.} \\ &Ax = b \\ &T(\omega x) + W(\omega).y(\omega) = h(\omega), \forall\omega \in \Omega \\ &\eta - (C^T x + q^T(\omega).y(\omega)) \le S(\omega), \forall\omega\in\Omega \\ &S(\omega) \ge 0, \forall\omega \in \Omega \\ &x \in X, y(\omega) \in Y, \forall\omega\in\Omega \end{aligned} \tag{27}$$

where η is an auxiliary variable and $S(\omega)$ is a continuous non-negative variable equal to maximum of $\eta - (C^T x + q^T(\omega).y(\omega))$ and zero. β is a weighting factor that quantifies the importance of risk and α shows the confidential level of decision-maker in taking risk.

5 | CASE STUDY, RESULTS, AND DISCUSSION

In this paper, a hypothetical residential microgrid with 2000 residential units and a PV power plant with a nominal capacity of

TABLE 1 Parameters of the CCHP system

Parameters	Value	Parameters	Value
$P_{gt}^{Min/Max}$	1(MW)/5(MW)	η_{gt}	0.3
$P_{CCHP,Grid}^{Buy/Sell,Max}$	1(MW)/1(MW)	η_{hr}	0.75
Q_{hr}^{Max}	10(MW)	η_{gb}	0.8
Q_{gb}^{Max}	2 (MW)	η_{he}	0.9
Q_{he}^{Max}	10 (MW)	κ_{ec}	4
Q_{ac}^{Max}	5 (MW)	κ_{ac}	1.2
Q_{ec}^{Max}	5 (MW)	α	2.3

TABLE 2 Parameters of the IDR program

Parameters	Value	Parameters	Value
Pr_{gas}	0.045 (€/kWh)	$P_{Grid,LA}^{Max}$	2 (MW)
U_e	0.2 (€/kWh)	T_{in}^{Opt}	21°C
$P_{el}^{In,Max}$	300 (kW)	T_{in}^{Min}	18°C
$P_{el}^{Out,Max}$	500 (kW)	T_{in}^{Max}	24°C

TABLE 3 Price steps for cooling, heating, and electricity of the CCHP

Step		I	II	III
Price (€/kWh)	Pr_{el}	0.17	–	–
	C_b^i	0.0115	0.073	–
	C_i^{Cold}	0.0115	0.2249	0.3

700 kW is considered. This system has been studied in terms of climate in two summer and winter seasons, and 27 different scenarios are considered. In these scenarios, the changes in electricity load demand, power transaction prices with the main grid, and the amount of PV power plant generation are considered. This section is intended to examine the economic dispatch in different scenarios and study the impact of the risk index on this scheduling.

The CCHP and IDR program parameters used for the case study along with the price of CCHP generation in different steps are presented in Tables 1–3.

It is worth mentioning that, because of the complicated nature of the power system, like other engineering systems, it is necessary to consider simplification assumptions to make its analysis possible. However, these assumptions will turn to challenge when it is gone from theory to real-world implementation. In the case of this study, some of the main factors worth mentioning are the load and behaviour forecast, transmission constraints, and different dynamics of heating and cooling compared with electricity. More accurate load and market behaviour predictions create a slight edge in competition for LA. However, the highly random nature of human behaviour makes this task a significant challenge. For simplicity in this study, some of the operational constraints of microgrids are neglected. For instance, it is assumed that transmission of electricity, heating, and cooling is done without any loss. In contrast to the heat and cold generation part of the microgrid, the electrical demand and generation have a much faster dynamic. Since these two parts are highly dependent on each other, in some cases, the demand for heating or cooling can cause congestion in the electricity part of the microgrid and vice versa.

5.1 | Summer season

In this subsection, the proposed method's performance is investigated in the summer season. Before examining how LA manages the required power load and how CCHP works in different scenarios, it is necessary to introduce them and represent the available information.

As can be seen in Figure 2, the scenarios $\omega_1 : \omega_9$ are the most probable scenarios. In the following, to avoid the complexity of the diagrams and their analysis, only results of these scenarios are reported. For the sake of avoiding complexity and better presentation of results, scenarios with similar effects on load demand, transaction prices, and PV power generation are bundled, as shown in (28), and the information about these scenario bundles is shown in Figures 2–5.

$$\left.\begin{array}{l}\Omega = \{\omega_1, \omega_2, \dots, \omega_{27}\} \\ \Omega = \Omega_1 \cup \Omega_2 \cup \dots \cup \Omega_9\end{array}\right\} \rightarrow$$

$$\begin{cases}\Omega_1 = \{\omega_1 : \omega_3, \omega_{10} : \omega_{12}, \omega_{19} : \omega_{21}\} \\ \Omega_2 = \{\omega_4 : \omega_6, \omega_{13} : \omega_{15}, \omega_{22} : \omega_{24}\} \\ \Omega_3 = \{\omega_7 : \omega_9, \omega_{16} : \omega_{18}, \omega_{25} : \omega_{27}\} \\ \Omega_4 = \{\omega_1, \omega_4, \omega_7, \omega_{10}, \omega_{13}, \omega_{16}, \omega_{19}, \omega_{22}, \omega_{25}\} \\ \Omega_5 = \{\omega_2, \omega_5, \omega_8, \omega_{11}, \omega_{14}, \omega_{17}, \omega_{20}, \omega_{23}, \omega_{26}\} \\ \Omega_6 = \{\omega_3, \omega_6, \omega_9, \omega_{12}, \omega_{15}, \omega_{18}, \omega_{21}, \omega_{24}, \omega_{27}\} \\ \Omega_7 = \{\omega_1 : \omega_9\} \\ \Omega_8 = \{\omega_{10} : \omega_{18}\} \\ \Omega_9 = \{\omega_{19} : \omega_{27}\}\end{cases} \tag{28}$$

For summary, this system is examined in the following three cases:

1. Investigation of the system behaviour in possible scenarios without considering the risk
2. Investigation of the effect of confidential level on system behaviour in possible scenarios
3. Investigation of the risk weighting factor (β) effect on system behaviour in possible scenarios

It should be noted that in each of the above cases, the impact of DSM is also considered.

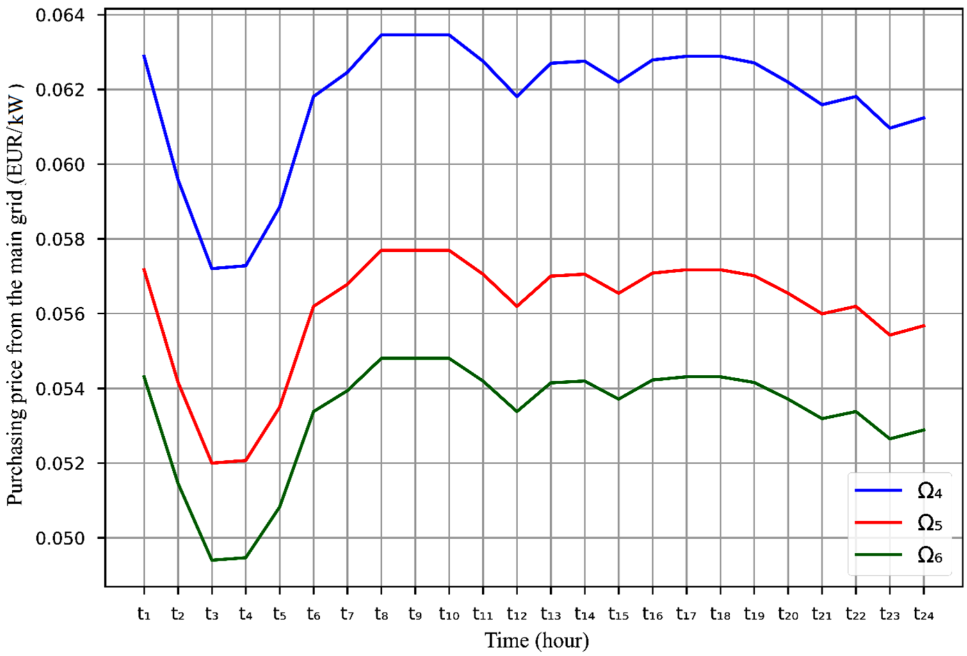

FIGURE 5 Purchasing price from the main grid

5.1.1 | Investigation of the system behaviour in possible scenarios without considering the risk

For the sake of studying the system in risk-neutral mode, the value of β will be set to zero in Equation (2). So, the term of the risk index will be removed, and the problem will become a simple stochastic problem. Before examining the behaviour of LA, it is necessary to express the cooling energy demand. This energy is directly a function of the temperature and insulation structure of residential buildings, which is mentioned in the IDR program. Therefore, according to the average temperature of a summer day shown in Figure 6, the required cooling energy can be obtained through the relationships expressed in the IDR program. It is important to note that considering the slow dynamics of ventilation systems compared with the microgrid system, taking into account the different temperature scenarios in a day-ahead scheduling problem increases the computational burden drastically without significantly impacting the scheduling process. The data needed for air temperature is extracted from historical data and is considered deterministic.

