energies

Article

An Incentive-Based Implementation of Demand Side Management in Power Systems

Vasileios M. Laitsos [1,*], Dimitrios Bargiotas [1], Aspassia Daskalopulu [1], Athanasios Ioannis Arvanitidis [1] and Lefteri H. Tsoukalas [2]

[1] Department of Electrical and Computer Engineering, University of Thessaly, 38334 Volos, Greece; bargiotas@uth.gr (D.B.); aspassia@uth.gr (A.D.); atarvanitidis@uth.gr (A.I.A.)
[2] School of Nuclear Engineering, Purdue University, West Lafayette, IN 47907, USA; tsoukala@purdue.edu
* Correspondence: vlaitsos@uth.gr

Abstract: The growing demand for electricity runs counter to European-level goals, which include activities aimed at sustainable development and environmental protection. In this context, efficient consumption of electricity attracts much research interest nowadays. One environment friendly solution to meet increased demand lies in the deployment of Renewable Energy Sources (RES) in the network and in mobilizing the active participation of consumers in reducing the peak of demand, thus smoothing the overall load curve. This paper addresses the issue of efficient and economical use of electricity from the Demand Side Management (DSM) perspective and presents an implementation of a fully-parameterized and explicitly constrained incentive-based demand response program The program uses the Particle Swarm Optimization algorithm and demonstrates the potential advantages of integrating RES while supporting two-way communication between energy production and consumption and two-way power exchange between the main grid and the RES.

Keywords: demand side management; Demand Response; smart grid energy system; particle swarm optimization; energy efficiency

check for updates

Citation: Laitsos, V.M.; Bargiotas, D.; Daskalopulu, A.; Arvanitidis, A.I.; Tsoukalas, L.H. An Incentive-Based Implementation of Demand Side Management in Power Systems. *Energies* **2021**, *14*, 7994. https://doi.org/10.3390/en14237994

Academic Editors: Elpiniki I. Papageorgiou and Katarzyna Poczęta

Received: 7 November 2021
Accepted: 23 November 2021
Published: 30 November 2021

1. Introduction

Global electricity demand is constantly growing, and conventional power systems cannot meet production demands reliably. Global population growth, which results in higher energy consumption, and climate change, which calls for fossil fuel reduction, render conventional power systems incapable of responding to such demands. Their slow response due to mechanical switches, the one-way communication between electricity generation and demand, and the low level of information processing, are some of the disadvantages these conventional power systems present [1].

Hence novel energy management techniques are sought, which render transmission and distribution systems flexible and transform them from traditional to smart grids. The term Smart Grid (SG) refers to a power supply system that deploys digital technologies with large distribution networks to optimize energy consumption [2]. Whereas the sole function of a traditional grid is to transmit and distribute energy from the plant to the end user, the SG can detect values in normal as well as in error conditions along the entire length of its transmission lines (sensing along the transmission lines). Moreover, it can deploy computational tools, which aid significantly in efficient operation and planning. Novel Artificial Intelligence techniques and big data processing open up a whole new area of potentially useful applications, among which Demand Side Management features prominently [3,4].

The concept of Demand Side Management (DSM) first appeared in the late 1970s as an attempt to respond to the rising cost of electricity [5]. Essentially, it involves the planning, implementation and monitoring of all activities, which are designed to influence the customers' electricity consumption behavior with the ultimate goal of producing significant beneficial changes to the load curve [4]. The main advantages afforded by Demand Side Management in modern energy systems include [5,6]:

- Reduction of demand peaks (peak shaving) at the level of an entire country and power leveling, which is applied to each household separately.
- Reduction of total operation costs and reduction of costs for new construction of electricity generation and distribution infrastructure, such as long transmission lines and substations.
- Reliability and system stability.
- Environmental benefits, by reducing CO_2 emissions and thus reduction of the greenhouse effect.

Depending on the timing and the impact of the applied measures on the customer process, DSM can be categorized into the following four main types, as shown in Figure 1 [7,8].

