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Optimal Operation of Sustainable Virtual Power Plant Considering the Amount of Emission in the Presence of Renewable Energy Sources and Demand Response

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Abstract: One of the significant environmental issues is global warming, and governments have changed their procedures to reduce carbon emissions. Sustainability is commonly described as having three dimensions: environmental, economic, and social. There are numerous environmental impacts associated with energy systems and the significance of energy for living standards and economic development. Therefore, the movement towards intelligent energy systems and virtual power plants (VPPs) is being pursued more rapidly due to economic and environmental issues. The VPP is one of the technologies used to increase the entire system's efficiency. Moreover, because of environmental pollution, increased greenhouse gas production, and global warming, countries' policies have changed towards reducing the use of fossil fuels and increasing the penetration of renewable energy sources (RESs) in distribution networks. However, RESs, such as wind turbines (WT) and photovoltaic (PV) panels, exhibit uncertain behavior. This issue, coupled with their high penetration, poses challenges for network operators in terms of managing the grid. Therefore, the sustainable virtual power plant (SVPP) is a suitable solution to overcome these problems and reduce the emissions in power systems. This study examines the cost of optimal operating of the SVPP and the amount of produced pollution in four different scenarios in the presence of a demand response program (DRP), energy storage system (ESS), etc., and the results are compared. The results indicate that the simultaneous implementation of DRPs and utilization of ESS can lead to a decrease in costs and pollution associated with SVPPs by 1.10% and 29.80%, respectively. Moreover, the operator can resolve the shortage and excess power generation that occurs during some hours.

Keywords: sustainable virtual power plant; energy storage systems; renewable energy source; emissions; demand response program

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1. Introduction

1.1. Background

In recent years, energy use has increased due to population growth and energy demand. Fossil fuels have had the leading role in providing the largest share of energy demand in the past years. However, these fuels are the biggest reason for increased greenhouse gas emissions. One of the significant environmental issues is global warming, and governments have changed their procedures to reduce carbon emissions [1]. Sustainability is a societal goal related to people's ability to co-exist on Earth for a long time safely. Definitions of this term are difficult to agree on and have varied with literature, context, and time. Sustainability is commonly described as having three dimensions: environmental, economic, and social. Many publications state that the environmental dimension is the most important. For this reason, in everyday use, sustainability is often focused on countering major environmental problems, such as climate change, loss of biodiversity, loss of ecosystem services, land degradation, and air and water pollution. It can resolve the issues around the environment. The world is moving to utilize distributed generations, particularly based on renewable energy sources (RESs), to decrease the greenhouse gas emissions from the power generation system [2]. The RESs have made broad contributions to the power grid, and the dependence on the power grid is with the increasingly severe environmental problems brought by conventional energy sources [3]. Photovoltaic (PV) panels and wind turbines (WT) are the innovations with the most growth rate in Distributed Energy Resources (DER). Virtual power plants (VPPs) are the technology that can pack away different kinds of DERs through communication technologies, advanced control, and metering, which can take part in grid and power market operations as a whole [4]. The primary role of VPP is to supply technical support and a framework for access to large-scale renewable energy power [5]. In this regard, sustainable virtual power plant (SVPP), with its features, can help in the environmental field and cause sustainability.

1.2. Literature Review

Due to the small capacity of DERs, they cannot participate in the energy market as a unified entity and the SVPP concept offers a potential solution to address this issue. The integration of DERs within the SVPP enables greater active participation in the electricity market [6]. The concept of SVPP offers the potential to generate environmental and economic benefits while also enabling the efficient operation of DERs within the power system. The SVPP is composed of different components such as photovoltaic (PV) panels, wind turbine (WT), energy storage system (ESS), dispatchable DERs and loads that through optimal management and coordination of components can minimize the costs of operation and emissions and which leads to user satisfaction. Moreover, the optimal scheduling of components within the SVPPs ensures power balance during the planning phase. As a result, various studies propose different approaches to managing the capabilities of SVPPs. The most prevalent objective in these studies is the optimization of operations while considering economic aspects. In Ref. [7], a VPP consisting of ESS, WTs, and conventional generators and non-flexible users submits its bid strategy for independent system operator (ISO) in the day-ahead market. The VPP aims to minimize its costs; therefore, it collects the information of net load and conventional generator to determine maximum capacity and ramp limit for submission to ISO. Lucchi reviewed the integration of the RESs into historic buildings [8]. The benefits and barriers of this issue are investigated from the economic, environmental, technical, information, and policy points of view. Ref. [9] describes the flexibility capabilities of end-user technologies, including ESS, electric vehicles, PV, heat pumps, and boilers. The involvement of flexible end-users in the day-ahead market and intraday spot market leads to a reduction in their overall costs. The optimization procedure is based on a rolling horizon approach, and the problem is solved using mixed-integer programming (MIP) with hourly and daily scheduling.

In Ref. [10], the stochastic optimal management of a commercial VPP is investigated. The VPP consists of a distributed system, ESS, and users. In this study, the VPP operator actively participates in the day-ahead electricity market. The VPP operator, acting as a price-maker, aims to minimize costs associated with real-time supply and demand imbalances while maximizing their day-ahead profit with the growing penetration of RESs and their substantial impact on VPP scheduling. Uncertainty modeling is inevitable in VPP operation. However, the uncertainty of the output power of WTs and PVs is not considered in [10]. In Ref. [11], various uncertainties of different sources have been dandled to VPP's operator that anticipates the behavior of components accurately. Therefore, the VPP's operator can select an optimal bidding strategy for participating in the energy and reserve market. Baringo et al. evaluated the effect of short- and long-term uncertainties on the expected VPP's profit [12]. Therefore, investment decisions are made about installing new conventional, RES, and ESS units, which are parameters of uncertainty related to consumption level, cost of production power, and market prices in short and long terms. Benxi et al. presented a model to aggregate WT and PV power in the VPP to reduce the residual load peak–valley difference [13]. Hydropower plant compensates the forecast errors of WT and PV output power. In Ref. [14], authors aim to integrate large- and small-scale DERs and irrigation systems to meet demand and maximize the profit of the system. This approach causes a reduced dependence on the main grid. During critical hours, power has been purchased from the main grid to match generation and consumption.

Due to the stochastic nature of RESs, there is a potential for power generation shortages or surpluses during the planning horizon. Therefore, effective solutions to address this challenge include methods such as energy storage, conversion to other forms of energy, and the implementation of DRPs. These measures help mitigate the variability of RESs and ensure a balanced power supply. Integration of DERs, ESS, and microgrids such as a VPP is presented as minimizing the annual cost of electricity generation [15]. In that study, the effectiveness of the proposed algorithm was evaluated by comparison with particle swarm optimization (PSO) and genetic (GA) algorithms. The operation of MG is carried out in isolated mode and there is no electricity exchange with the main grid. In Ref. [16], the optimal operation of renewable energy sources in standalone micro-grids was investigated. Moreover, an energy management model was tested with two different scenarios that resulted in minimizing the costs of operation and emissions with a focus on using the whale meta-heuristic algorithm to manage microgrids. Kang et al. focus on the role of ESS in reducing shortcomings of intermittent RES output power, namely PVs [17]. The goal of this study is the minimization of system costs and keeping the voltage in a normal range. Therefore, in a study conducted by Sadeghian et al. [18], an optimal long-term investment approach was employed to determine the most efficient ESS and its appropriate sizing within a VPP. In this structure, power is exchanged between VPP and the main grid. Since the market price results in the change of generation and subsequently affects the sizing ESS problem, the risk of ESS investment and uncertainty of the price market are modeled in MINLP. Corinaldesi et al. [19] proposed the utilization of automated DRPs as a cost-effective approach in the management of distribution systems. Additionally, they suggest that providing monetary incentives by the DSO to end-users can enhance the flexibility of the system. Day-ahead optimal operation of VPP is proposed using the PV prediction model and DRP in [20]. Authors have considered a hierarchical model for the MGs and VPP management simultaneously [21]. The results show that time of use (TOU) based DRP bring higher profit for the VPP operator compared to real-time pricing (RTP). In Ref. [22], a price-based unit commitment is developed considering the consumers' participation in DRP and their effect on load flow. The game theory approach as one of the demand side management types is established between the plant and demand side of VPP in [23]. This proposed framework increases the benefit of VPP's operator and users. In the study [24], the authors discussed the energy management system (EMS) considering the electric vehicle in parking lots of industrial VPPs and proper use of DRP. The proposed structure has increased profits of industrial VPP and grid reliability under peak conditions. In addition, load shedding of industrial VPPs has been reduced. Vahedipour et al. have suggested participation of VPP users in DRPs such as load curtailment and load shifting to minimize their bills [25].

With the development of integrated energy resources, the VPP has evolved into the multi-energy VPP to promote energy efficiency. In Ref. [26], a multi-energy VPP is considered which involves electricity, thermal, cooling, and natural gas sectors. The robust stochastic method has minimized operational costs in the worst-case scenarios. The day-ahead scheduling of a VPP consisting of conventional generators, PV, WT, and

PV–thermal solar system, has been performed in [27]. A PV–thermal solar system that generates electricity and thermal simultaneously decreases the dependence of VPP on boiler and combined heat and power (CHP) for responding to thermal loads. Since PV generates power during certain times, the effect of wind speed variations on the profit of VPP is greater than solar irradiance. Several studies have taken into account multi-objective modeling in the management of VPP. A multi-objective function is analyzed in [28] by choosing maximum operation profit and minimum DER operation risks. Weight coefficients of the objective function's terms are calculated using an iterative algorithm. Moreover, some studies have already been performed concerning both economic and environmental issues as a multi-objective problem. The maximization of operational revenue and the minimization of carbon emissions are modeled as objective functions in [29], taking into account uncertainties related to PV, WT, and loads. Additionally, various technologies, including power-to-gas, carbon capture in gas-power plants, and waste incineration power, are considered within the context of rural VPPs. Finally, a cooperative game theory approach is established among entities to balance multiple aspects such as risks, benefits, and emissions reduction. In Ref. [30], the VPP's operator is introduced, which participates in energy and reserve markets. In this regard, the VPP's operator aims to maximize their profit and utilize RESs and the storage capability of EVs to alleviate air pollution. Nevertheless, for the sake of the importance of the environmental issue further modeling of emissions is required. The profit and air pollution of VPP have been modeled as a multi-objective function in [31]. Moreover, purchased energy from the main grid during critical hours generates pollution for VPPs, which is not modeled in the objective function. Utilizing ESS is an appropriate option for the reduction of purchased energy from the main grid to reduce carbon emissions. Ref. [32] proposed a VPP hub to manage the demands of data centers, adjacent buildings, and EVs. In this regard, the VPP hub operator plans to maximize their profit and minimize carbon emissions in which ESS has a significant impact on economic and environmental issues. In Ref. [33], a VPP was considered whose primary purpose is minimizing the costs and emissions of the VPP's generations. The VPP's operator takes into account RESs and ESS in operation but the uncertainty of WT and PV input data and the impact of DRP on emissions are not modeled.