In the following, the LA day-ahead scheduling is performed, and the result is presented for high probable scenarios.

As illustrated in Figure 7, in these scenarios, LA's purchase and sale of electrical power follow the trend of changes in electricity demand. Using this strategy, in the early and last hours of the day, when electricity demand decreases, the amount of power sold to the network will be increased. In the mid-hours of the day, the power exchange trend changes from selling power to the main grid to buying needed power from it to meet the demand increase. It can be seen from the figures the sale of electrical power in probable scenarios has a similar trend and is consistent with changes in demand and price.

In this case study, since the main purpose of the problem is maximizing the LA profit, many decisions are not necessarily the best technical decisions. For example, let us look at the effect of DSM on the load profile in the possible scenarios as illustrated in Figure 8. It can be seen that the DSM did not necessarily smooth the profile, but LA has tried to move the load in such a way that it could maximize the profit in a period. For example, in some scenarios, the load is removed from the off-peak hour and transferred to the mid-load period. Since the electricity purchasing price is the same at all hours, LA prefers to increase its free capacity during off-peak hours and use it on power selling to the network and then using profit obtained to compensate for the required power through purchase from the main network. It should be noted that although the sample structure of the case study is hypothetical, but the prices are extracted from the MIBEL (Iberian Electricity Market) [26]. Therefore, it can be said that the existence of incentive policies makes it possible for load management private companies to take advantage of such a possibility, which does not necessarily mean a technical improvement of the network situation.

This strategy obviously will show its effect on the different costs of LA and its total profit. In Table 4, the impact of DSM on LA and CCHP trades, on the LA's profit from trading with the main grid, and finally on the total profit obtained by LA is investigated.

It can be seen that in most scenarios, the use of DSM has significantly reduced the cost of purchasing power from CCHP. In some scenarios such as scenarios 3, 5, and 7, the cost of purchasing power from CCHP has not changed. With day-ahead scheduling in consideration, changes in the price and load have created circumstances that allow LA to use the purchased electricity from CCHP for maximizing its profit and act as a broker between CCHP and the main grid and which

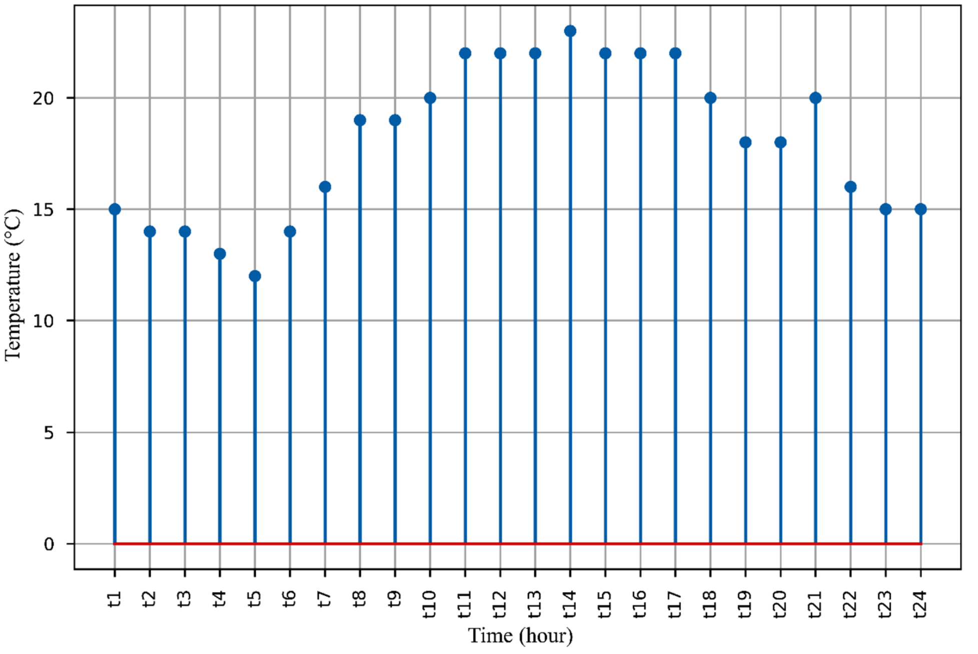

FIGURE 6 Forecasted temperature

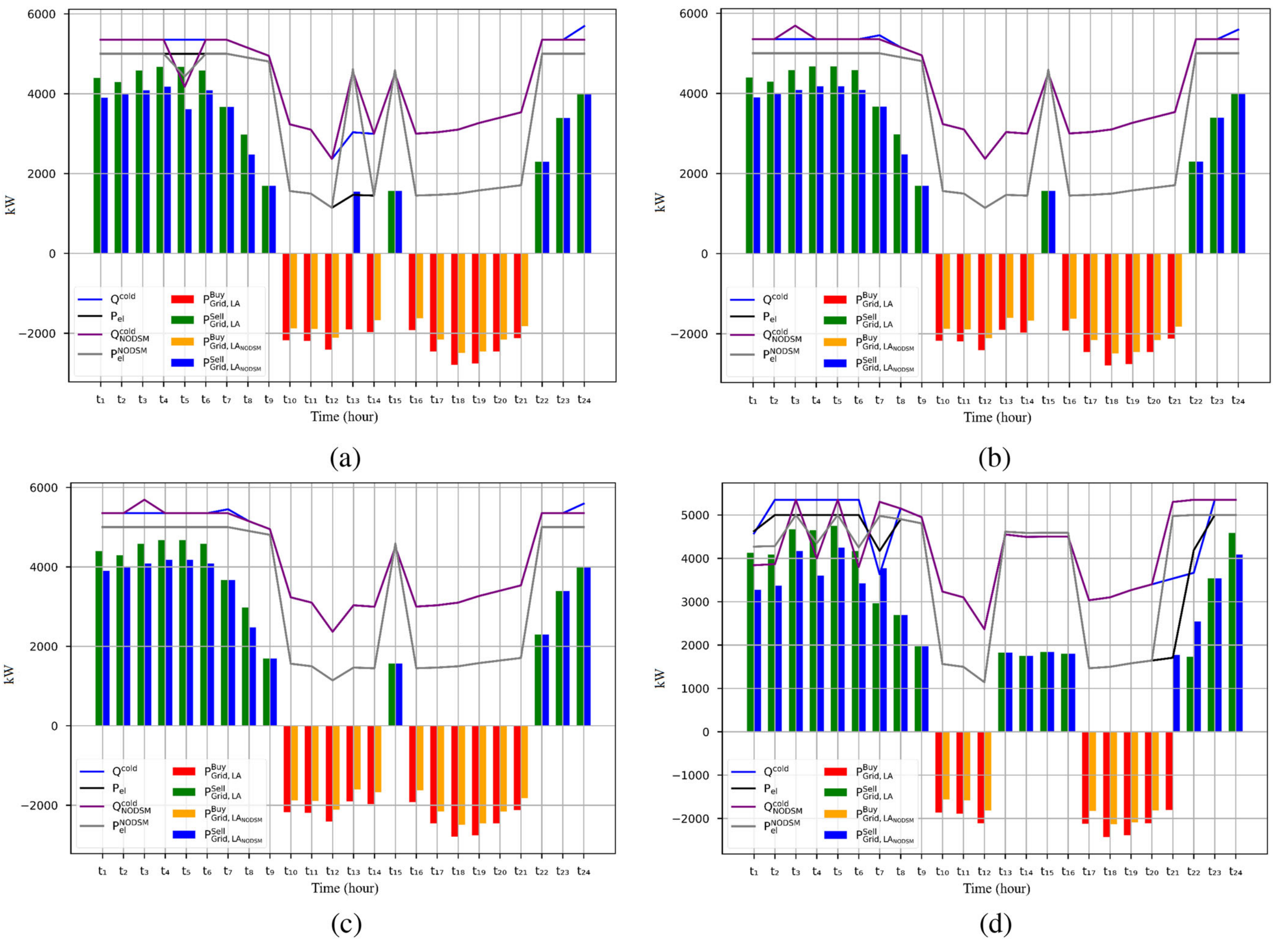

FIGURE 7 LA & grid trades in most probable scenarios in summer: (a) to (i) are related to scenarios ω_1 to ω_9