A. Energy Efficiency (EE)
B. Spinning Reserve (SR)
C. Time of Use (TOU)
D. Demand Response (DR)

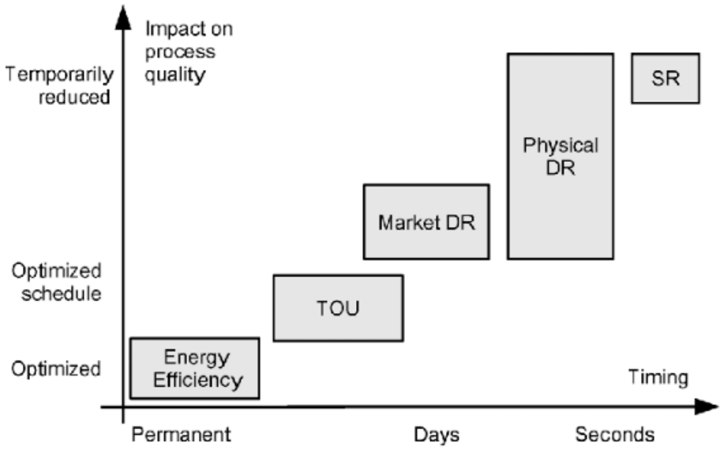

Figure 1. Demand Side Management Categories [8].

Energy Efficiency refers to measures taken by a consumer, or the electricity transmission management company, to remedy energy waste. This includes any permanent equipment changes, such as the replacement of an old, low-performance ventilation system with a new, more modern one, or improvements to the technical characteristics of a system (for example, adding additional insulation to a building) that aim to eliminate losses and increase overall efficiency. Such measures lead to immediate and permanent savings of energy, and lower gas emissions and are, therefore, an efficient method of saving technical and financial resources [8].

The term Spinning Reserve is used as a general concept throughout the electricity systems community and is defined as the sufficient amount of output reserved to be used to generate active power over a given period of time, should disturbances occur during the operation (e.g., some generator loss, failure on a transmission line etc.) or during the peak power demand. The purpose of SR is to restore the balance between generation and load, to restore frequency to its nominal value and to remedy power exchange on the tie-lines in the interconnected systems. Peak load reduction increases the reserve capacity and this in turn results in increasing the system security margins [9].

Time of Use is a load management method that proposes the measurement and charging of customers' electricity consumption based on the time it takes place, i.e., when it is used [10–12]. Time of use zone tariffs are the most common way of controlling consumer demand. Basically, the price will be expensive at times of high electricity demand and cheap at times of low demand. Prices for these periods are predetermined and communicated to consumers in advance, for them to adjust their daily habits and the way of using electricity based on the respective charges [11,12].

Figure 2 shows the price ratios of a TOU 2 tariff program "G12" (two zone tariff) for household consumers compared to the flat rate of "G11" (flat tariff), proposed to customers in north-western Poland in 2013 [11].

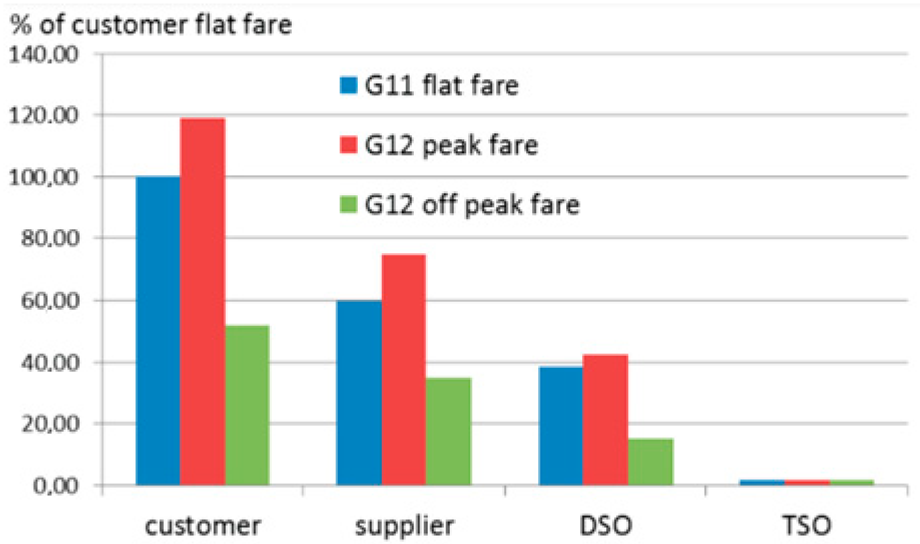

Figure 2. Time of Use pricing [11].