Although valuable and promising research has been published about VPPs, it seems that the research gap is about the emissions of a VPP's resources. As reviewed in this work, some studies focus on using clean energy sources or RESs. However, due to the stochastic generation of these sources, shortage and surplus power generation may occur during special hours. Therefore, several studies reveal that utilizing ESS can store excess energy and respond to demand during critical hours. Nevertheless, since the penetration of RESs has increased in recent years, the operation and maintenance of many ESSs require a high investment cost. Thus, these presented solutions cannot overcome all challenges of VPPs solely. It is noteworthy that less attention has been paid to using DRPs to reduce the emission and operational costs of VPPs simultaneously. Furthermore, considering the demand for different energy forms, a multi-energy SVPP is needed to satisfy electrical, heat, and cooling loads. Therefore, a comprehensive approach should be provided in SVPP scheduling. From this perspective, in addition to considering technical and economic issues, it is necessary to evaluate the impact of an SVPP's components and the schemes of decision-makers on the environmental problem.

In this paper, a comprehensive approach is proposed for the day-ahead scheduling of SVPPs. In other words, the proposed approach has considered technical, economic, and environmental aspects of an SVPP's operation. Furthermore, to make the system more realistic, various types of energy sources including electrical, natural gas, heating, and cooling are modeled in the structure of an SVPP. Therefore, the presented SVPP is a multi-energy type that involves different types of supply to meet the demand of users. Furthermore, the SVPP can reduce the negative effect of power generation on the environment and be environmentally sustainable. In other words, to use an SVPP is to manage generation pollution. Since there are intermittent sources in the structure of an

SVPP, it is important to handle the uncertainty parameters of these RESs. Hence, a fast and robust approach is used to model uncertainty parameters such as RES generations and the price of energy. Therefore, this problem is modeled as a stochastic multi-objective economic and emission problem. In this regard, RESs, DGs, and transferring power from/to the main grid are considered in the first step. After that, ESS capability and DRP are utilized to evaluate the effect of the proposed approach on the costs and emissions of the SVPP's resources. The main contributions of this paper are as follows:

(1) Considering a new stochastic multi-objective system for SVPP management to minimize the operational costs and emissions.
(2) Proposing a multi-energy SVPP that includes electrical, natural gas, heating, and cooling sectors to meet the type of user demand and balance supply and demand at all times.
(3) Investigating the effect of cost-effective and environment-friendly sources such as PVs, WTs, and ESS on the operation and scheduling of an SVPP.

The rest of the paper's sections are organized as follows: In Section 2, the proposed SVPP and its components are introduced. The formulation of the problem is implemented in Section 3. Case studies and the effectiveness of the proposed approach are presented in Section 4. Finally, the conclusion is provided in Section 5. Abbreviations part provide the list of acronyms and symbols, respectively.

2. System Model

2.1. Multi-Energy Sustainable Virtual Power Plant (SVPP) Architecture

A combination of several flexible production and consumption units controlled by a central intelligent system is the main idea of the VPP. In this way, a VPP can provide services in the market that the same large central power plants or industrial consumers are able to do. The capacity of VPPs can reach the total capacity of one or more nuclear power plants. However, this amount is constantly changing due to fluctuations in RESs. If the wind is blowing or the sun is not shining, the PV and WT generators contribute less to the VPP. It is necessary to combine all types of energy sources in an SVPP to avoid power imbalance and reduce the environmental problems. Due to the limited storage capacity of the grid, only approximately the same amount of power consumed can be injected into the grid. The integrated units in an SVPP can be power producers, energy storage units, power consumers, and special devices such as large power plants converting electricity to heat. Some of these units are very valuable because of their flexibility. The units can compensate for electricity supply changes caused by low wind speed, cloudiness, etc., in both negative and positive directions. Figure 1 shows the general structure of an SVPP. This SVPP is connected to the main grid for buying and selling power.

2.2. SVPP Operation Model

When the different kinds of energy are developed into electricity, heating, cooling, and natural gas in the SVPP, the SVPP evolves into multi-energy SVPP and controls different supply and conversion equipment to meet multi-energy loads [26]. The structure of the multi-energy SVPP is shown in Figure 2. The multi-energy SVPP operating architecture studied in this paper comprises the energy supply, demand, and conversion sectors. In the supply part, RESs and conventional energy attend. RESs involve PVs and WTs. In the conversion sector, the transformer is responsible for converting the electrical energy from input to electrical energy with different voltage levels in the demand sector. The natural gas enters the furnace, and then the furnace releases the gas fuel in the form of heat, directs some of this heat to consumption and demand, and directs another part of the heat to the chiller boiler. The chiller boiler also converts the heat received from the furnace into cooling and transfers it to the demand side. Finally, the demand side comprises electricity, heating, and cooling. In this section, the converted energies are used in the consumption sector. Due to the importance of sustainability, the utilization of SVPP components and the management of the different sectors are carried out in a way so as to improve the environmental indicators.

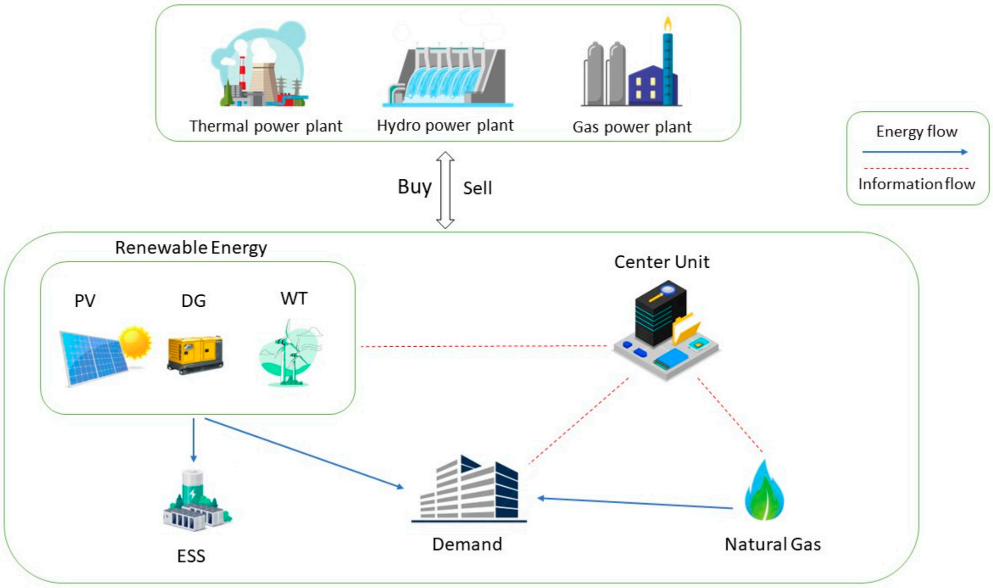


Figure 1. The structure of proposed SVPP.

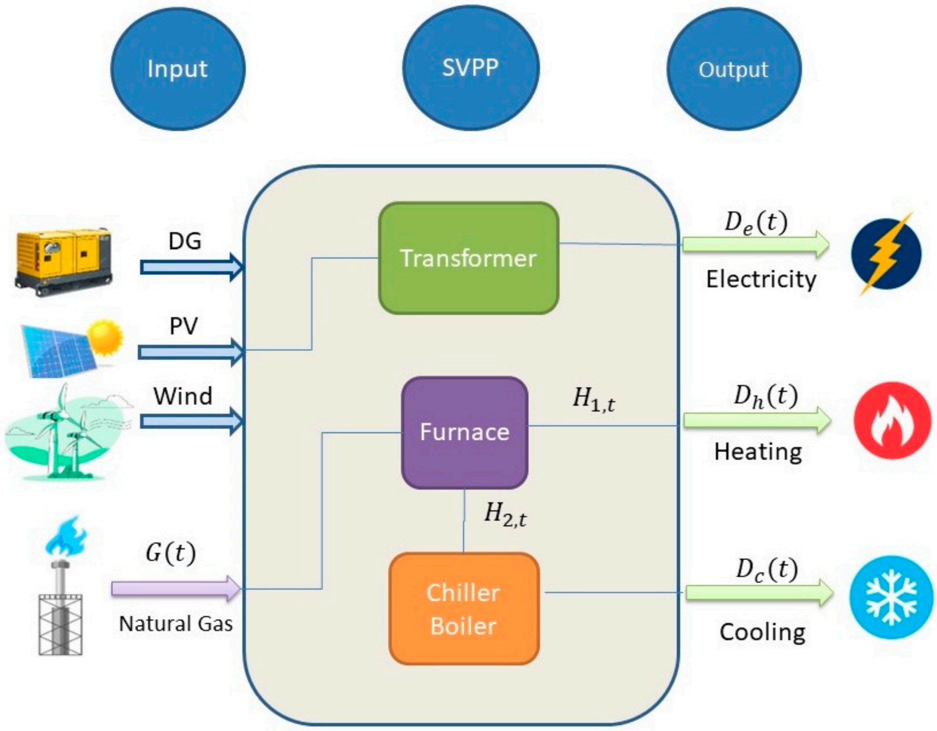


Figure 2. The component and various sectors of SVPP.

3. The Mathematical Model

As mentioned, the components of SVPP in this paper are PV, WT, ESS, transformer, furnace, chiller boiler, and DGs. The objective function of the SVPP operator is to minimize operational costs and emissions simultaneously. Therefore, the modeling of the SVPP's components is described in this section.

3.1. Wind Turbine (WT)

The output power of WT is modeled using Equation (1) [34]. In this equation, $\mathrm{P_{WT_i}(t)}$ and $\mathrm{P_{rated_i}}$ are output and rated power, respectively. Moreover, output power of WT depends on wind speed. Therefore, four conditions are considered in Equation (1). Where **v** denotes wind speed and $\mathrm{v_r}$, $\mathrm{v_{ci}}$ and $\mathrm{v_{co}}$ stand for rated, minimum, and maximum wind speed.

$$P_{WT_i}(t) = \begin{cases} 0, & 0 \leq v \leq v_{ci} \\ P_{rated_i} \times \frac{v-v_{ci}}{v_r-v_{ci}}, & v_{ci} \leq v \leq v_r \\ P_{rated_i}, & v_r \leq v \leq v_{co} \\ 0, & v_{co} \leq v \end{cases} \tag{1}$$

Moreover, the balance formula between output power and input power in WTs in the SVPP is modeled in Equation (2), where η_{ee} is 0.98, which shows the efficiency of the transformer [35].

$$\eta_{ee} E1_{WTi}(t) = P_{WT_i}(t) \tag{2}$$

3.2. Photovoltaic (PV)

There are materials in the structure of PV that converts solar radiation to electric power. The output power of PV has a direct relationship with environmental conditions such as ambient temperature and solar radiance. Moreover, the module properties affect the power generation of PV. Therefore, the output power of PV can be determined as follows [36]:

$$P_{PV_j}(t) = \begin{cases} P_{sn_j} \frac{(G(t))}{G_{std} R_c} & 0 < G(t) < R_c \\ P_{sn_j} \frac{(G(t))}{G_{std}} & G(t) > R_c \end{cases} \tag{3}$$

$$\eta_{ee} E2_{PVj}(t) = P_{PV_j}(t) \tag{4}$$

where $G(t)$ represents solar radiation and G_{std} equals to 1000 W/m^2 that is solar radiation in the standard test conditions. P_{sn_j} denotes rated power of PV and R_c is related to certain radiation point (150 W/m^2). In Equation (4), modeling of transformer efficiency is performed for PV.