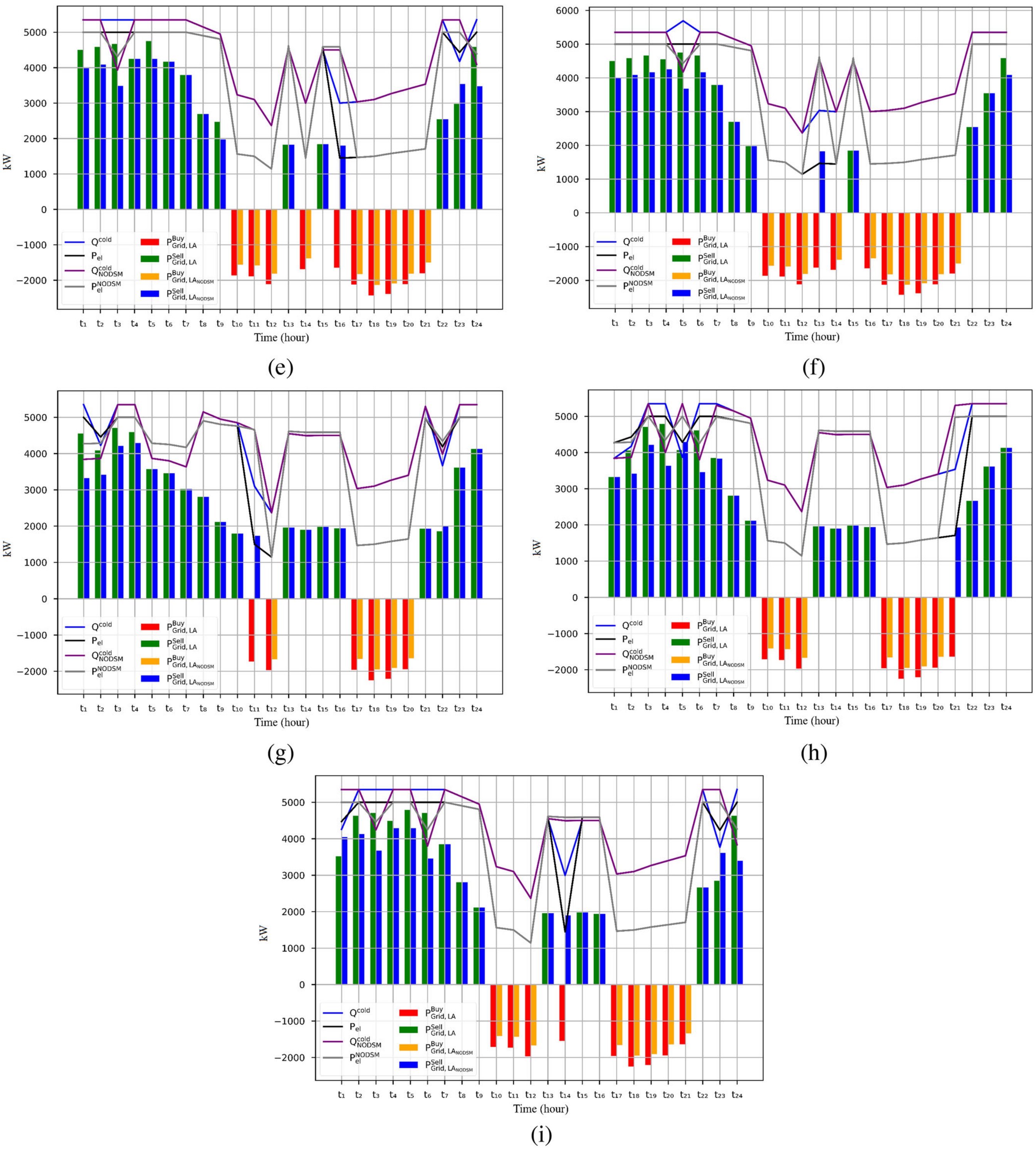

FIGURE 7 Continued

is not necessarily desirable for CCHP. Another factor affecting LA profit is the profit from its transactions with the network (the middle columns of Table 4), which the positive effect of DSM is evident in this situation. Finally, the result of all these factors shows its final impact on LA profits that are shown in the right columns of Table 4.

As can be seen, in all scenarios without exception, the use of DSM puts the LA at a better level of profitability. It is noteworthy that since all of these scenarios are related to the day-ahead scheduling and each of them comes with inherent probability, the final expected profit is the measure of the DSM effectiveness.

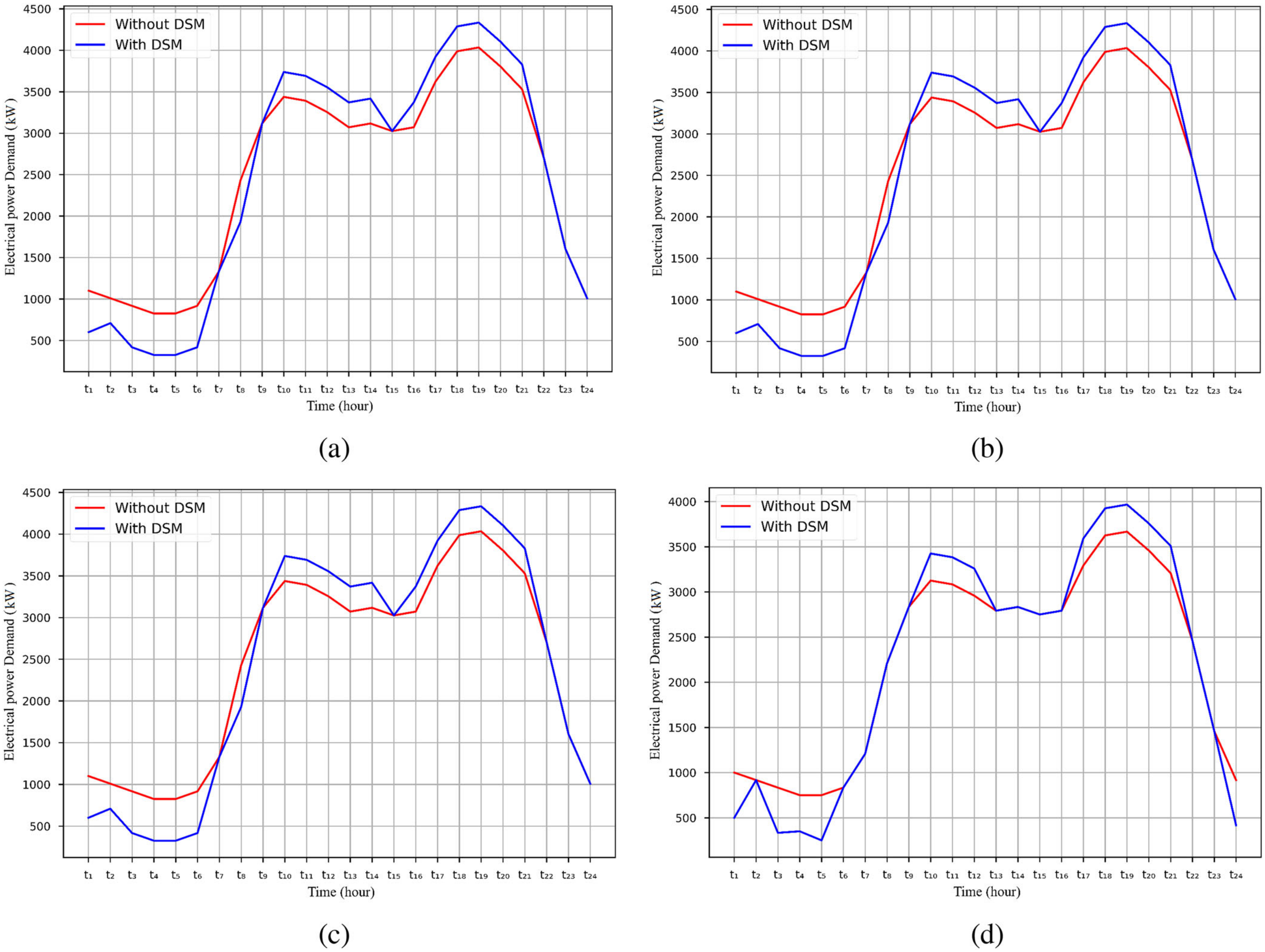

FIGURE 8 Effect of the DSM on electrical demand curve in summer: (a) to (i) are respectively related to scenarios ω_1 to ω_9

So if this relationship will be calculated for each of the 27 scenarios, it will be reached the approximate amount of €2678 in case of using DSM and €2460 in case of neglecting it. These numbers mean that with using the DSM, the LA will eventually make an expected profit of €2678 on the next day, and also similarly for the case without DSM. Note that the expected value, as its name implies, is an expected value and never means that LA will necessarily earn a profit equal to the expected value in one day; rather, it means it is expected that given the 27 scenarios considered and their analysis, the LA profit is acceptable in a neighbourhood of expected value.