These charges include the price of the power supply and the grid transmission and distribution costs, which vary according to time zones. Participating customers are charged based on the prices of the Time Zone program of two zones in relation to the fixed pricing. Part of the cost corresponds to the supply side and the rest corresponds to distribution and transmission fees for the Distribution System Operator (DSO) and the Transmission System Operator (TSO) respectively [11].

The main purpose of these types of tariffs is to influence consumer habits, encouraging customers to shift the load out of peak zones, thus facilitating energy production and contributing to better use and maintenance of equipment. The latter, extends the lifecycle of a device and indirectly leads to saving resources and money. The variation of fares for each tariff zone should also reflect the expected benefits arising for all the parties that contribute to the production and distribution of the necessary energy [11].

The main advantage of the Time of Use (TOU) programs is the opportunity to meet the needs of high energy demand (such as heating) in periods of low load demand (off-peak), when market prices are below average, thus enabling energy to receive competitive prices and be comparable with other forms of heating. The prices offered to the consumers for the periods of non-peak energy demand, are much lower than the fixed prices, thus offering sufficient motivation to a customer to reduce his load and shift it to periods of low demand. [11]. Empirical results of the TOU pricing have shown that it is effective and decreases the peak energy demand [10]. TOU can be viewed as a crude form of Demand Response, i.e., without two-way communication or interaction between energy production and consumption.

This paper is concerned with the fourth kind of DSM, namely Demand Response programs, and presents an implementation of a model that we constructed which uses incentives, constraints, and the Particle Swarm Optimization algorithm to demonstrate the way in which the customer's consumption can be induced. First, Section 2 discusses Demand Response approaches in more detail, with emphasis on incentive-based techniques, relating them to DSM methods that aim to control the consumer's load curve. Section 2 concludes with a detailed presentation of the proposed implementation at the heart of which lie constraints. Section 3 provides the results obtained and Section 4 discusses them. Finally, Section 5 includes conclusions and directions for future work.

2. Demand Response Methods and Implementation

Demand Response was once a fundamental new way to maintain grid capability and utility at the optimal level. During the past two decades, Demand Response programs have become extremely interesting for the global research community, because they introduce new ways of maintaining the power balance between supply and demand [13]. Instead of the system administrator activating additional industrial power sources to meet the increased demands of peak loads, the demand is offset by the consumers. According to this approach, utility grid operators can exploit industrial, commercial, and domestic consumers for the benefit of the smooth operation and deployment of the power system [14].

The main reason these programs are called "Demand Response Programs" is because they are used in response to a request to limit electricity consumption, based on changes in pricing or at times when wholesale prices are high, or the reliability of the system is compromised. Demand Response is also a modern way for locally installed energy resources to add reciprocal value to both the power grid and consumers.

i. Demand Response Benefits

Demand Response creates benefits mainly from saving resources that improve electricity supply significantly. It is essential to track the flow of these benefits through the market to determine who is earning and how much. It is therefore important to identify the key benefits that these programs offer, which are described below [15]:

- Lower operating costs and savings on customer billing accounts.
- The lower prices in the wholesale market resulting from DR create reduced supply costs for retailers, with the result that almost all retail customers usually benefit from the savings of their accounts.
- Greater stability and robustness of the power system.
- Environmental benefits, including better land use, as a result of avoiding the installation of new electricity generation and distribution infrastructure [16].
- Real-time communication between the supply and the demand side.
- Sustainability: by shifting loads during peak hours and keeping the grid working steadily, DR programs help protect the system by managing real-time demand, achieving maximum efficiency, and ensuring back-up conditions [14].

ii. Participation of Demand Response Programs in the Wholesale Energy Market

Demand Response proves to be beneficial for both the supply and the demand side, as it restrains the ability of large companies in the market to influence and manipulate the price of electricity. DR program participants have more choice in the market, can manage their consumption efficiently and can influence the market, especially with market-based and dynamic pricing programs [15].

Figure 3 illustrates in a simplified way the impact of a DR program to the prices of the wholesale energy market.