3.3. Diesel Generator (DG)

DG is an appropriate option to supply power especially when the generation of RESs is not enough to respond to the whole demands. This resource of power generation requires less capital investment compared to other existing technologies [37]. The cost and operation of the DG are modeled in this sub-section.

3.3.1. Costs of DG

To coordinate production and consumption, the quadratic function is used for modeling the power generation costs of DG. Therefore, if the demand is high, the cost of generation increases accordingly. The cost function of the output power of DG can be calculated as follows:

$$Co_{DG_m}(t) = a_k E3^2_{DG_m}(t) + b_k E3_{DG_m}(t) + c_k \tag{5}$$

In Equation (5), a_k, b_k and c_k are the pricing coefficients and $E3_{DG_m}(t)$ denote input power generation during each time planning.

3.3.2. DG Generation Constraints

The output power of DG should be satisfied by the following equation:

$$P^{min}_{DG_m}(t) \times I_{DG_m}(t) \leq P_{DG_m}(t) \leq P^{max}_{DG_m}(t) \times I_{DG_m}(t) \tag{6}$$

In the above equation, $P_{DG_m}^{min}(t)$ and $P_{DG_m}^{max}(t)$ is the minimum and maximum power generation of each DG. The variable $I_{DG_m}(t)$ is binary and represents the status of on/off DG m. Moreover, $P_{DG_m}(t)$ is output power generation of DG m.

The unit commitment problem is considered to generate cost-effective power. In this regard, the ramp-up/down rates are limited to a certain amount according to resource characteristics as follows:

$$P_{DG_m}(t) - P_{DG_m}(t-1) \leq RU_{DG_m}(t) \times (1 - y_{DG_m}(t)) + P_{DG_m}^{min}(t) \times y_{DG_m}(t) \quad (7)$$

$$P_{DG_m}(t-1) - P_{DG_m}(t) \leq RD_{DG_m}(t) \times (1 - z_{DG_m}(t)) + P_{DG_m}^{min}(t) \times z_{DG_m}(t) \quad (8)$$

In Equations (7) and (8), $RU_{DG_m}(t)$ and $RD_{DG_m}(t)$ are related to ramp-up and ramp-down limitation for DG m at time t, respectively. $y_{DG_m}(t)$ and $z_{DG_m}(t)$ are binary variables that denote start-up and shut-down modes, respectively. For other equations of unit commitment DG m modeling, Equations (9)–(11) are applied.

$$y_{DG_m}(t) - z_{DG_m}(t) = I_{DG_m}(t) - I_{DG_m}(t-1) \quad (9)$$

$$y_{DG_m}(t) + z_{DG_m}(t) \leq 1 \quad (10)$$

$$y_{DG_m}(t), z_{DG_m}(t) \in \{0, 1\} \quad (11)$$

Based on Equation (9), the unit commitment problem is modeled. Equation (10) guarantees that each unit only can be in start-up or shut-down modes at each time slot. The minimum up-time and minimum down-time should be considered in the unit commitment problem that are indicated by Equations (12) and (13).

$$\sum_{c=t}^{t+UT_{DG_m}-1} I_{DG_m}(t) \geq UT_{DG_m} \times y_{DG_m}(t) \quad (12)$$

$$\sum_{c=t}^{t+DT_{DG_m}-1} \left(1 - I_{DG_m}(t)\right) \leq DT_{DG_m} \times z_{DG_m}(t) \quad (13)$$

where, UT_{DG_m} and DT_{DG_m} are the minimum up-/minimum down-time of DG m, respectively. Moreover, the efficiency of the transformer should be taken into account and is stated as follows:

$$\eta_{ee} E3_m(t) = P_{DG_m}(t) \quad (14)$$

3.4. Energy Storage System (ESS)

ESS can store excess energy in the special interval and deliver it to SVPP for supply to demand of users. Based on Equation (15), the power of ESS is calculated by subtracting the storage energy of past time from current time. Moreover, considering construction technology and operation conditions, stored energy should be limited to a certain bound that is specified by Equation (16). Moreover, in this paper, efficiency of charge/discharge modes is taken into account by Equation (17). Moreover, this equation shows that ESS cannot be charged/discharged more than a special amount in each time interval. Total storage limitation in time horizon planning is presented by Equation (18). Furthermore, only charge or discharge mode can be operated in each time interval, which is modeled by Equation (19).

$$P_{ES_n}(t) \times T = ES_{e_n}(t) - ES_{e_n}(t-1) \quad (15)$$

$$ES_{e_n}^{min} \leq ES_{e_n}(t) \leq ES_{e_n}^{max} \quad (16)$$

$$\begin{cases} \frac{P_{ES_n}(t)}{\eta_{dch}^{ES_n}} \le P_{ES_n-dch}^{max} \times dis_{ES_n}(t) & discharge : P_{ES_n}(t) > 0 \\ -\eta_{ch}^{ES_n} \times P_{ES_n}(t) \ \le P_{ES_n-ch}^{max} \times ch_{ES_n}(t) & charge : \ P_{ES_n}(t) < 0 \end{cases} \tag{17}$$

$$ES_{e_n}^{min} - ES_{e_n}(0) \le \sum_{t=1}^{t_n} P_{ES_n}(t) \times \theta \le ES_{e_n}^{max} - ES_{e_n}(0) \tag{18}$$

$$ch_{ES_n}(t) + dis_{ES_n}(t) \le 1 \tag{19}$$

$P_{ES_n}(t)$, $ES_{e_n}(t)$, and θ are the power and energy of ESS and interval of operation, respectively. Moreover, $ES_{e_n}^{min}$ and $ES_{e_n}^{max}$ are minimum and maximum of stored energy of ESS. In Equation (17), $\eta_{ch}^{ES_n}$ and $\eta_{dch}^{ES_n}$ represent efficiency of charge/discharge modes, respectively. Furthermore, $ch_{ES_n}(t)$ and $dis_{ES_n}(t)$ are binary variables of charge/discharge modes.

3.5. Heating and Cooling Loads

The natural gas was utilized as the input fuel for furnace to supply heating and cooling loads. The output energy from furnace can directly respond to the heating load and also the air cooling is applied to provide energy for cooling loads. Therefore, the heating and cooling loads are modeled by Equations (20) and (21).

$$H_1(t) = D_h(t) \tag{20}$$

$$H_2(t) = \eta_{hc} D_c(t) \tag{21}$$

$H_1(t)$ and $H_2(t)$ stand for the amount energy for demand side. Moreover, η_{hc} is the efficiency of the chiller boiler.

3.6. Objective Function

The objective of this study is to consider economic and environmental issues and both aspects are modeled by minimizing the operational costs and emissions of SVPP. The objective function is calculated by Equation (22).

$$min(OF) = \sum_{t=1}^{T} Cost(t) + \sum_{t=1}^{T} Cem(t) \tag{22}$$

3.6.1. Costs of SVPP's Operator

The term $Cost(t)$ in Equation (22) constitutes the cost of components namely, PVs, WTs, ESS, DGs, natural gas and cost/revenue of buying/selling power from/to the main-grid that represents based on Equation (23).

$$COST(t) = \sum_{t=1}^{T} (C_{WT}(t) + C_{PV}(t) + C_{ESS}(t) + C_{DG}(t) + C_{NG}(t) + C_{buy}(t) - R_{sell}(t)) \tag{23}$$

The total costs of the SVPP includes operational, maintenance, and constant costs that can be modeled as follows (23):

$$C_{WT}(t) = \sum_{i=1}^{I} E1_i(t) \times C_{OWT_i}(t) + C_{CWT_i}(t) \tag{24}$$

$$C_{PV}(t) = \sum_{j=1}^{J} E2_j(t) \times C_{OPV_j}(t) + C_{CPV_j}(t) \tag{25}$$

$$C_{DG}(t) = \sum_{m=1}^{M} Co_{DG_m}(t) \tag{26}$$

$$C_{ESS}(t) = \sum_{n=1}^{N} P_{ES_n}(t) \times C_{ES_n}(t) + C_{MESS_n}(t) \tag{27}$$

$$C_{buy}(t) = P_{buy}(t) \times C_{ebuy}(t) \tag{28}$$

$$R_{sell}(t) = P_{sell}(t) \times C_{esell}(t) \tag{29}$$

$$C_{NG}(t) = G_{NG}(t) \times C_{eNG}(t) \tag{30}$$

The operational and constant costs are considered for WTs, PVs, and DGs that are stated in Equations (24)–(26). By Equation (27), the operational and maintenance costs of ESS have been calculated. Moreover, the cost of buying energy and revenue of selling energy from/to the main grid are indicated by Equations (28) and (29). Equation (30) is related to the total costs of natural gas that $G_{NG}(t)$ represents the amount of produced natural gas in each time interval and $C_{eNG}(t)$ is the cost of natural gas. In the above equations, $C_{OWT_i}(t)$, $C_{OPV_j}(t)$, and $C_{OESS_n}(t)$ are operational cost of WT, PV, and ESS, respectively. Moreover, $C_{CWT_i}(t)$ and $C_{CPV_j}(t)$ are constant cost of WT and PV. $C_{MESS_n}(t)$ is the maintenance cost of ESS.

3.6.2. Emission

Utilizing RESs in the context of SVPP causes a reduction of emissions. Among the available sources, PVs and WTs are the clean type ones that do not generate emissions in the SVPP. However, DG generates air pollutants such as CO_2, SO_2, and NO_X that are modeled in the objective function. Furthermore, since the power generation of the main grid is based on conventional resources, the purchased energy from the main grid causes air pollution by the SVPP. Therefore, the emissions of DGs and purchased energy from the main grid is incorporated into Equation (31). To model the emission function in the overall objective function, a model based on cost-emission has been considered, which is represented by Equation (32).

$$EM(t) = \sum_{t=1}^{T} \left(P_{buy}(t) \times \left(CO_2^{buy} + SO_2^{buy} + NO_X^{buy}\right) + \sum_{m=1}^{M} E3_{DG_m}(t) \times \left(CO_2^{DG_m} + SO_2^{DG_m} + NO_X^{DG_m}\right)\right) \tag{31}$$

$$Cem(t) = \sum_{t=1}^{T} \left(\left(P_{buy}(t) \times \left(CO_2^{buy} + SO_2^{buy} + NO_X^{buy}\right)\right) \times COST_{em}^{buy} + \sum_{m=1}^{M} E3_{DG_m}(t) \times \left(CO_2^{DG_m} + SO_2^{DG_m} + NO_X^{DG_m}\right) \times COST_{em}^{DG_m}\right) \tag{32}$$

In Equation (31), CO_2^{buy}, SO_2^{buy}, NO_X^{buy}, $CO_2^{DG_m}$, $SO_2^{DG_m}$, and $NO_X^{DG_m}$ are the amount emissions for purchased energy and operation of DGs in kg, respectively. Moreover, $COST_{em}^{buy}$ and $COST_{em}^{DG_m}$ are the cost of emissions in $\$/kg$, respectively.