5.1.2 | Investigation of the risk effect on system behaviour

Whenever the effect of risk is considered in a problem, it will be transformed to NP-hard, which means that there is not necessarily a single solution to them and usually a trade-off is a final solution. It will be found out that in some cases, when the impact of risk is considered high and the level of confidence close to one, the amount of expected profit will be negative in the sense that LA scheduling will be loss-making. That is why it is necessary for LA to choose a reasonable level of risk and confidence level to plan accordingly. Another point to note is that in this study, load shedding is not considered an option for LA. Hence, LA only has to maximize the profit by moving the load and changing its production units' loading and transactions with the main network. Therefore, the best way to plan the amount of expected profit is the scheduling without risk, but in that case, all the calculated expected profit is at risk.

When discussing the impact of risk indicators rises, two main parameters are confidential level and risk-weighting factor. In the following, the effect of these parameters on the expected profit and the value of the CVaR index is shown, and also the procedure for reaching the best trade-off mode is explained. Here, calculations are performed for confidence levels of 0.00, 0.25, 0.5, 0.75, and 0.99, and for the weighting values of 0.3, 0.5, 0.7, and 0.9. It is important to note that this programming can be computed for any value of $0 \le \beta \le 1$, $0 \le Con \le 1$, but since the calculation of all of

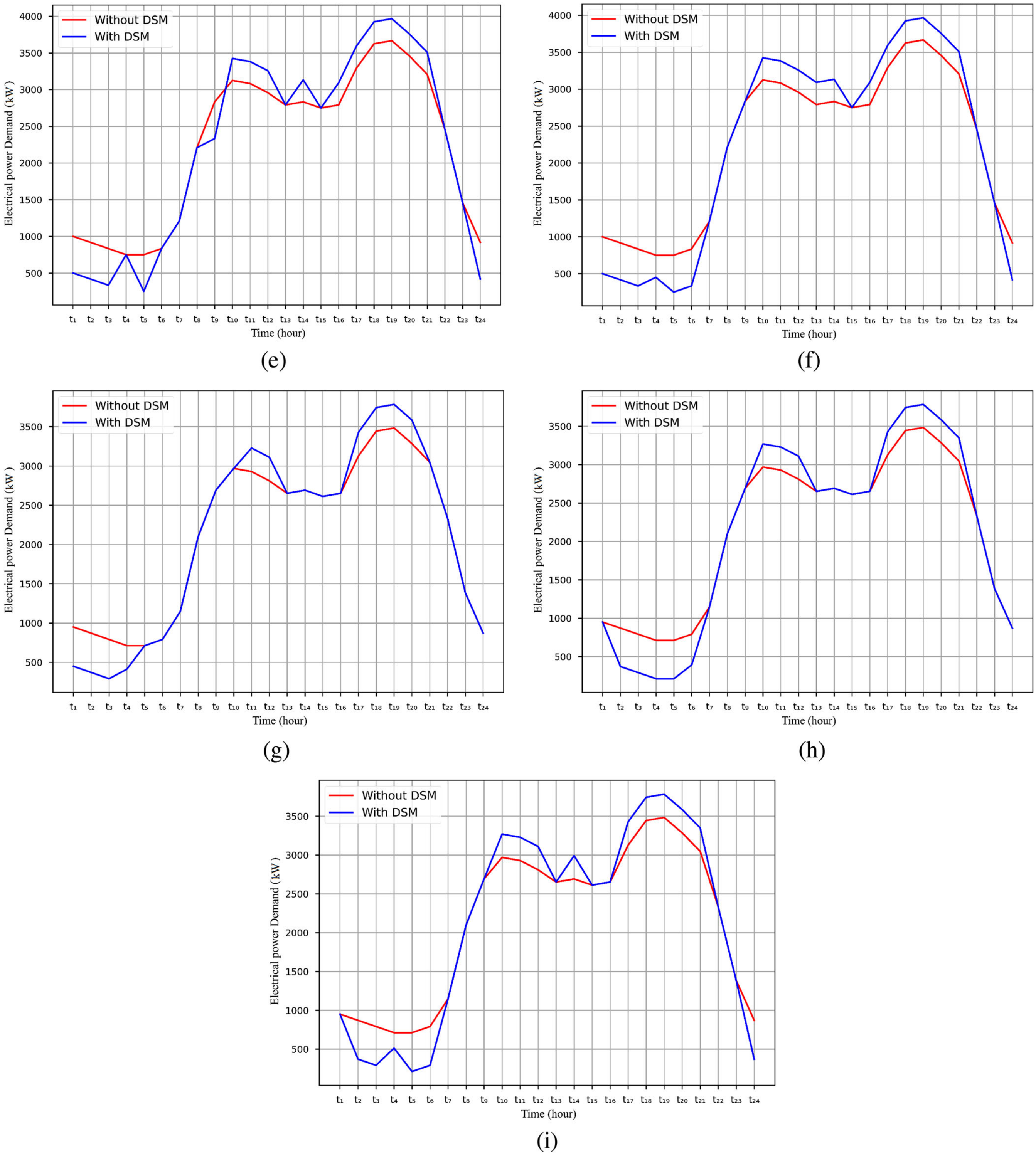

FIGURE 8 Continued

these cases does not contribute to the results, this seeks and only increases the computations time, so it is avoided reporting them.

To begin with, the expected profit versus the CVaR index, known as the efficient frontier, is illustrated. Figure 9 shows the efficient frontier for the summer season in the absence of DSM, each of the curves represents a certain weight given to the risk index, and different points on them represent a certain level of investor confidence. As can be seen, all curves eventually end at a point at which the confidence level's value is zero, and this is a limit state in terms of the mathematical definition of the risk index.

TABLE 4 Effect of the DSM on LA cost via trades with the CCHP, LA profit by trading with the grid, and LA total profit in different scenarios in summer

Scenarios	LA cost via trades with the CCHP			LA profit by trading with the grid			LA total profit		
	with DSM (€)	without DSM (€)	Difference (%)	with DSM (€)	without DSM (€)	Difference (%)	with DSM (€)	without DSM (€)	Difference (%)
ω_1	14,320	14,731	−2.87	18,030	17,511	2.88	3109	2780	10.59
ω_2	13,882	14,320	−3.16	16,030	15,533	3.10	1488	1212	18.56
ω_3	13,882	13,882	0	15,229	14,336	5.86	687	454	33.84
ω_4	15,141	16,373	−8.14	19,855	20,390	−2.70	4233	4016	5.11
ω_5	15,141	15,141	0	18,050	17,360	3.82	2428	2218	8.62
ω_6	14,731	15,141	−2.79	16,803	16,492	1.85	1532	1350	11.84
ω_7	16,373	16,373	0	21,606	21,129	2.21	4932	4755	3.60
ω_8	15,963	16,373	−2.57	19,303	19,208	0.49	2980	2834	4.90
ω_9	15,141	15,963	−5.42	17,658	17,844	−1.06	2036	1881	7.61

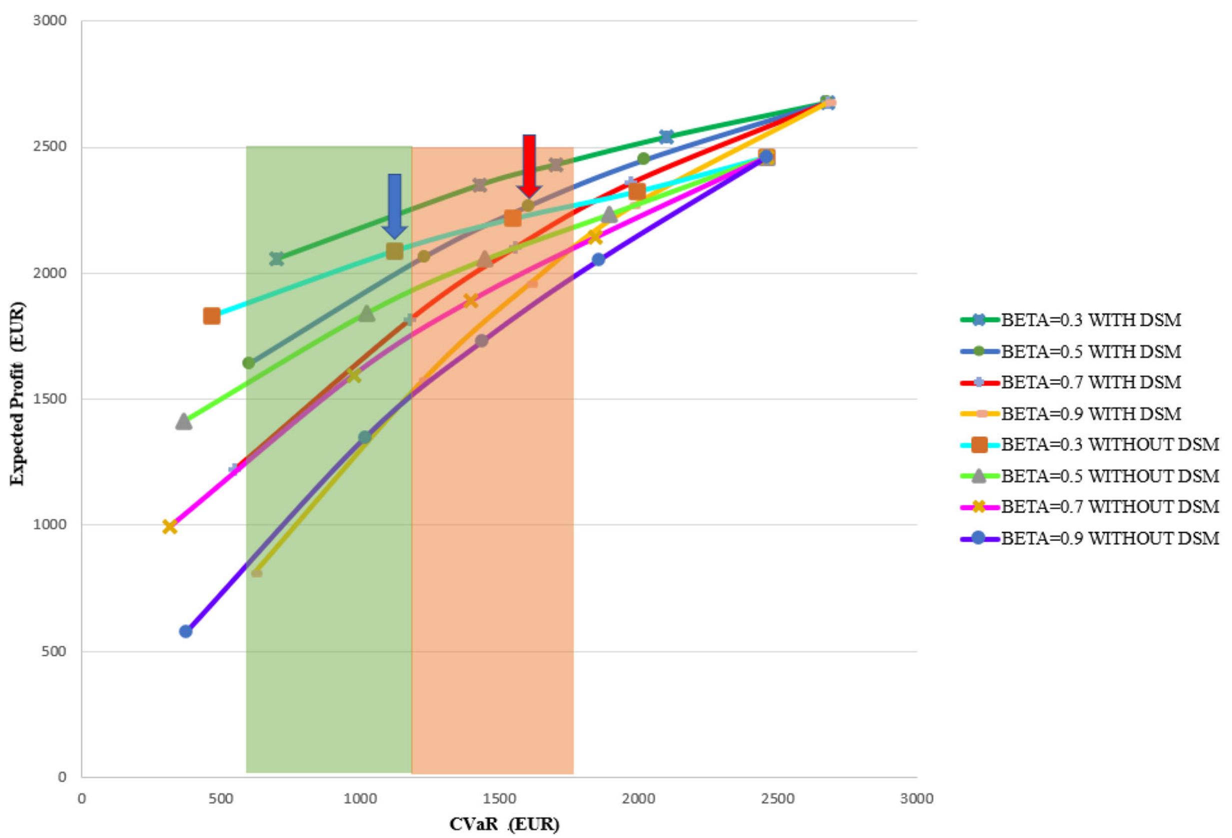

FIGURE 9 Efficient frontier for different risk-weighting factors with and without DSM showing work points in summer season