The single selling price of electricity is determined by the intersection of the cumulative supply and demand curves. The cumulative supply curve has an upward trend, while the cumulative demand curve has a downward trend. Consumer DR has been shown to curb the ability of companies with a large market share to exert their power and shape price. During the California crisis of 2000–2001, it was reported that a small decrease in demand, close to 5% could result in a decrease in price close to 50% and this is because in places close to its maximum power system tendencies increase exponentially. A small reduction in demand would lead to a large reduction in production costs and in turn to a reduction in the electricity price. The fact that the supply curve is becoming steeper as energy capacity increases is a consequence of the tendency to maximize profit on the production side or is due to the high operating costs required to produce very high amounts of power [16].

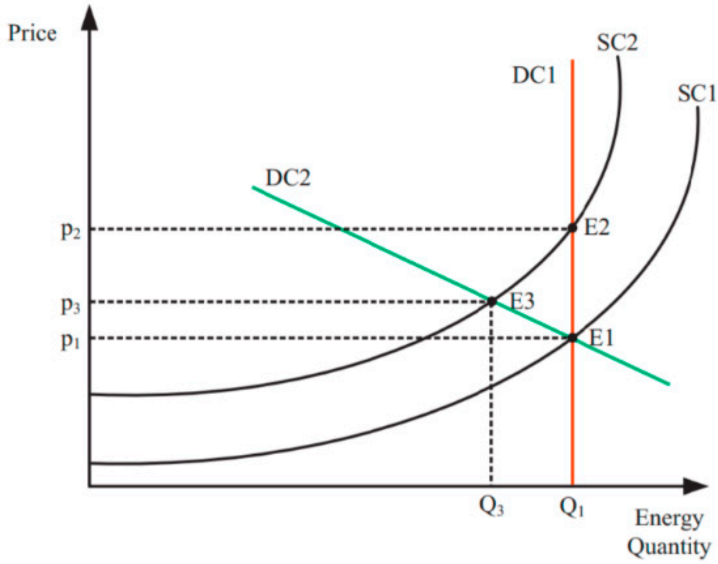

Figure 3. Impact of Demand Response on Electricity Market Prices [15].

The initial DC1 demand curve is vertical because it is initially assumed that DR programs are not implemented in the market. DR programs introduce a negative slope in the demand curve of participating customers and lead to a small reduction in demand and a fairly high reduction in the market price, as in the DC2 curve. The equilibrium value p_1 is the value at which the quantity offered, and the quantity demanded are equal and E_1 is the equilibrium point at which the curves DC1 and EC1 intersect. If consumer demand is represented by DC1, then the supply side will be able to manipulate and shape the price of electricity, thus shifting the supply curve to DC2 and increasing the market price to p_2, which corresponds to the new equilibrium point E_2. On the other hand, in case the demand side participates in DR market programs, it will be able to respond to prices, thus limiting price manipulation and achieving a different equilibrium point, E_3 and at a lower value (p_3).

In other words, the number of suppliers in the market is increasing through the improvement of the competition and the prices are becoming more and more consumer friendly.

iii. Categories of Demand Response

Demand Response programs can be classified according to their type and the way in which participating consumers respond according to their load profile. They are categorized into the Price-based programs and the Incentive- based programs. The two Demand Response categories with their subcategories are presented in Figure 4 [8].

The main difference between these two categories is that in the Incentive-based Demand Response programs, customers are offered payments to achieve the reduction of a certain amount of load in a given period of time, while in Price-based programs the customers voluntarily respond to the reduction of the load by reacting to some economic signals, depending on the offered market prices, i.e., there is no defined amount of load to which they are called to respond [15].