3.7. Problem Constraints

The balance power and energy constraint are important equations in the operation of SVPP. Furthermore, concerning characteristic and technical issues of the SVPP's components, the optimal constraints must be considered in the problem solution. The constraints are modeled as follows:

$$D_e(t) = \sum_{i=1}^{I} P_{WT_i}(t) + \sum_{j=1}^{J} P_{PV_j}(t) + \sum_{m=1}^{M} P_{DG_m}(t) + \sum_{n=1}^{N} P_{ES_n}(t) + P_{buy}(t) - P_{sell}(t) \tag{33}$$

$$\eta_{gh}^{f} G_{NG}(t) = H_1(t) + H_2(t) \tag{34}$$

$$P_{buy}(t) \le P^{maxline} \tag{35}$$

$$P_{sell}(t) \le P^{maxline} \tag{36}$$

In the above equations, η_{gh}^{f} and $P^{maxline}$ are the furnace efficiency and maximum capacity of the transmission line, respectively.

3.8. Modeling of Demand Response Program (DRP)

In the proposed framework, TOU-based DRP is used to decrease the amount of emission as well as reduction of operational costs. The elasticity concept is considered in DRP modeling in which users shift or reduce their demand when the electricity price increases, namely during peak hours. In this regard, the calculation of users' demand is as follows:

$$DR(t) = D_e(t) \times (1 + \frac{\vartheta \times (\rho_2(t) - \rho_1(t))}{\rho_1(t)}) \tag{37}$$

In Equation (37), $DR(t)$ and $\rho_2(t)$ are the amount of power demand and electricity price after implementing DRP. Moreover, $\rho_1(t)$ is the electricity price before implementation of DRP and ϑ is defined demand sensitivity with respect to price [38]. Furthermore, the constraint is taken into account for the users' demand so that the maximum reduction of electricity consumption does not exceed 30%.

$$DR(t) \geq 0.7 \times D_e(t) \tag{38}$$

3.9. Uncertainty Modeling

This paper proposes a fast and robust model to tackle uncertainty parameters such as wind speed, solar radiation, and electricity prices. The uncertainties have a direct effect on the objective function of the SVPP's operator; therefore, choosing the appropriate approach is very important in dealing with uncertainty parameters. Different methods exist for uncertainty modeling, including the truncated Taylor series expansion method, the discretization method, the point estimate method (PEM), and the Monte Carlo simulation [39]. The truncated Taylor series expansion method involves evaluating derivatives with respect to each parameter, which can be complex and time-consuming for problem-solving. The discretization method replaces continuous probability distribution with discrete probability distribution. In contrast, PEM can overcome calculation difficulties without requiring perfect knowledge of probability functions for stochastic variables [40]. PEM utilizes mean, variance, skewness, and kurtosis of parameters, requiring less data information compared to other methods mentioned. Additionally, while the Monte Carlo method with multiple scenarios can enhance accuracy, it also requires significant computation time. Thus, a trade-off exists between computation time and the number of scenarios. Among these methods, PEM is an accurate approach that processes data efficiently. In this context, 2PEM, a specific type of PEM, is employed. Only $2 \times M$ scenarios are required for implementing 2PEM with M random variables. The definition of $L = \{l_1, l_2, \ldots, l_l, \ldots, l_m\}$ is a random variable with a mean of μ_{lv} and standard deviation of σ_{lv}. Moreover, Z is a random variable that denotes $Z = f(l)$. In this regard, a random variable l_v and weight ω_{vs} are defined for each two concentrations. The concentration of l_{vs} is represented by Equation (39) [41].

$$l_{vs} = \mu_{lv} + \xi_{vs}.\sigma_{lv} \tag{39}$$

In the above equation, ξ_{vs} is the standard location of l_{vs}. The standard location and weight of the l_{vs} is calculated by Equations (40) and (41).

$$\xi_{v1} = \frac{\lambda_{v3}}{2} + \sqrt{m + (\frac{\lambda_{v3}}{2})^2},\ \xi_{v2} = \frac{\lambda_{v3}}{2} - \sqrt{m + (\frac{\lambda_{v3}}{2})^2} \tag{40}$$

$$\omega_{v1} = -\frac{\xi_{v2}}{m(\xi_{v1} - \xi_{v2})},\ \omega_{v2} = -\frac{\xi_{v1}}{m(\xi_{v1} - \xi_{v2})} \tag{41}$$

In which, λ_{v3} is defined skewness of the l_{vs} and is determined as follows:

$$\lambda_{v3} = \frac{E\left[(v_l - \mu_{lv})^3\right]}{(\sigma_{lv})^3} \tag{42}$$

At each iteration, $Z_{v,s}$ is calculated using variable concentration point and mean value of other random variables:

$$Z_{v,s} = F\{x_{v1},\ x_{v2}, \ldots, x_{vs}, \ldots, x_{vm}\} \tag{43}$$

Moreover, the row moments of the random output variable are determined by Equation (44).

$$E(Z) \cong E(Z) + \sum_s W_{vs}.Z_{vs} \tag{44}$$

Finally, the results are shown in the form of mean and standard deviation. Speed wind, solar radiation, and TOU-based prices are considered as the uncertainty parameters in this paper and are modeled by flowchart Figure 3 [41].

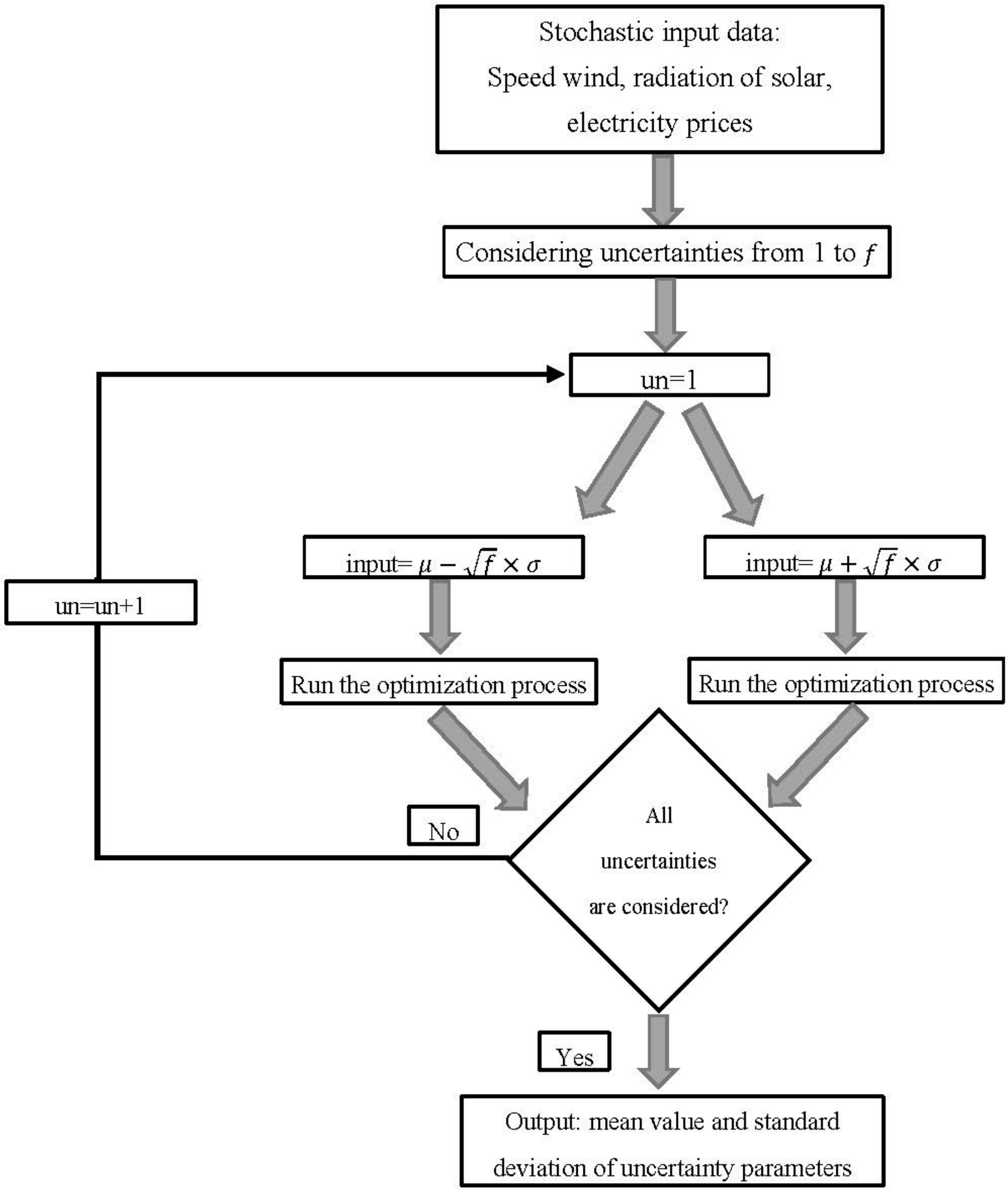
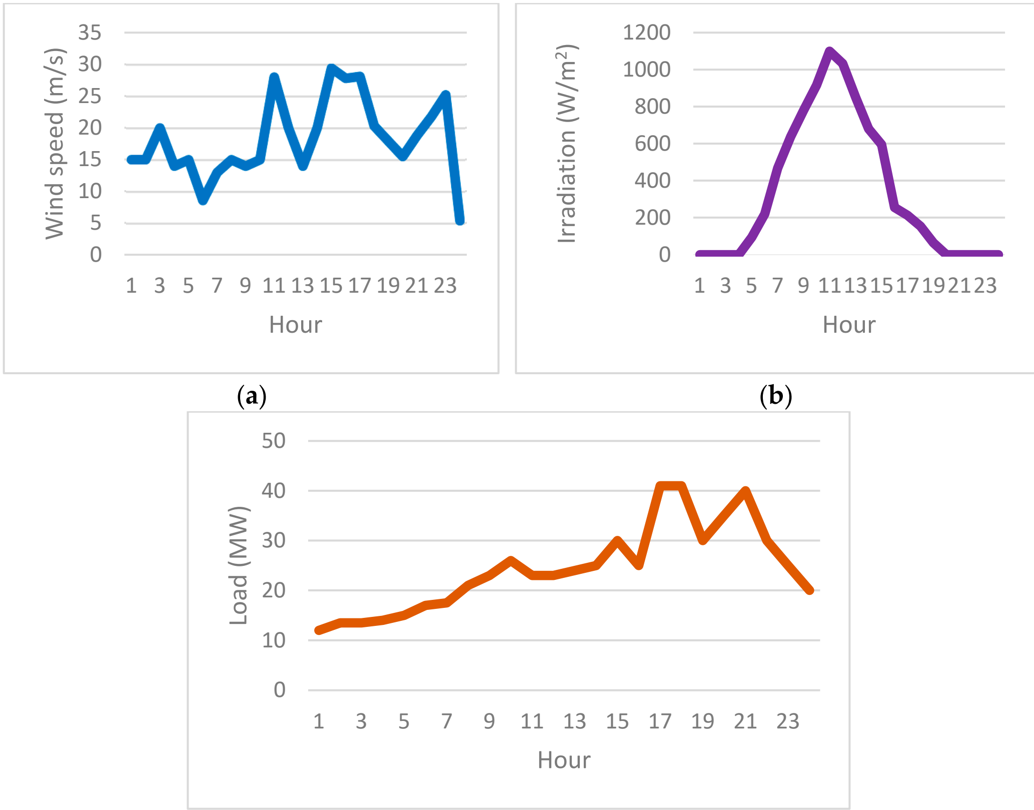


Figure 3. The flowchart of the two-point estimate method (2PEM) [41].