From the economic point of view, this means that LA has no confidence in this investment, so all its expected profits are at risk, which can be seen in Figure 9. On the other hand, to examine the results for different weighting factors, it can be seen that by increasing these coefficients, the difference between expected profit will be increased significantly while the confidence level is changing. In this case, it is observed that in weighting values close to zero, because the impact of risk is less, as expected, the amount of expected profit from transactions and the amount of capital at risk is also high. Now, according to these results, to choose the best values for the level of confidence and risk weight, the point that has the highest expected profit and at the same time has the lowest CVaR value will be selected. Note that this statement is not always necessarily true because in some cases, LA may take more or less risk because of chosen policies. For example, in microgrids operating under government agencies, LA chooses a much higher level of confidence because it is confident of government support. It should be noted that LA also has the option of using the DSM. The efficient frontier is also illustrated for this mode in Figure 9. It can be seen that the general trend of the system behaviour is similar to the previous case, except that the expected profit has increased as expected.

In this case, since these two charts intersect, LA has more options to choose the right level of confidence and weighting factor. For example, suppose LA is willing to accept a risk around €600 to €1200 according to its policies; in this case, the set of points that LA can choose are displayed in the green area of Figure 9.

Now, in this area, the point that has the highest expected profit and the lowest CVaR value should be selected. Here, the point displayed with the blue arrow is the best point. At this point, the expected profit is around €2090 and the CVaR value is equal to €1125. This point corresponds to the weighting factor of 0.3 in the absence of DSM and a confidence level of 0.75. In this case, it can be seen that using the DSM does not necessarily lead to an optimal decision. It should be noted that this is not required for the whole spectrum. For example, suppose LA decides that the acceptable CVaR value is between €1200 and €1700. In this case, the area in which to choose the optimal point is shown by orange colour. The best choice in this area is the point displayed with the red arrow, which corresponds to the weighting factor of 0.5 when using DSM and a confidence level equals to 0.5. It is important to note that in both green and red areas, the zero confidence level curve is not considered because it is a limit state and has only a theoretical aspect.

Therefore, it can be observed that, in accordance with LA policies, the parameters selected for the risk may be relevant to the state with or without the DSM.

5.2 | Winter season

In the same fashion as the last section, the most probable scenarios are first identified for the winter season, and the evaluation for this condition is conducted. It can be seen in Figure 10 that, ω_1, ω_5 are the most likely scenarios and after them, ω_8, ω_9 are the scenarios with the most probabilities. It is assumed here that in order to represent the impact of seasonal changes on risk more accurately, the amount of PV power generation and the transaction price with the grid are considered in the probability of changes. With this assumption, it is moved on to how LA behaves in the face of scenarios ω_1, ω_5 and ω_8, ω_9 (Figure 11). As done in the previous subsection, it is first examined the risk-neutral mode and then it is moved on to the impact of risk on LA scheduling.

The effect of DSM on electrical demand curve is drawn in Figure 12. With an accurate looking at the figure, one of the important points is that the DSM does not affect scenario ω_8. If this scenario will be examined in detail, it will be found out that it is related to the situation where the electricity demand is reduced along with the increase of the PV unit power generation. In such a scenario, the electric demand can be supplied mainly through a PV power plant and purchased power from the CCHP unit, and the surplus can be sold to the main grid. Hence, with the use of DSM the LA's compensation cost will be increased. The question that may arise here is why such a situation did not occur for the same scenario in the summer. To answer this question, it should be considered that in the summer, in addition to the electric demand of consumers, a large part of the electric demand is imposed on the problem by the electric chillers existed in CCHP. However, in the cold season, since the heating load is supplied as a by-product of the electric demand, there will be no additional electric demand, so there is no need to move the load for optimization. In Table 5, the impact of DSM on LA's overall costs and profits will be examined.

According to the table (the scenarios are sorted from highest probability to the lowest one), it can be seen that DSM mostly results in cost reduction and profit increase in the effective scenarios. With looking more closely at these scenarios, it is eminent that first of all these scenarios are in the lower probability, and secondly, this effect is not very much significant. Hence, it is safe to say that DSM does not significantly increase the efficiency in winter. The reason behind this behaviour has been explained in scenario ω_8.

5.2.1 | Investigating the effect of risk on system behaviour

Similar to what was stated in the summer case study, to determine the optimal point of LA performance, it is necessary to illustrate efficient frontiers for various parameters of risk weighting and confidence levels select it based on the LA's acceptable range.

First, the state without DSM and its effect on the efficient frontier is explained. Previously, in the summer, the meaning of this diagram was discussed in detail; therefore, it will be only reported the results and analysis of the specific cases here.

As said before, if the impact of risk in studies is considered more than a certain limit, it is possible that the system be into a loss state. For example, as seen in Figure 13, if the β is equal to 0.7 and 0.9 at the low confidential levels, the system will be into loss situation. In other words, LA will lose money regardless of the scenario and the day-ahead plan. Another important point to note here is the lower curvature of the efficient frontier curve compared to the summer case. It can be explained by the fact that unlike the summer scenarios, they are primarily risk-neutral as a trade-off. Therefore, the system in each scenario is on the verge of profitability and loss. However, in the cold season, the risk-neutral states are mostly in a profitable state, and if we do not consider the weight of risk too high, it is unlikely that the system will go into a loss-making state.

Since DSM does not have a considerable effect in the cold season, the effect of DSM on efficient frontiers is reported and the impacts of its presence and absence are compared through Figure 13.

One of the important points that was mentioned in the summer season was the discussion of determining an optimal