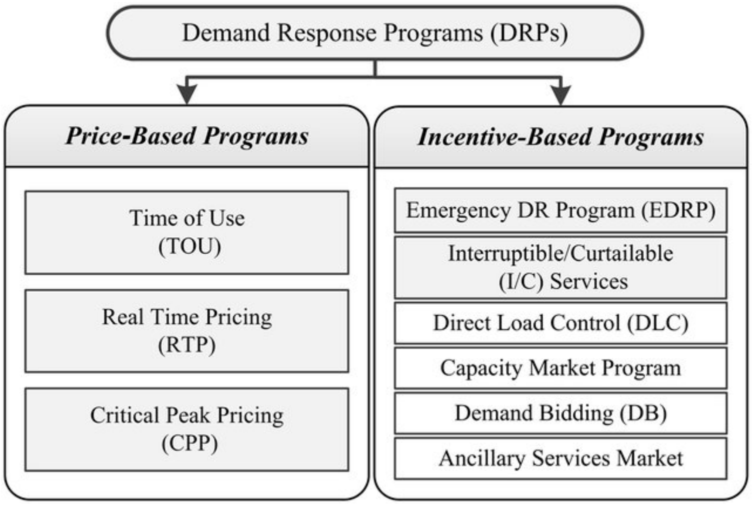

Figure 4. Categorization of Demand Response programs [17].

a. Price-based programs [8]

In Price-based programs, customers adjust electricity consumption in response to energy prices given to them. The main Price-based programs are described below:

- Time-Of-Use rates (TOUr): where a fixed pricing program is applied depending on the period of consumption.
- Real-Time Pricing (RTP): where end consumers are charged with prices that vary at short intervals.
- Critical Peak Pricing (CPP): where utilities anticipate high wholesale prices or system emergency conditions for certain periods of time and predetermine electricity sales prices in order to address these situations.

b. Incentive-based programs [8]

These programs are based on the response to strong incentives that are offered to customers, for them to modify their energy demand. The main Incentive- based programs are described below:

- Emergency Demand Response Programs (EDRP): where participating consumers respond voluntarily to emergency signals.
- Interruptible/Curtailable rates (I/C): where customers, in exchange for lower prices, must reduce energy consumption in a short period of time, which usually involves periods of high demand.
- Direct Load Control (DLC): where the operator or power distribution company can freely control, interrupt or postpone customer power consumption with a remote-control switch.
- Capacity Market Programs: where customers are guaranteed to contribute to meeting the needs of the grid when needed.
- Demand Bidding Programs (DB): where customers can submit consumption restriction bids at attractive prices.
- Ancillary Services Market: these are power system support services and are necessary to maintain the quality of power and reliability of the system.

This paper focuses on Incentive-based Demand Response, and specifically on emergency programs and interruptible/curtailable services. In an indirect way, depending on the agreement between the power provider and the consumer our approach can be viewed as related to Direct Load Control as well. The concept of incentive is based on the Time of Use approach.

2.1. Demand Side Management Methods

Six basic types have been established as techniques for DSM to control the consumer load curve, as shown in Figure 5 [18].

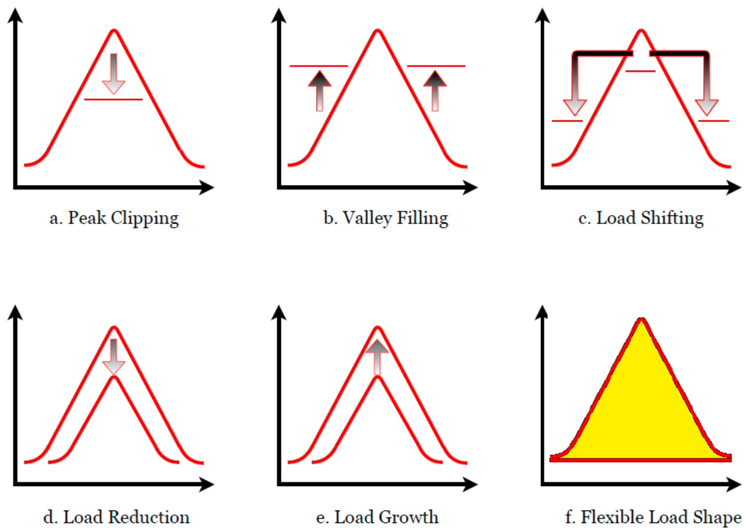

Figure 5. Methods of Demand Side Management.

a. Peak Clipping: The peak load reduction technique aims to limit consumer demand through direct control of consumer equipment utilities or through pricing contracts, where customers are required to reduce their load consumption at specific times of the day [19].

b. Valley Filling: Programs that use this technique aim to increase the energy consumption during off-peak hours. This results in a smoothing of the final load curve of the consumers. Therefore, the equipment of power plants, such as generators, transformers, transmission, and distribution lines, is loaded at 80–90% of their nominal values, instead of 15–20% during the hours of low demand, resulting in higher efficiency and reduced operating costs due to the improved load factor of the system [20].