4. Simulations and Discussion

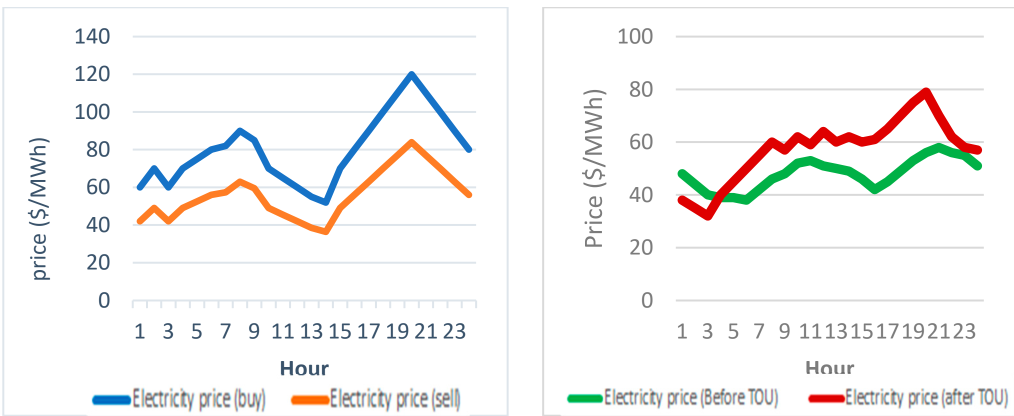
4.1. Basic Data

In this paper, an SVPP includes 10 PVs, five WTs, and two ESS. Moreover, four DGs are considered that are responsible for power generation and ESS assists the operator of the SVPP to balance the supply- and demand-side in each time horizon planning. Moreover, the SVPP consists of thermal and electrical loads and mentioned resources and natural gas are utilized to respond to the loads. Since excess or shortage of power generation may occur during special hours, a transmission line is modeled for the exchange of power to the main grid in the simulation. In addition to providing power for loads, this approach makes a profit for the SVPP's operator by selling electricity to the main grid. It is noteworthy that the optimization problem is modeled for the future 24 h and each time part is 1 h. The speed of the wind, solar irradiance, and users' load curve are demonstrated in Figure 4. Figure 5a shows buying/selling power from/to the main grid. Based on this figure, the price of buying is greater than the selling price to guarantee the profit of the main grid's operator. In Figure 5b, the prices of electricity before and after implementing TOU-based DRP are demonstrated, in which they are changed in the DRP case study to influence the consumption pattern of users. The demand for cooling and heating energy of users is shown in Figure 5c. The parameters of DGs are given in Table 1, which includes the minimum and maximum rate of power generation and unit commitment parameters [42]. Moreover, the cost coefficients of DG generation are shown in Table 2 [42]. The technical information and input data of PV and WT are available in Table 3. Moreover, parameters related to ESS modeling are described in Table 4. The emission rate of DGs and resources of the main grid are listed in Table 5. Since the main grid utilizes the conventional power plants, the emission of the main grid is more than the emission of DGs. The impact of emission on the SVPP is estimated based on an oriented-cost approach in which the emission cost is \$30/ton [43]. Moreover, the maximum amount of buying/selling energy from/to the main grid is limited to 20 MW in each time horizon.



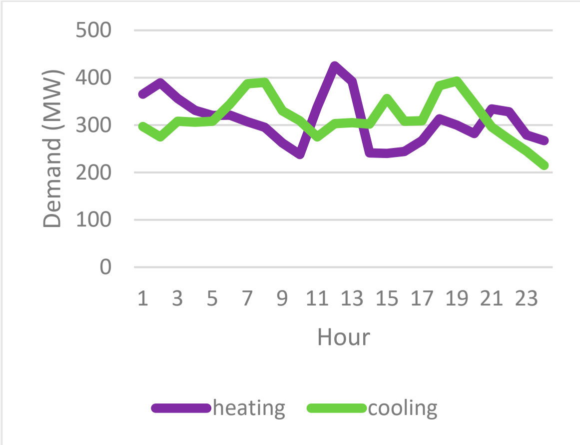
(**a**) (**b**) (**c**)

Figure 4. (**a**) Wind speed (m/s) [44], (**b**) Solar irradiance (W/m^2) [45], and (**c**) Load (MW) curve [45] for the next day.



(**a**) (**b**)

Figure 5. *Cont.*



(**c**)

Figure 5. (**a**): Data for buying/selling prices of power from/to the main grid. (**b**): Electricity prices before and after implementing TOU based DRP. (**c**): The heating and cooling demand curve for the 24 h.

Table 1. DG parameters [42].

DGs	Start-Up Cost ($)	Minimum-Up/Down Time (h)	Maximum Ramp-Up/Down Rate (MW/h)	P^{max}	P^{min}
DG1	15	2	1.8	3.5	1
DG2	25	1	1.5	3	0.75
DG3	28	1	1.5	3	0.75
DG4	26	2	1.5	4.1	1

Table 2. Operational cost coefficients of DGs [42].

DGs	$a_i(\frac{\$}{MWh^2})$	$b_i(\frac{\$}{MWh})$	$c_i(\$)$
DG 1	0.0025	87	27
DG 2	0.0035	87	25
DG 3	0.0035	92	28
DG 4	0.184	81	26

Table 3. Technical information and input data of PV and WT.

Wind Turbine [45]			PV [36]		
Parameters	**Amount**	**Unit**	**Parameters**	**Amount**	**Unit**
$\mathbf{P_r}$	2.05	MW	P_{sn}	1.1	MW
$\mathbf{V_{ci}}$	2	m/s	G_{std}	1000	W/m^2
$\mathbf{V_r}$	14	m/s	R_c	150	W/m^2
$\mathbf{V_{co}}$	25	m/s			

4.2. Case Studies (CSs)

Several case studies (CSs) are simulated to verify the optimization procedure. The four CSs are based on the following conditions:

Case 1: There are RESs such as PV and WT in this case. Moreover, the SVPP's operator can make the decision about buying/selling energy from/to the main grid. Furthermore, the DGs and electricity, cooling, and heating loads are incorporated into the simulation.

Case 2: In addition to the assumptions of CS#1, the TOU based on DRP is implemented for the demand side.

Case 3: All descriptions of the CS#1 are modeled in this case. Moreover, the impact of ESS on operational cost and emission issues is considered in CS#3.

Case 4: In this case, a hybrid solution including CS#2 and CS#3 is proposed and the role of ESS and TOU-based DRP is determined in economic and environmental aspects.

Each CS as a mixed-integer non-linear programming (MINLP) problem has been solved by DICOPT solver of GAMS software on a Corei7 PC with 2.7 GHz CPU and 8 GB RAM.

Table 4. Technical parameters, maintenance and operational costs of ESS [45].

Parameters	Amount	Unit
$\mathbf{ES_e^{min}}$	0.2	MW
$\mathbf{ES_e^{max}}$	2	MW
$\mathbf{P_{ES-dch}^{max}}$	0.5	MW
$\mathbf{P_{ES-ch}^{max}}$	0.5	MW
$\mathbf{ES_e(0)}$	0.2	MW
η_{ch}^{ES}	90	%
η_{dch}^{ES}	80	%
$\mathbf{C_{MESS}}$	0.001	\$/h
$\mathbf{C_{OESS}}$	15	\$/MWh

Table 5. The emission factor of DG and the main grid resources (kg/MWh).

Emission Factor	DG [46]	Main-Grid [47]
$\mathbf{CO_2}$	73.98	921.25
$\mathbf{SO_2}$	1.02	3.583
$\mathbf{NO_X}$	0.09	2.295

4.3. Simulation Results and Discussion

Since the behavior of RESs is stochastic and cannot be estimated, the output generation of these sources, speed of wind and solar irradiance are assumed as uncertain inputs of the problem. Therefore, the results of all CSs have been shown in the mean form. Moreover, the electricity prices before and after participating users in TOU-based DRP are uncertain parameters in CS#2 and CS#4.

In CS#1, PVs, WTs, and DGs are used to provide energy for the users, Then, shortage or surplus power is managed by buying/selling energy from/to the main grid. Figure 6 illustrates the output power of PVs, WTs, and DGs. As can be seen from the figure, the WTs produce approximately 11 MW in the first hour, after that, the output power increases to 22 MW in some hours. On the other hand, the PVs generate power from 5:00 to 19:00 and both WTs and PVs reduce the operational costs and emissions. However, the generation power of RESs is not enough to respond to the demand of users. Therefore, all DGs are operated in cases in which the amount of output power of DGs depends on the operational and emission costs. The comparison of operational and emission costs of all DGs is carried out in Figure 7. It is clear that DG#4 generates power with the lowest cost; therefore, using DG#4 takes the highest priority in operational scheduling. As seen in Figure 4, the demand for power is increased from 17:00 to 23:00. Although the output power of DGs increases during these hours, the power generation of PVs stops at 20:00 and the production of WTs decreases from 18:00 compared to previous hours. Therefore, the operator of the SVPP faces a critical situation in network operation and is forced to buy power from the main grid that is shown in Figure 8. Moreover, the production of RESs is in excess during some hours and the operator sells power to the main grid during hour 1, 3, 8, 11, 12, 14, 15, 16, and 23 to overcome the surplus power generation issue of the SVPP. The results show that operational and maintenance costs and emissions of SVPP are \$238,077.95 and 74,580.2 kg, respectively. Out of the total emissions, 86.76% is related to purchased power from the main grid. Therefore, a solution should be used to reduce the dependence on the main grid.

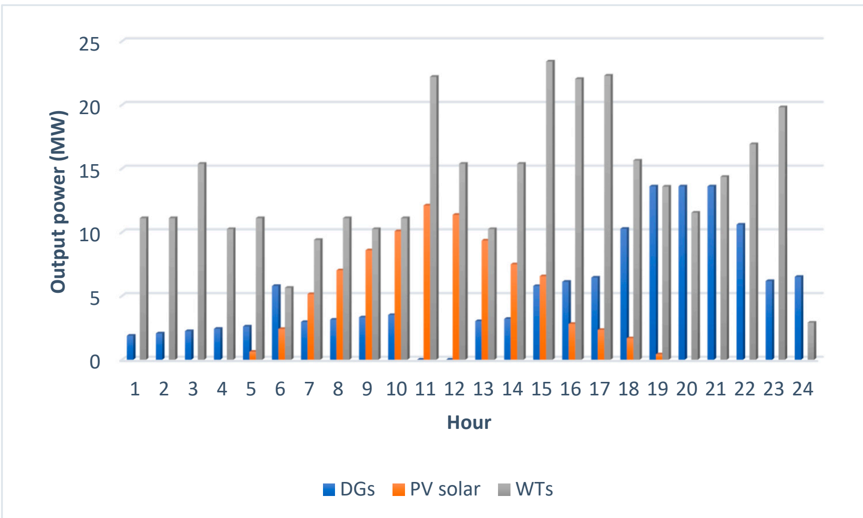


Figure 6. The output power of PVs, WTs, and DGs during 24 h in CS#1.