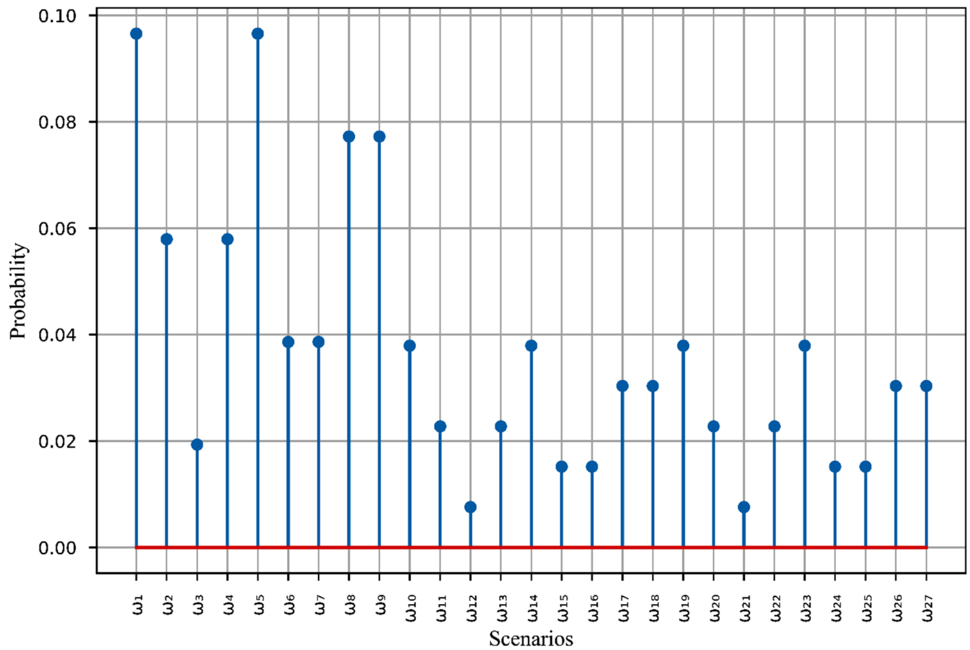

FIGURE 10 Electrical power demand

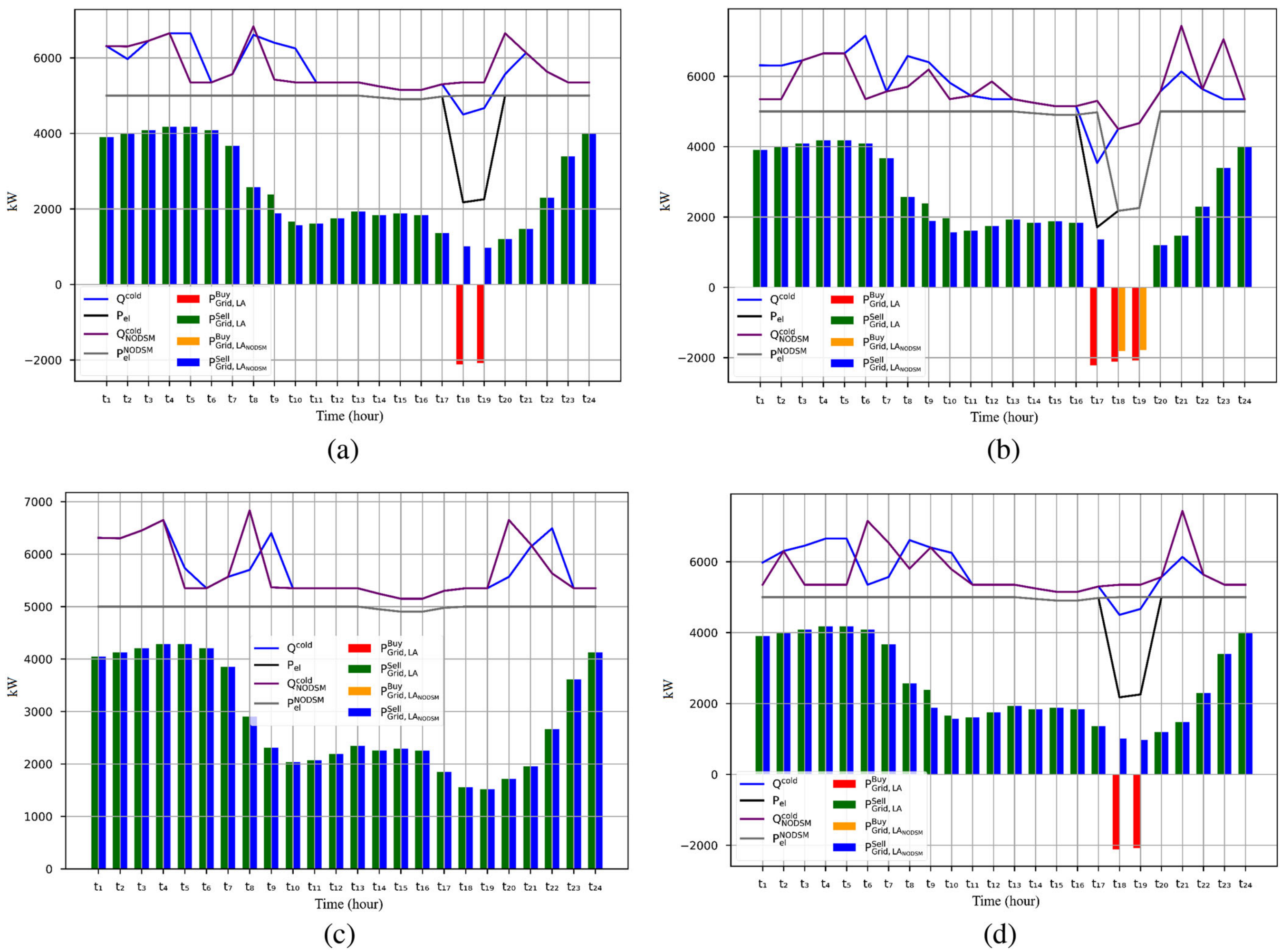

FIGURE 11 The LA & grid trades in most probable scenarios in winter: (a) scenario ω_1, (b) scenario ω_5, (c) scenario ω_8, (d) scenario ω_9

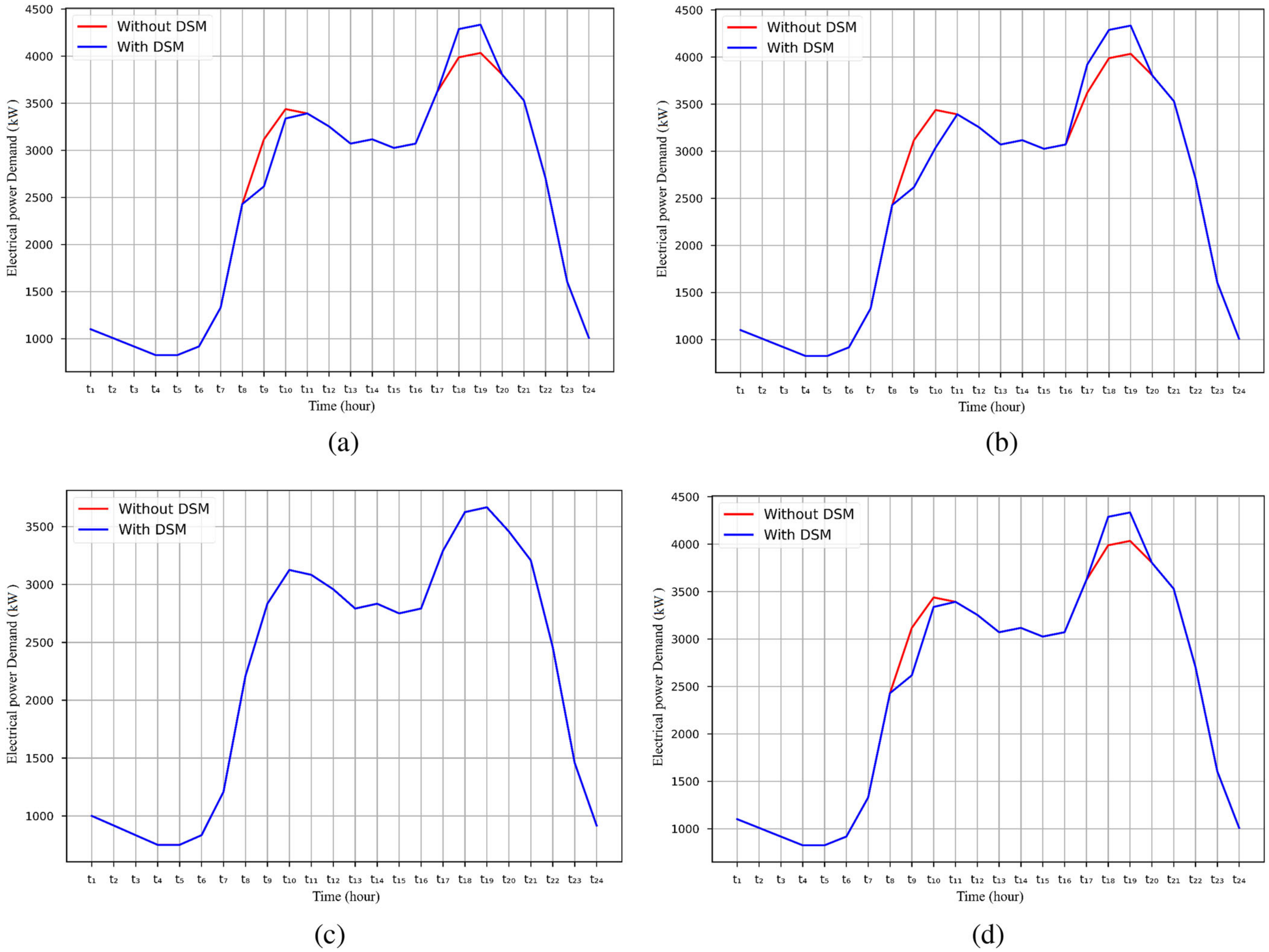

FIGURE 12 Effect of the DSM on electrical demand curve in winter: (a) scenario ω_1, (b) scenario ω_5, (c) scenario ω_8, (d) scenario ω_9

TABLE 5 Effect of the DSM on LA cost via trades with the CCHP, LA profit by trading with the grid, and LA total profit in different scenarios in winter