c. Load Shifting: The load shifting technique involves shifting consumers load from peak to off-peak periods by reducing peak demand, but without a change in overall energy consumption. This is the reason why this method of load management is one of the most important ones [19].

d. Load Reduction: This method is also called as Energy Conservation. It is based on reducing electricity consumption, as evenly as possible during all or most hours of the day and is a non-traditional technique of managing and controlling the load. Under normal circumstances it is not considered a method of load management, because it manages consumption on a more general basis and its programs also include a reduction in the selling price of electricity, as well as modifications to the way it is used for consumer needs [20].

e. Load Growth: This method is also called as Load Building. It involves increasing market loads, resulting in an overall increase in electricity sales through new applications, such as investments in industrial automation systems and advanced electric cars. Figure 5 shows the overall shift of the demand curve upwards, as a result of the reported increase [20].

f. Flexible Load Shape: The main idea on which this method is based is the establishment of contracts between utilities and participants in consumer programs in order for the latter to change their electricity demand, when necessary, in exchange for financial incentives. In these programs, participating consumers should have the flexibility to change the demand curve and adjust their needs either for the immediate purposes of meeting increased grid demand or for indirect ones, such as securing the system's energy reserves [20].

The implementation described in this paper addresses mainly Load Shifting, Peak Clipping and Valley Filling. There are works in the area of Load Shifting and Peak Clipping (such as [21,22]), which demonstrate the effects of such techniques on system reliability. In [23] constraint programming is used in order to construct an optimal schedule for home appliances. In [24] the MOGA algorithm is used for load scheduling. Our implementation regards the optimal power reduction of a system at a specific time period, where the system comprises a main grid, a microgrid of RES and a conventional generating unit, and consumers. Emphasis is placed on using as much as possible RES and the application of Demand Response when most of the load must be covered by conventional generation. The main value of our implementation is in the model construction via mathematical formulations and in the explicit use of constraints that guide the application of the optimization algorithm.

2.2. Implementation of Incentive-Based Demand Response Program

The implementation on Demand Side of a pilot incentive-based DR program is supported with the programming platform MATLAB, and it concerns the period of one day (24 h). A first attempt was presented in [25]. The system consists of the Supply and Demand Side subsystems [26].

Supply Side contains the following two subsystems:

i. Microgrid: Microgrids have proved to be a critical technology to harness the Renewable Energy Sources (RES), to increase network stability and reliability and reduce the carbon footprint to the environment. In the implementation, it consists of a conventional diesel fuel generator, a wind turbine, and an installed array of photovoltaic cells.
ii. Main Grid: The role of the main grid is to meet the required demand in cases where the power generated by the microgrid is unable to meet the increased needs of consumers. There is also the possibility that in case the microgrid has excess power, it can sell it back to the main grid, and as a result have a financial profit from the transaction.

Demand Side contains two low-consumption commercial consumers, who participate in a Demand Response program based on incentives. The pilot implementation of the program concerns the participation of consumers actively throughout the 24 h, while giving them strong incentives to limit their demand.

Figure 6 shows the simplified model that is analysed, comprising the main grid, the connected microgrid and the two commercial customers.

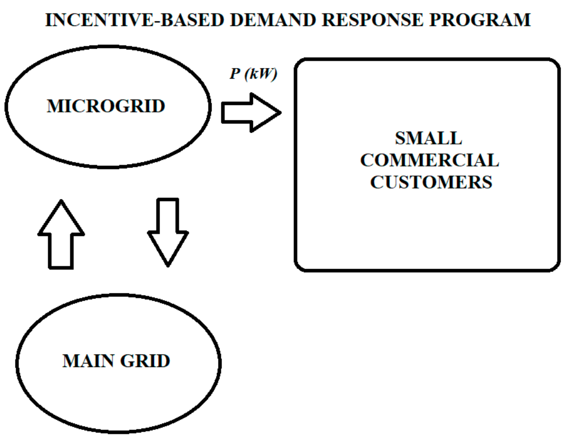

Figure 6. Simplified Power System.