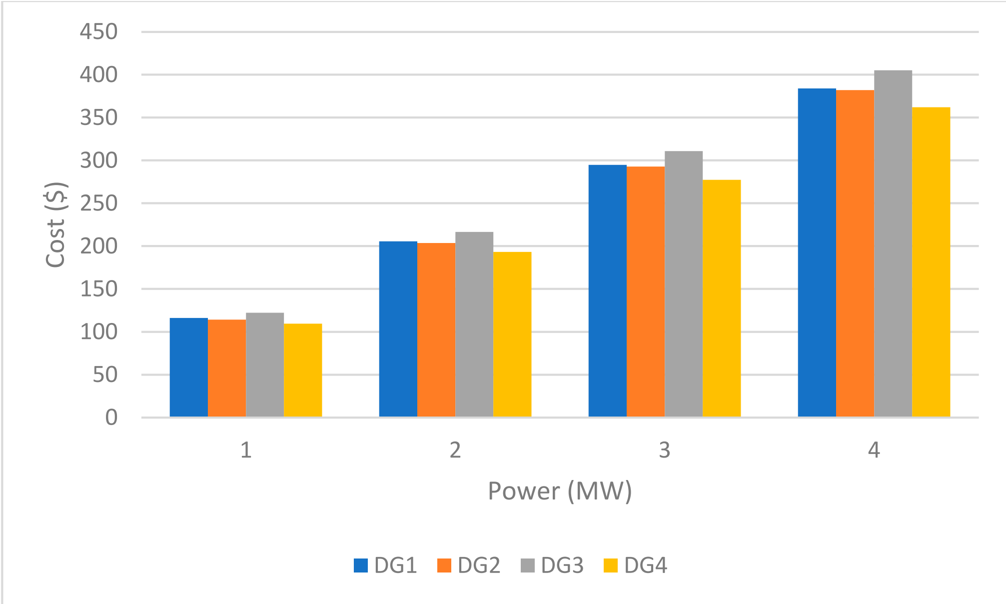


Figure 7. Total operational and emission costs of DGs for different power values.

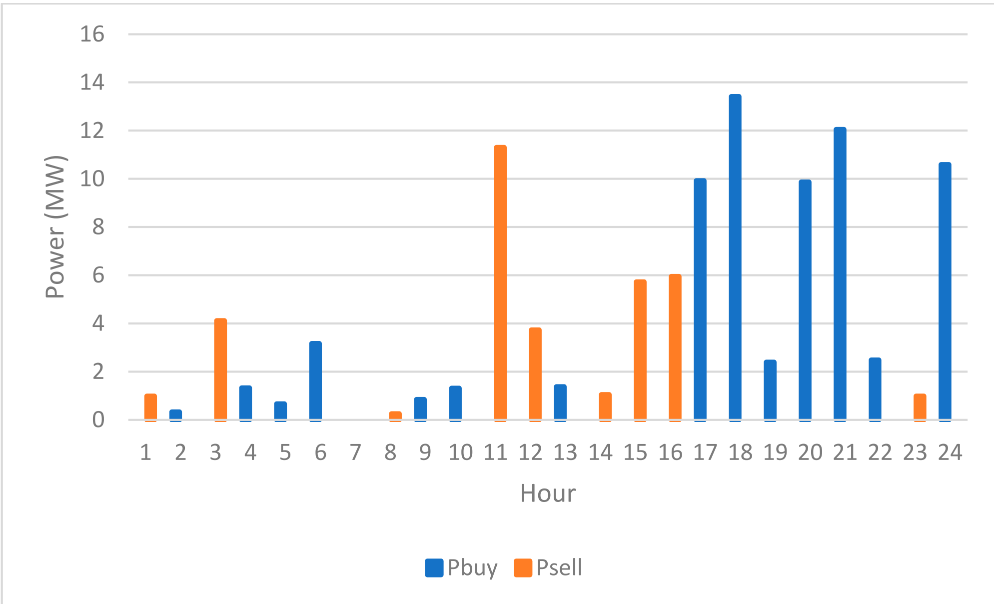


Figure 8. The amount of exchange power between SVPP and the main grid in time horizon planning in CS#1.

In CS#2, in addition to the assumptions of CS#1, TOU-based DRP is considered by the targeted selection of the electricity prices that result in the change in the users' behavior. Figure 9 presents the output of natural gas generation for responding to cooling and heating demand. According to the results, the SVPP's operator makes a decision about selling energy. In this regard, the operation of PVs, WTs, and DGs is operated to keep the power balance each time and the operator earns revenue from selling energy to the main grid. As shown in Figure 10, all DGs generate power at the maximum capacity from 19:00 to 21:00. In spite of production power by the four mentioned resources, there is a shortage of power during these hours. Therefore, the operator buys energy from the main grid, especially from 17:00 to 22:00 to maintain the power balance. The amount of imported power during 21:00 is approximately 11.2 MWh and this critical situation results in air pollution. Moreover, 40.8 MWh is sold to the main grid to compensate the part of the SVPP costs.

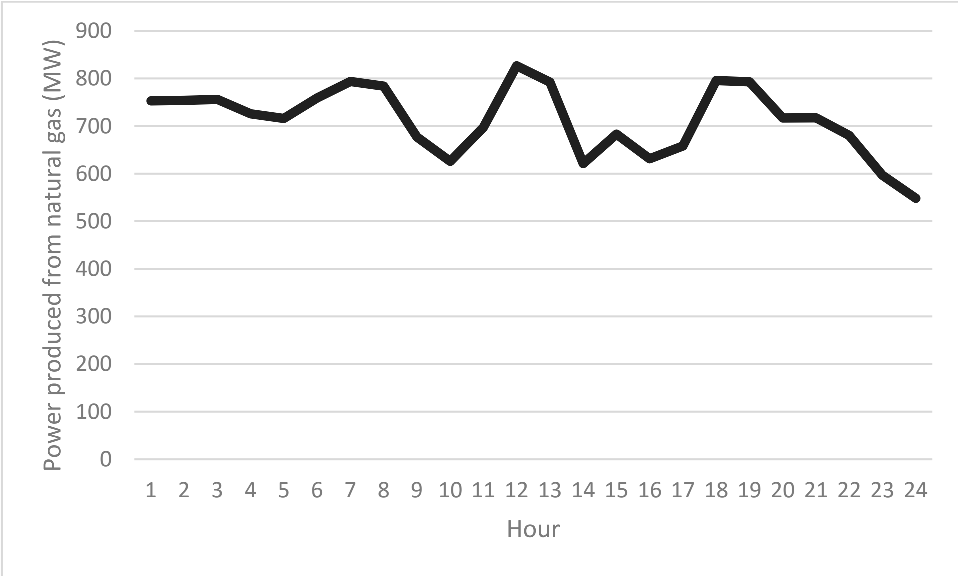


Figure 9. The amount of power produced from natural gas in CS#2.

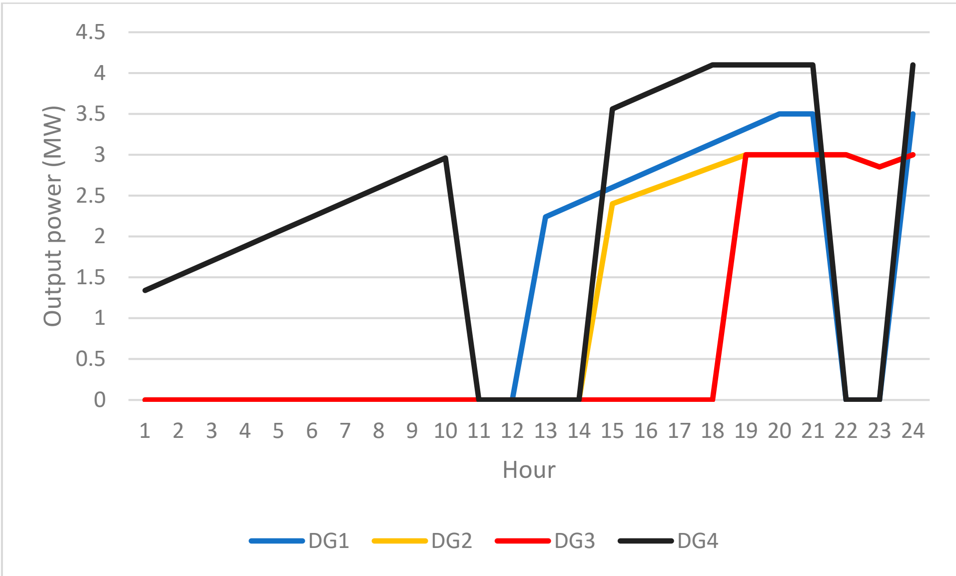


Figure 10. The output power of DGs in operational scheduling in CS#2.

However, both total cost and emission values are decreased compared to CS#1 by implementing TOU-based DRP. In this regard, the cost and pollution of the SVPP with the proposed approach are $236,937.56 and 67,359.99 kg. Figure 11 addresses that the implementation of DRP in scheduling leads to modifying the usage pattern by decreasing demand from 584.5 MW to 570.6 MW.

In CS#3, the effect of ESS on the operation and emission of SVPP is investigated. In other words, in addition to introducing the SVPP's components in CS#1, the ESS is embedded in the operation of the SVPP. Therefore, excess production of RESs is stored in ESS during 1:00 and 14:00 to deliver energy to the SVPP during critical hours, namely 19 to 21. Figure 12 presents the output power of DGs and all DGs are operated in this case. The results show that DGs generate power more than previous CSs when the ESS is considered in the simulation. In this regard, DG#2 and DG#4 produce more power due to the lower operational and emission costs compared to other DGs. Figure 13 reflects the decision of the SVPP's operator regarding the amount of buying/selling power from/to the main grid. As seen, the SVPP's operator is faced with a surplus power generation problem and sold power to the main grid to resolve this issue and the operator earns a revenue equal to $1715.18. Moreover, from 17:00 to 22:00, SVPP purchases power due to the limitation of RESs output in operational scheduling. The results show that the total costs are $237,801.2 and the emissions are 61,717.98 kg that the emission share of the main grid is 82.03% in air pollution.

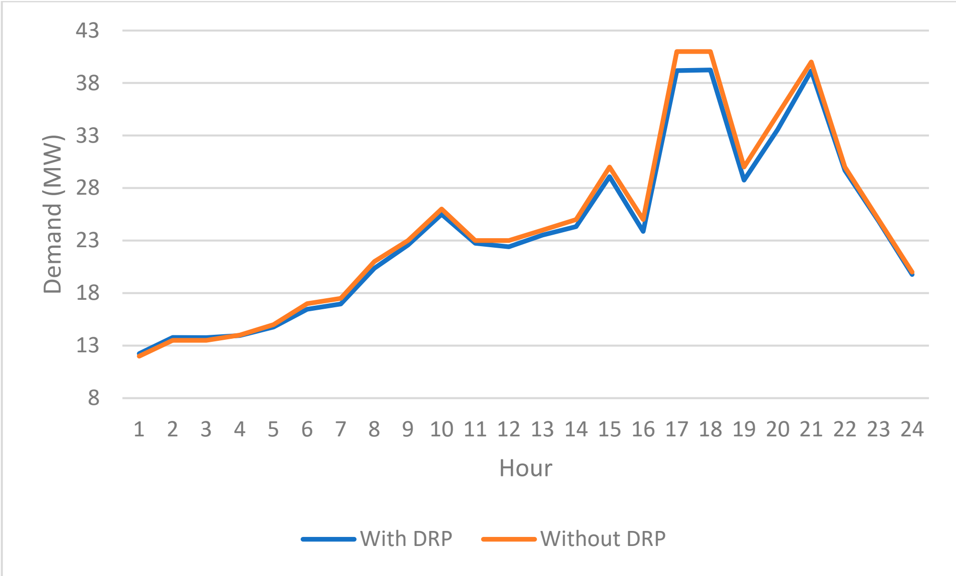


Figure 11. The consumption pattern of users before and after implementation DRP in CS#2.