	LA cost via trades with the CCHP			LA profit by trading with the grid			LA total profit		
Scenarios	with DSM (€)	without DSM (€)	Difference (%)	with DSM (€)	without DSM (€)	Difference (%)	with DSM (€)	without DSM (€)	Difference (%)
ω_1	19,611	20,558	−4.83	21,476	22,257	−3.63	1745	1698	2.67
ω_5	20,558	20,558	0	22,059	22,059	0	1501	1501	0
ω_8	20,558	20,558	0	22,972	22,972	0	2414	2414	0
ω_9	20,558	20,558	0	21,824	21,824	0	1265	1265	0
ω_2	19,055	19,611	−2.92	19,036	19,350	−1.65	−199	−260	−30.97
ω_4	20,558	20,558	0	24,265	24,265	0	3707	3707	0
ω_6	20,558	20,558	0	20,956	20,956	0	398	398	0
ω_7	20,558	20,558	0	25,270	25,270	0	4711	4711	0
ω_{10}	19,611	20,558	−4.83	21,476	22,257	−3.63	1745	1698	2.67
ω_{14}	20,558	20,558	0	22,059	22,059	0	1501	1501	0
ω_{19}	19,611	20,558	−4.83	21,476	22,257	−3.63	1745	1698	2.67
ω_{23}	20,558	20,558	0	22,059	22,059	0	1501	1501	0

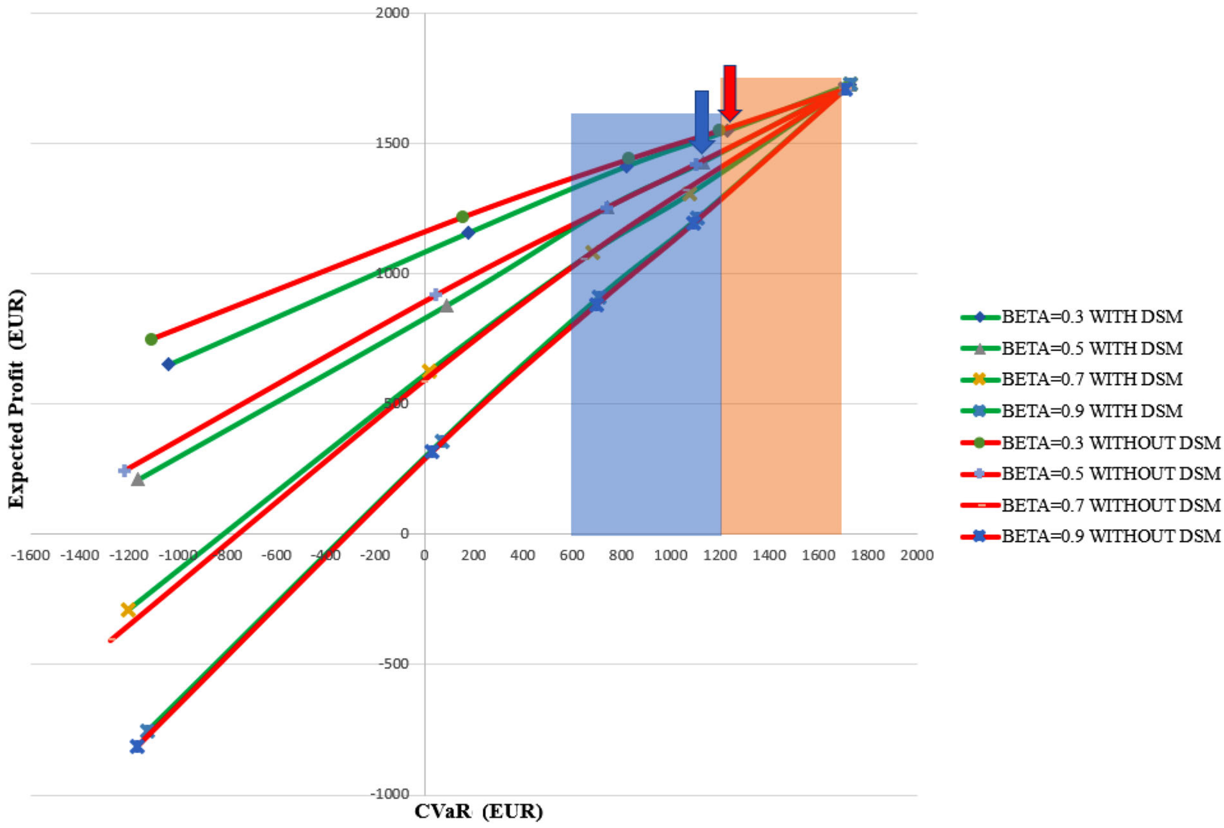

FIGURE 13 Efficient frontier for different risk-weighting factors with and without DSM showing work points in winter season

work point. Here, to reach a summary of the impact of the weather, two acceptable risk ranges for LA are examined that were expressed in the summer season. The result for the winter is illustrated in Figure 13 as an efficient frontier.

To begin with, it is assumed that the acceptable risk level for LA is between €600 and €1200. In this case, the points displayed in the blue area are the points where the system can work and the point with the highest expected profit and the lowest CVaR is needed. Therefore, if we do not consider the theoretical limit case like the summer season, the point displayed with the blue arrow will show the optimal point. This point corresponds to the expected profit of €1421. If we consider the acceptable area for risk between €1200 and €1700, in this case the optimal point is displayed with the red arrow, which is approximately equal to €1550. The matter that needs to be reminded again is that these points are not unique and these are obtained for the conditions considered in this study and the steps considered in it related to the risk weighting and confidence level values. By considering smaller steps, other points can be found and the selection of optimal point can be done from them. In addition, in the diagram illustrated, although the modes with and without DSM are very close to each other, but still their effect in the theoretical limit case is clear. For instance, pay attention to the red arrow at this point where the risk limit is €1200. The value of two modes with and without DSM is small, but if we consider the accuracy of selecting the optimal point as small, the point corresponding to the mode with DSM is selected as the optimal point.

6 | CONCLUSIONS

In this paper, a new scheduling procedure is proposed based on a proposed structure for a multi-energy microgrid. The microgrid scheduling aims to maximize the LA's profit by considering the power trades with the main grid. The presented microgrid contains a PV unit, a CCHP agent, and a LA operator. Some beneficial conclusions are obtained with implementing the proposed plan that is as follows. It is observed that the decisions made by the LA (as a private agent with the aim of profit maximization) are not necessarily the best technical decisions. For instance, it was observed that although DSM increased the profit but did not help to improve the load profile. This means that the existing incentive scheme allows private load management companies to manage load regardless of technical issues in a form to maximize their final profit. In the summer, the cost of trading between LA and CCHP is decreased as expected in many scenarios with the DSM. On the other hand, in general, LA's profit in the case of considering the load management is higher in all probability scenarios than in cases without load management. It is observed in the study of the risk assessment on the scheduling, in both summer and winter, the selection of the optimal point is NP-Hard, and the risk level of LA strongly influences the choice of the optimal point. Another important point that needs to be mentioned is the impact of DSM and risk on DSM. It is shown that the use of DSM is not necessarily better in considering the risk indicators and depends on the LA demand. But, as expected under the same conditions, using the DSM will bring a higher amount of expected profit in terms of risk index. In comparing the summer and winter seasons, it is observed that the effect of the load management scheduling in winter is less effective than the summer season.