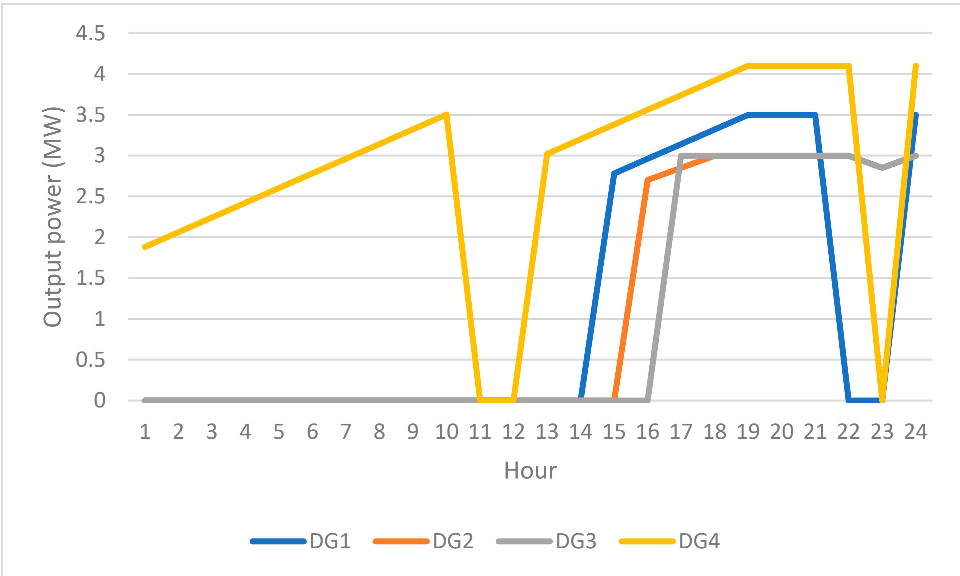


Figure 12. The output power of DGs in CS#3.

Due to the decreasing trend of SVPP costs and emissions with the proposed structures in previous CSs, it seems that both factors can be reduced by the adoption of a comprehensive solution. Therefore, a hybrid approach is used in CS#4 in which TOU-based DRP and ESS capability are utilized to reduce costs and pollution of the SVPP. The results of CS#4 are shown in Figures 14–16. Figure 14 shows that the operator keeps the power balance of the SVPP during each time horizon by optimal scheduling of available resources and purchasing power during each time horizon. The WTs, PVs, and all DGs generate power at maximum capacity during critical hours to meet the demand of users. Moreover, ESS is charged during 1:00, 3:00, and 12:00 and is discharged during the critical hours, as shown in Figure 15. From the point of view that the ESS is utilized in the operation of the SVPP, the dependence on the main grid is reduced. Therefore, as seen in Figure 16, the imported power decreases from 54.6 MWh to 46.25 MWh over CS#3, which results in the reduction of costs and air pollution. Moreover, the surplus power generation is exported to the main grid during hour 3, 7, 8, 11, 12, 15, 16, and 22 and a revenue equal to $950.37 is achieved for the SVPP's operator. Furthermore, using the DRP causes a reduction in the demand of users by 2.49%, especially during peak hours. Therefore, the imported power from the main grid is lower than other CSs because of using ESS and DRP. Finally, the total operational, constant, and maintenance costs of the SVPP are $235,473.46 and the emissions of the SVPP are equal to 52,354.95 kg.

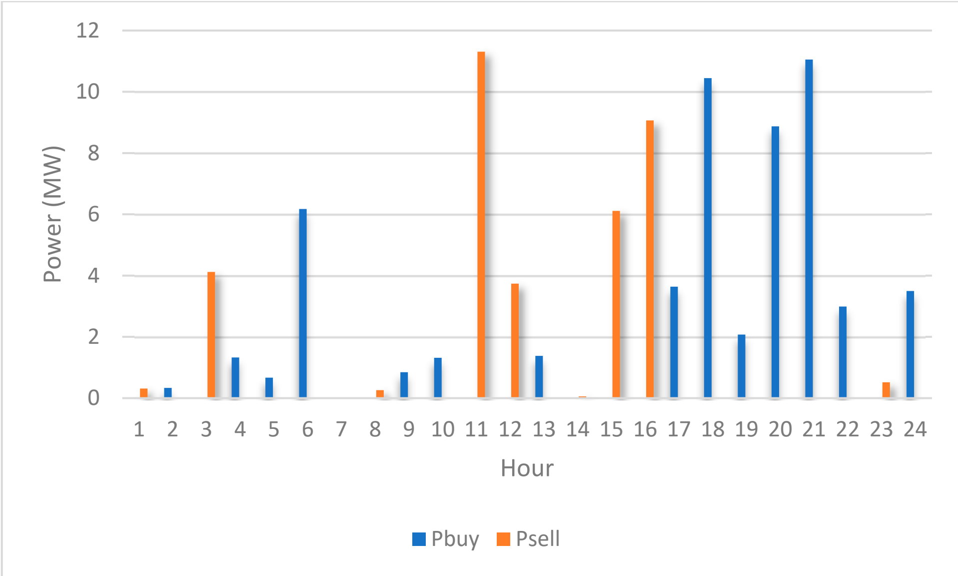


Figure 13. The amount of purchased/sold energy from/to the main grid in CS#3.

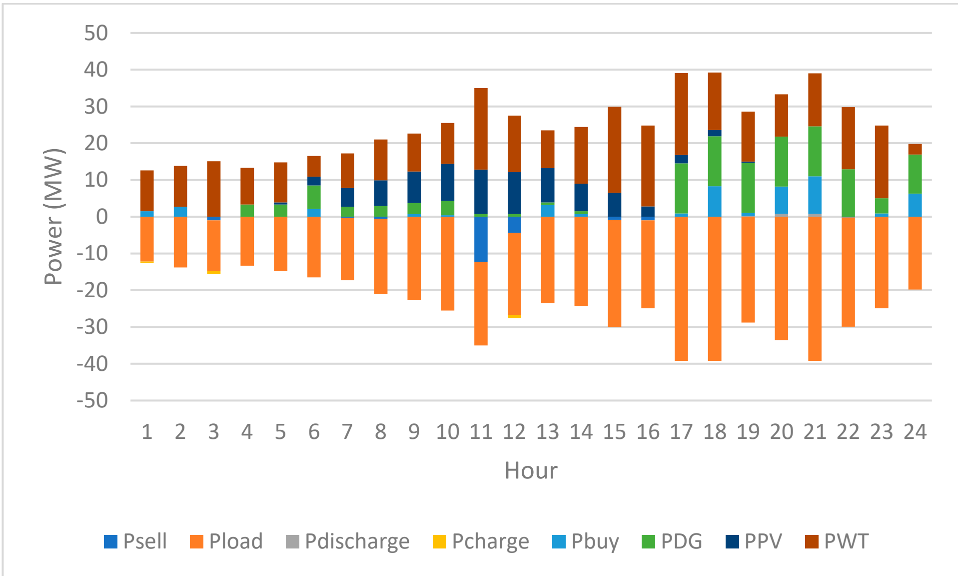


Figure 14. The balance of power during each time horizon planning in CS#4.

According to the results of the four CSs, the gradual reduction of emissions of SVPP is obvious from CS#1 to CS#4, respectively. In CS#3, the costs of the SVPP are more than in CS#2, which represents that utilizing the ESS increases the costs slightly. However, storing excess energy and delivering it to the SVPP when there is a shortage of power reduces pollution by reducing imported power from the main grid. Table 6 shows the cost and emission values of various CSs. To confirm the effectiveness of the proposed combined approach, the percentage of cost and emission reduction compared to CS#1 is listed in Table 6.

Table 6. The value of costs and emissions of SVPP in various CSs.

CS	Cost	Variation * (%)	Emission	Variation * (%)
CS#1	238,077.95 $	-	74,580.2 kg	-
CS#2	236,937.56 $	0.47	67,359.99 kg	9.68
CS#3	237,801.2 $	0.11	61,717.98 kg	17.24
CS#4	235,473.46 $	1.10	52,354.95 kg	29.80

* The results of these columns are negative values.

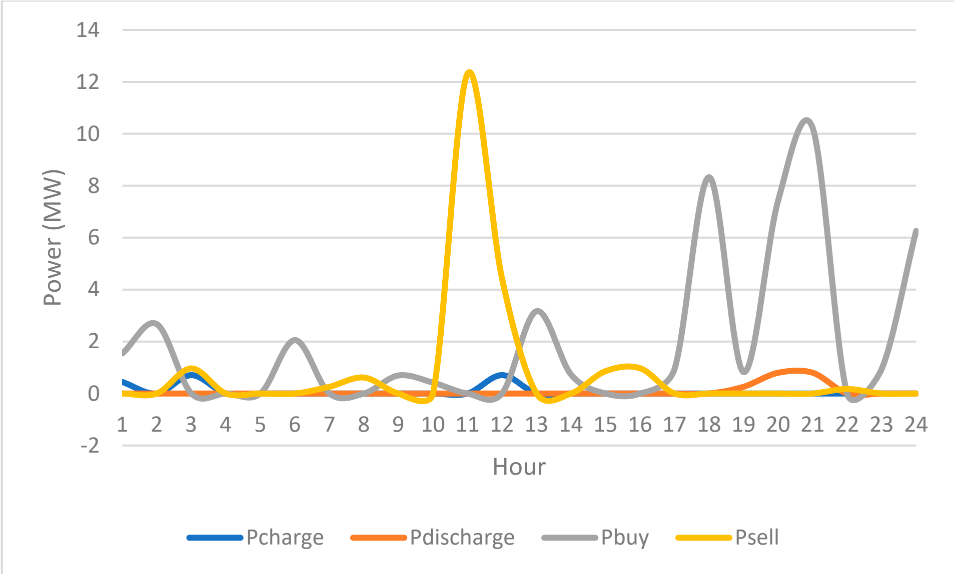


Figure 15. The amount of charged/discharged power of ESS and imported/exported power from/to the main grid in CS#4.

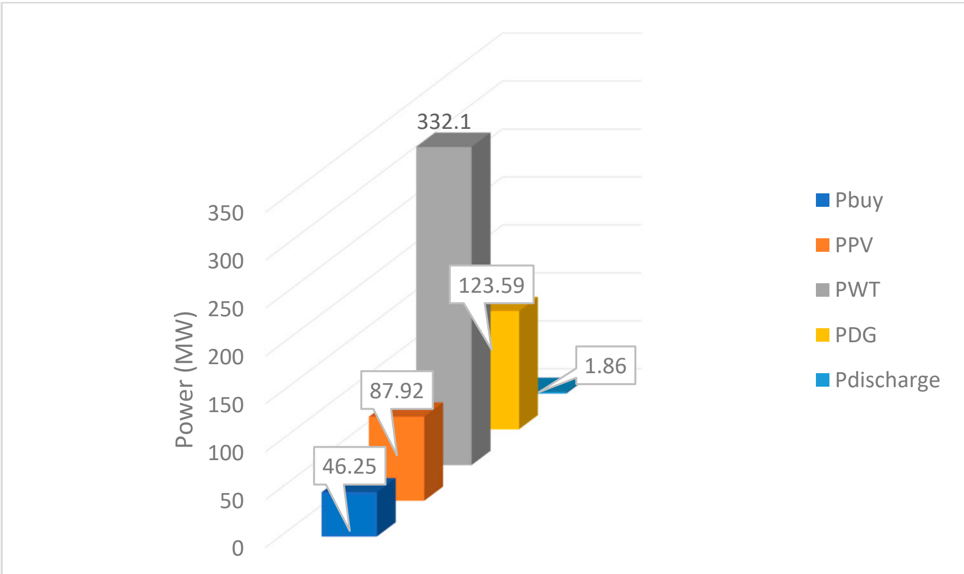


Figure 16. The share of power supply by the components of the SVPP in CS#4.

Different factors are effective in achieving such optimal planning and their role is investigated in this section. Due to the operational cost of DGs being higher than RESs, optimal management of DGs is very important in the operation of an SVPP. Moreover, the cost of purchased power is lower than the cost of power generation of DGs during some hours; therefore, it is better to purchase power from the main grid economically. The total output power of DGs and the amount of purchased power from the main grid are demonstrated in Figure 17. As seen, the reduction trend of purchased power from CS#1 to CS#4, respectively, leads to a decrease of pollution of an SVPP. However, storing energy in ESS causes an increase in the amount of power generation of DGs in CS#3 and part of this power is stored in ESS and supplied to demand during critical hours. Moreover, the TOU-based DRP in CS#2 and ESS in CS#3 lead to a decrease in the demand value and purchased power from the main grid, respectively. Therefore, the combination of CS#2 and CS#3 enables the operator to decrease the overall costs and emissions. Hence, the final strategy is economically and environmentally superior to other strategies.

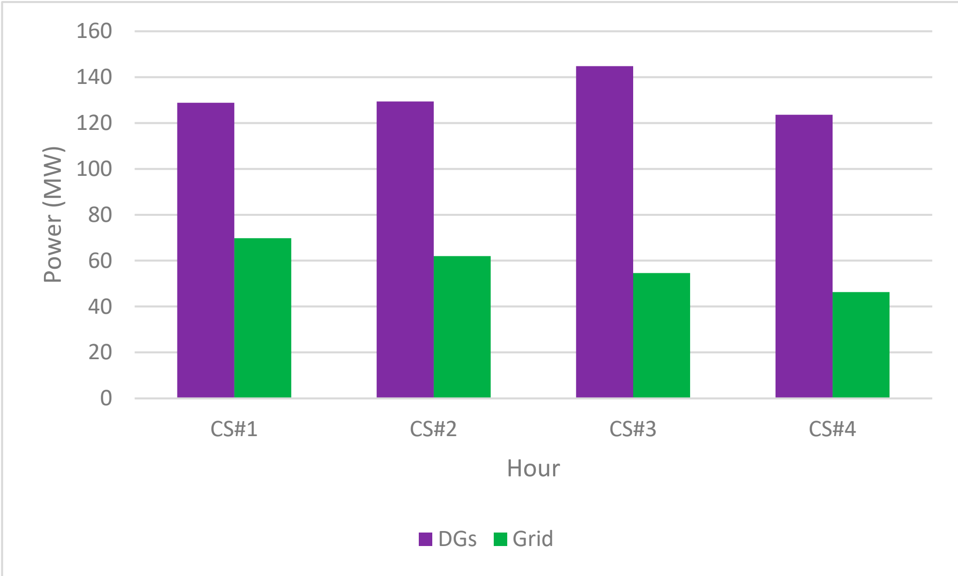


Figure 17. The value of purchased power from the main grid and production power of DGs in various CSs.

When the uncertainty is not considered in the final strategy, the amount of costs and emissions obtained are $234,573.23 and 48,866.27 kg. A comparison of deterministic and stochastic cases in the final strategy reveals that considering the uncertainty slightly increases costs and emissions. Since the output power of PVs and WTs fluctuates in time horizon planning, the SVPP's operator prefers to rely on DGs and power purchase when the uncertainties are modeled in simulations. In spite of increment of costs and emissions in the stochastic case, this strategy is robust against the fluctuations of PVs, WTs, and prices. Moreover, the results of the deterministic case are unrealistic, because the amount related to PVs, WTs, and prices always have uncertain behavior.

5. Conclusions

In this paper, the day-ahead scheduling of DERs was performed within the SVPP. The objective of this scheduling was to minimize the costs of the SVPP while optimizing the objective function to reduce both costs and pollution. The SVPP consists of various components such as DGs, WTs, PVs, a transformer, ESS, a furnace, and a chiller boiler. Due to the uncertain behavior of RESs in power generation, the operator faces challenges in balancing supply and demand during specific hours. To address these operational challenges, all the capabilities of the SVPP are utilized, with DGs and ESS compensating for the shortcomings of RESs.

To enhance the realism of the results, uncertainties related to wind speed, photovoltaic radiation, and electricity prices are considered using a fast and robust method called 2PEM. Four different case scenarios (CS#1, CS#2, CS#3, and a combined solution) are simulated and compared to examine the influence of the proposed approach. CS#1 assumes the operation of only PVs, WTs, and DGs, resulting in air pollution due to DGs and power purchase from the main grid. CS#2 investigates the impact of TOU-based DRP on costs and emissions, resulting in peak shaving and a 2.4% reduction in demand. CS#3 explores the use of energy storage, which significantly reduces pollution compared to CS#1 and CS#2 by reducing DG power generation and purchased power. The combined solution of DRP and ESS performs better than the other CSs, resolving excess power generation and shortage power supply issues while improving both objective function indicators. Considering user satisfaction and billing functions adds complexity to the problem-solving process but can encourage user participation in DRP and enhance economic and environmental aspects. Future work can involve the integration of electric vehicles to eliminate the need for power imports from the main grid and further reduce pollution. Additionally, investigating the effect of economic dispatch on the objective function during planning can provide insights for further improvements.

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Abbreviations

List of acronyms.

Symbol	**Meaning**
2PEM	Two-Point Estimate Method
CHP	Combined Heat and Power
DER	Distributed Energy Resource
DG	Diesel Generator
DRP	Demand Response Program
DSO	Distributed System Operator
EMS	Energy Management System
ESS	Energy Storage System
GA	Genetic Algorithm
ISO	Independent System Operator
MINLP	Mixed-Integer Non-linear Programming
PSO	Particle Swarm Optimization
PV	Photovoltaic
RES	Renewable Energy Source
SVPP	Sustainable Virtual Power Plant
TOU	Time of Use
VPP	Virtual Power Plant
WT	Wind Turbine

List of symbols.

Abbreviation	**Meaning**
$i,\ I$	Index for WT
$j,\ J$	Index for PV
$m,\ M$	Index for DG
$n,\ N$	Index for ESS
$t, c,\ T$	Index for time (hour)
un	Index for uncertainty parameters
$a_k,\ b_k,\ c_k$	Coefficients of DG cost function
$C_{ES_n}(t),\ C_{MESS_n}(t)$	Operational ($/MWh) and maintenance costs of ESS ($)
$C_{OPV_j}(t),\ C_{CPV_j}(t)$	Operational ($/MWh) and constant costs of PV ($)
$C_{OWT_i}(t),\ C_{CWT_i}(t)$	Operational ($/MWh) and constant costs of WT ($)
$C_{NG}(t),\ C_{eNG}(t)$	Total ($) and operational costs of natural gas ($/MWh)
$CO_2^{DG_m},\ SO_2^{DG_m},\ NO_X^{DG_m}$	Emission factor of DG (kg/MWh)
$CO_2^{buy},\ SO_2^{buy},\ NO_X^{buy}$	Emission factor of main grid (kg/MWh)
$COST_{em}^{buy},\ COST_{em}^{DG_m}$	Cost of emission main grid and DG ($/kg)
$C_{ebuy}(t),\ C_{esell}(t)$	Cost of buying/selling power from/to the main grid ($/MWh)
$D_h(t),\ D_c(t)$	Heating and cooling loads (MW)
$DT_{DG_m},\ UT_{DG_m}$	The minimum up/minimum down-time of DG (hour)
$ES_{e_n}(0)$	Initial state of charge of ESS (MWh)
$ES_{e_n}^{min},\ ES_{e_n}^{max}$	Minimum and maximum energy of ESS (MWh)
G_{std}	Solar radiation in standard test condition (W/m^2)
$G(t)$	Solar radiation for normal operating cell temperature (W/m^2)
$D_e(t)$	Amount of load (MW)
$P^{\max line}$	Maximum capacity of transmission line (MW)
$P_{ES_n-ch}^{max},\ P_{ES_n-dch}^{max}$	Maximum charge and discharge rates of ESS (MW)
P_{rated_i}	Rated power of WT (MW)
P_{sn_j}	Rated power of PV (MW)
$P_{DG_m}^{min},\ P_{DG_m}^{max}$	Minimum and maximum power in operating of DG (MW)
R_c	Certain radiation point for PV (W/m^2)

$v_{ci},\ v_{co}$	Minimum and maximum wind speed (m/s)
v_r	Rated wind speed (m/s)
v	Wind speed (m/s)
ϑ	Elasticity
$\eta_{hc},\ \eta_{gh}^{f}$	Efficiency of chiller boiler and furnace (%)
$\eta_{ch}^{ES_n}, \eta_{dch}^{ES_n}$	Efficiency of charge and discharge (%)
η_{ee}	Efficiency of the transformer (%)
$\rho_1(t), \rho_2(t)$	Electricity prices before and after DRP
θ	Interval of operation
$Co_{DG_m}(t)$	Cost function of DG *m* ($)
$C_{DG}(t)$	Cost of all DGs ($)
$C_{ESS}(t)$	Cost of all ESSs ($)
$C_{PV}(t)$	Cost of all PVs ($)
$C_{WT}(t)$	Cost of all WTs ($)
$C_{buy}(t)$	Cost of buying energy ($)
$EM(t)$	Total emissions (kg)
$ES_{e_n}(t)$	Energy of ESS
$G_{NG}(t)$	Amount of energy for cooling and heating sector (MW)
$H_1(t),\ H_2(t)$	Amount of produced natural gas (MW)
$I_{DG_m}(t)$	Binary variable for on/off state DG *m*
$y_{DG_m}(t)$	Binary variable for start-up state DG *m*
$z_{DG_m}(t)$	Binary variable for shut-down state DG *m*
$P_{DG_m}(t)$	Amount produced power of DG *m* (MW)
$P_{PV_j}(t)$	Amount produced power of PV *j* (MW)
$P_{WT_i}(t)$	Amount produced power of WT *i* (MW)
$R_{sell}(t)$	Total costs of sold energy ($)
$ch_{ES_n}(t), dis_{ES_n}(t)$	Binary variable of charge and discharge modes
$Cost(t)$	Total costs of SVPP ($)
$DR(t)$	Power demand after implementation DRP (MW)
$E1_{WTi}(t),\ E2_{PVj}(t),\ E3_{DGm}(t)$	Power of WT, PV, and DG considering efficiency transformer (MW)
OF	Objective Function
$Cem(t)$	Total costs of emissions ($)

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