NOMENCLATURE

P_{el}^{fix}	fixed electrical load of users
P_{el}^{random}	random electrical load of users
α	heat–electricity ratio of gas turbine
β	risk measure weighting factor
$\Delta Q(t,\omega)$	wasted heat power of CCHP system
ε_{el}	state of buying electricity from CCHP system
$\varepsilon_{el}^{In/out}$	binaries to determine the status of shifting in/out
$\varepsilon_{Grid,LA}^{Buy/Sell}$	binary variables that determine buy or sell signal for LA
ε_{hl}^{i}	binaries to determine the steps of heat demand, $i = \mathrm{I, II}$
ψ_{i}^{Cold}	auxiliary variables to determine the steps of cool demand $i = \mathrm{I,II,III}$
$\zeta_{air}^{+}, \zeta_{air}^{-}$	relative value of the downward/upward fluctuation of Q_{air}
C_{h}^{i}	heat energy price of CCHP system at step $i = \mathrm{I,II}$
C_{i}^{Cold}	cool energy price of CCHP at step $i = \mathrm{I,II,III}$
$\mathrm{Cost}_{CCHP}^{Buy}(\omega)$	total cost of buying power from CCHP
$P_{CCHP,Grid}^{Buy/Sell,Max}$	maximum electrical power that the CCHP system exchanges with the main grid
$P_{CCHP,Grid}^{Buy/Sell}$	electrical power that the CCHP system exchanges with the main grid
$P_{el}^{In/out,Max}$	maximum shiftable electrical load of users
$P_{el}^{In/out}$	electrical load shifted in and out
$P_{el}^{shiftable}$	shiftable electrical load of users
$P_{Grid,LA}^{Buy}$	power purchased from main grid by LA
$P_{Grid,LA}^{Max}$	maximum power that LA exchanges with the main grid
$P_{Grid,LA}^{Sell}$	power sold to main grid by LA
$P_{gt}^{Min/Max}$	minimum/maximum electrical power of gas turbine
$\mathrm{Pr}_{Grid,LA}^{Buy}$	purchase price of power from the main grid by LA
$\mathrm{Pr}_{Grid,LA}^{Sell}$	selling price of LA power to the main grid
Pr_{Grid}^{Buy}	price of electricity bought from the main grid
$\mathrm{Pr}_{Grid}^{Sell}$	price of electricity sold to the main grid
Q_{Air}^{F}	forecasted heat demand for maintaining the indoor temperature
Q_{hl}^{i} :	heat power at step i = I,II,III that LA buys from CCHP
Q_{i}^{Cold} :	cool power at step i = I,II,III that LA buys from CCHP
$T_{in}^{Min}, T_{in}^{Max}$	allowable indoor temperature
T_{in}^{Opt}	optimal indoor temperature
C_{comp}	cost of compensation
G_{bi}	forecasted solar radiation at band i
G_{std}	solar radiation in the standard environment
K	an auxiliary positive number that is big enough but less than $+\infty$
P_{ac}	power of absorption chiller unit
P_{bi}	radiation to energy conversion function
P_{Demand}	electrical power demand of users
P_{ec}	electrical power of electrical chiller
P_{el}	electrical power sold by CCHP
Pr_{el}	price of electrical power sold by CCHP
P_{res}	power generated by renewable resources
Pr_{gs}	heat price of natural gas
$Profit_{\mathrm{Grid}}$	LA's profit from trades with the main grid
$Profit_{\mathrm{LA}}$	LA's total profit
P_{sn}	equivalent rated capacity of the SCG [MW]
Q_{Air}	heat power that the load aggregator supplies to end users for indoor temperature
Q_{gb}	heat power of gas boiler
Q_{he}	heat power of heat exchanger unit
Q_{hr}	heat power of heat recovery unit
R_{c}	constant radiation point
t, T	time/set of 24 hours of a day
$T_{\mathrm{in}}, T_{\mathrm{out}}$	indoor/outdoor temperature of users
U_{e}	compensation factor of the shifted electrical load
η_{gb}	efficiency of gas boiler
η_{gt}	electrical efficiency of gas turbine
η_{he}	efficiency of heat exchanger unit
η_{hr}	efficiency of heat recovery unit
κ_{ac}	performance coefficient of absorption chiller
κ_{ec}	performance coefficient of electrical chiller
$\varphi(\omega)$	probability of different scenarios
ψ_{hl}	auxiliary variable to determine the steps of heat demand
ω, Ω	scenario/set of all scenarios

FUNDING INFORMATION

None

CONFLICT OF INTEREST

None

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID

Seyyed Mostafa Nosratabadi https://orcid.org/0000-0001-8239-3108

REFERENCES

1. Tan, B., Chen, H., Zheng, X.: Hierarchical two-stage robust optimisation dispatch based on co-evolutionary theory for multiple CCHP microgrids. IET Renewable Power Gener. 14(19), 4121–4131 (2020)
2. Nosratabadi, S.M., Jahandide, M., Guerrero, J.M.: Robust scenario-based concept for stochastic energy management of an energy hub contains

intelligent parking lot considering convexity principle of CHP nonlinear model with triple operational zones. Sustainable Cities Soc. 68, 102795, (2021)

3. Nosratabadi, S.M., Hemmati, R., Khajouei Gharaei, P.: Optimal planning of multi-energy microgrid with different energy storages and demand responsive loads utilizing a technical-economic-environmental programming. Int. J. Energy Res. 6985–7017 45(n/a) (2020). https://doi.org/10.1002/er.6286
4. Zheng, C.Y., Wu, J.Y., Zhai, X.Q.: A novel operation strategy for CCHP systems based on minimum distance. Appl. Energy 128, 325–335 (2014)
5. Li, L., Yu, S., Mu, H., Li, H.: Optimization and evaluation of CCHP systems considering incentive policies under different operation strategies. Energy 162, 825–840 (2018)
6. Mina-Casaran, J.D., Echeverry, D.F., Lozano, C.A.: Demand response integration in microgrid planning as a strategy for energy transition in power systems. IET Renewable Power Gener. 15(4), 889–902 (2021)
7. Nosratabadi, S.M., Hemmati, R., Jahandide, M.: Eco-environmental planning of various energy storages within multi-energy microgrid by stochastic price-based programming inclusive of demand response paradigm. J. Energy Storage 36, 102418 (2021)
8. Wang, Y., et al.: Energy management of smart micro-grid with response loads and distributed generation considering demand response. J. Cleaner Prod. 197, 1069–1083 (2018)
9. Ji, L., Zhang, B.-B., Huang, G.-H., Xie, Y.-L., Niu, D.-X.: Explicit cost-risk tradeoff for optimal energy management in CCHP microgrid system under fuzzy-risk preferences. Energy Econ. 70, 525–535 (2018)
10. Nojavan, S., Saberi, K., Zare, K.: Risk-based performance of combined cooling, heating and power (CCHP) integrated with renewable energies using information gap decision theory. Appl. Therm. Eng. 159, 113875 (2019)
11. Kumar, R.S., Raghav, L.P., Raju, D.K., Singh, A.R.: Intelligent demand side management for optimal energy scheduling of grid connected microgrids. Appl. Energy 285, 116435 (2021)
12. Cheng, Z., Jia, D., Li, Z., Si, J., Xu, S.: Multi-time scale dynamic robust optimal scheduling of CCHP microgrid based on rolling optimization. Int. J. Electr. Power Energy Syst. 139, 107957 (2022)
13. Yang, X., et al.: Multi-objective optimal scheduling for CCHP microgrids considering peak-load reduction by augmented ε-constraint method. Renewable Energy 172, 408–423 (2021)
14. Li, Y., Zhang, F., Li, Y., Wang, Y.: An improved two-stage robust optimization model for CCHP-P2G microgrid system considering multi-energy operation under wind power outputs uncertainties. Energy 223, 120048 (2021)
15. Tooryan, F., HassanzadehFard, H., Dargahi, V., Jin, S.: A cost-effective approach for optimal energy management of a hybrid CCHP microgrid with different hydrogen production considering load growth analysis. Int. J. Hydrogen Energy 47(10), 6569–6585 (2022)
16. Mianaei, P.K., Aliahmadi, M., Faghri, S., Ensaf, M., Ghasemi, A., Abdoos, A.A.: Chance-constrained programming for optimal scheduling of combined cooling, heating, and power-based microgrid coupled with flexible technologies. Sustainable Cities Soc. 77, 103502 (2022)
17. Seyfi, M., Mehdinejad, M., Mohammadi-Ivatloo, B., Shayanfar, H.: Scenario-based robust energy management of CCHP-based virtual energy hub for participating in multiple energy and reserve markets. Sustainable Cities Soc. 80, 103711 (2022)
18. Vahedipour-Dahraie, M., Rashidizadeh-Kermani, H., Najafi, H.R., Anvari-Moghaddam, A., Guerrero, J.M.: Stochastic security and risk-constrained scheduling for an autonomous microgrid with demand response and renewable energy resources. IET Renewable Power Gener. 11(14), 1812–1821. Available from: https://digital-library.theiet.org/content/journals/10.1049/iet-rpg.2017.0168
19. Tang, T., Ding, H., Nojavan, S., Jermsittiparsert, K.: Environmental and economic operation of Wind-PV-CCHP-based energy system considering risk analysis via downside risk constraints technique. IEEE Access 8, 124661–124674 (2020)
20. Vahedipour-Dahraie, M., Rashidizadeh-Kermani, H., Anvari-Moghaddam, A.: Risk-based stochastic scheduling of resilient microgrids considering demand response programs. IEEE Syst. J. 15(1), 971–980 (2021)
21. Liang, R.-H., Liao, J.-H.: A fuzzy-optimization approach for generation scheduling with wind and solar energy systems. IEEE Trans. Power Syst. 22(4), 1665–1674 (2007)
22. Jenkins, N.: Embedded generation. Power Eng. J. 9(3), 145–150 (1995)
23. Hu, Q., Li, F., Fang, X., Bai, L.: A framework of residential demand aggregation with financial incentives. IEEE Trans. Smart Grid 9(1), 497–505 (2018)
24. Bahrami, S., Sheikhi, A.: From demand response in smart grid toward integrated demand response in smart energy hub. IEEE Trans. Smart Grid 7(2), 650–658 (2015)
25. C.M., Conejo, A.J., Morales, J.M.: Risk management. In: Decision Making Under Uncertainty in Electricity Markets. Vol. 153 Boston, MA: Springer (2010)
26. MIBEL (Iberian Electricity Market)

How to cite this article: Nosratabadi, S.M., Moshizi, H.N., Guerrero, J.M.: Strategy for demand side management effectiveness assessment via a stochastic risk-based bidding approach in a multi-energy microgrid containing combined cooling, heat and power and photovoltaic units. IET Renew. Power Gener. 16, 2036–2058 (2022). https://doi.org/10.1049/rpg2.12482