The Particle swarm optimization algorithm (PSO) [27] is utilized to model and solve the problem. PSO is a computational method that finds an optimal solution to a problem by iteratively improving a candidate solution with reference to a given measure of quality, typically called objective function.

In our domain of investigation, we deploy PSO in order to find the best way for the power system to satisfy the total load of the two commercial consumers for the whole 24 h, giving priority to the use of the Renewable Energy Sources of the microgrid (installed Wind Turbine & Photovoltaic Array). The aim is twofold:

1. Minimize both the cost of purchasing energy from the main grid and the production costs of the conventional diesel generator; and
2. Maximize the financial benefit of the microgrid operator.

Now we turn to the mathematical formulation of the problem.

A. Mathematical Model Formulation Strategy

This subsection presents all mathematical models used in the PSO algorithm.

i. Mathematical Model of photovoltaic array

The hourly power generation of the photovoltaic array is given by the following equation [28,29]:

$$P_{PV} = n_{PV} * A_c * H_{(pu)} \quad (1)$$

where, n_{PV} is the efficiency of the photovoltaic array, A_c is the total area in m^2 it covers and $H_{(pu)}$ is the hourly index solar radiation ($KW * h/m^2$) on the PV array.

ii. Mathematical Model of Wind Turbine

The output power of a wind turbine depends on the direction and value of the wind speed, i.e., the stochastic behavior of the wind, which depends on the location of the wind turbine, the air density, the geometrical characteristics of the rotor blades and from the degree of conversion efficiency of the kinetic energy of the wind into electricity at the output of the wind turbine.

The mathematical model used to convert hourly wind speed to energy is as follows:

$$P_{wind} = 0.5 * \eta_w * \rho_{air} * C_p * A * V^3 \quad (2)$$

where, P_{wind} is the power generated by the wind turbine, η_w is the efficiency of the wind turbine given by the manufacturer, V is the wind speed at a specific height, ρ_{air} is the air density, C_p is the power factor of the wind turbine, which depends on its geometric characteristics, A is the scan surface of the wind turbine blades when the rotor rotates.

iii. Transfer Power Cost between Main Grid—Microgrid

The role of the main grid is to compensate for any lack of electricity that may exist due to high consumer demand, thus covering the "intermittent" operation of RES.

It is assumed that there is a trading program, according to which power can either be bought from the main electricity grid in case of shortage or sold to it from the microgrid in case of surplus. So, in case the supply of the microgrid cannot meet the total demand, then extra energy can be purchased from the main grid and vice versa. Our goal is for RES to take precedence over other sources of energy that can cover the demand that arises. Then, the total cost at time t (with t = [1, 24]) of the transferred power between main grid and microgrid at a given time is expressed by the following equation:

$$C_{trans}(t) = price * P_{trans}(t) \quad (3)$$

where, $C_{trans}(t)$ is the total cost of the transferred power between main grid and microgrid at time t, *price* is the charge price of the total electricity consumed in 1 h (€/KW) and $P_{trans}(t)$ is the transferred power.

This equation produces a positive value when power flows from the main grid to the microgrid ($P_{trans}(t) > 0$), a negative value when it flows from the microgrid to the main grid ($P_{trans}(t) < 0$), and zero when there is no transfer.

Hence, the first objective function $fun_1(t)$ is defined as:

$$fun_1(t) = \sum_{t=1}^{t=24} C_{trans}(t) \tag{4}$$

iv. Cost of Conventional Generator

The fuel cost function of the conventional generator $C_{gen}(t)$ is expressed in its square form and is as follows:

$$C_{gen}(t) = k_i * P_{gen}(t)^2 + m_i * P_{gen}(t) \tag{5}$$

where, $P(t)_{gen}$ is the generated power and $k_i,\ m_i$ the fuel cost coefficients. Thus, the second objective function $fun_2(t)$ is defined as follows:

$$fun_2(t) = \sum_{t=1}^{t=24} \left(C_{gen}(t)\right) \tag{6}$$

v. Consumer Contract Design

The cost of reducing the power of a consumer depends on both the type of consumer and the amount of power reduction, with the cost function of the customer $C(\theta, x)$ defined as [30]:

$$C(\theta, x) = K_1 * x^2 + K_2 * x - K_2 * x * \theta \tag{7}$$

In the above equation, the terms $K_1,\ K_2$ are the cost coefficients, x is the amount of reduction in consumption in KW and θ is a continuous variable that describes the type of customer participating in the program, taking values in the closed space 0–1. This variable allows us to model different types of customers, setting a different cost value for each type. Essentially, we set the value θ = 1 for customers who are more willing to reduce their electricity consumption and θ = 0 for those with the least desire. As for different customers θ changes, then the term $K_2 * x * \theta$ changes, accordingly, causing different values of the marginal cost. As the term θ increases, so does the marginal cost of each type of customer and vice versa. So, customers with low θ have lower marginal costs than those with higher θ and therefore a corresponding marginal benefit of reducing their costs. Note that the variable θ can also take discrete values, a scenario which will be used in the modeling that follows. For customers with zero reduction of their consumption power the cost $C(\theta, x = 0)$ is equal to 0.

vi. Demand Response Program

Parameter θ is not known to the utility company. Having a subjective estimate of the types of customers it serves, it develops the incentive function $y(x)$ to show how much it is willing to pay a customer for a certain amount of reduction in consumption, i.e., the value of this function is the sum of money which each customer will receive in return for reducing energy consumption.

The consumers participating in the program choose for themselves the amount of power they will reduce (quantity x) based on their knowledge of the incentive function given to them. It is obvious that consumers will not reduce their consumption unless they receive some economic benefit from such action. The benefit function of a consumer V_1 is defined as:

$$V_1 = y - c(\theta, x) = y - K_1 * x^2 - K_2 * x + K_2 * x * \theta \tag{8}$$

where, V_1 is the benefit function of a consumer, y is the incentive function given to a consumer, $K_1,\ K_2$ are the cost coefficients, x is the amount of reduction in consumption (KW) and θ is the continuous variable that describes the type of customer participating in the program.

Many DR programs, to encourage a new customer to participate, offer a one-off initial fixed amount as part of the total compensation customers will receive from power reduction. This scenario is considered in our implementation, as it would require a different conceptualization of the net monetary benefit of a consumer. In our case, for a new client to participate in the program, it is necessary for the following conditions to apply according to the theory of financial science contracts for each participant of the program [31]:

- A customer's decision to participate in the program should be encouraged by receiving a positive surplus. In other words, $V_1 \geq 0$ should apply, so that consumers can see a monetary benefit from reducing their consumption.
- The benefit function of a consumer (8) should be monotonic with respect to θ and non-decreasing with respect to x. According to the incentive compatibility mechanism, each participant in the program should be compensated according to the respective demand reduction he achieves. So, the determination of the amount of money each consumer is paid for participating in the power reduction at a specific hour t must be equitable and fair. This encourages each customer to be truthful about the index θ and to choose the right program for him. This is mathematically expressed as:

$$V_{1\theta} \geq V_{1\theta'} \tag{9}$$

where, θ' is the parameter of a customer preference if he stated it in the program incorrectly.

The utility can calculate the monetary value of its inability to supply a specific amount of power to a consumer. This value is parameterized by the factor λ, whose unit of measurement is (€/KW) and can be calculated using existing optimal power flow procedures. Essentially this factor is the cost incurred on the utility for not providing electricity to a consumer participating in the program. Knowledge of the factor λ allows the utility company to configure its own benefit function from a consumer $V_2(\theta, \lambda)$, as follows:

$$V_2(\theta, \lambda) = \lambda * x(\theta) - y(\theta) \tag{10}$$

where, $V_2(\theta, \lambda)$ is the utility benefit function, λ is the cost of not providing energy to a consumer, $x(\theta)$ is the amount of reduction in consumption (KW) and $y(\theta)$ is the incentive function given to a consumer and describes how much money the utility is willing to pay for a certain amount of power reduction.

The goal of the utility company is to maximize its benefit from the operation of the DR program for a whole day (t = 1:24 h), i.e., the maximization of the V_2 function. So, the third objective function $fun_3(t)$ is the following:

$$fun_3(t) = \sum_{t=1}^{t=24} \sum_{k=1}^{k=2} \{-V_2(\theta(k,t), \lambda(k,t))\} = \sum_{t=1}^{t=24} \sum_{k=1}^{k=2} \{y_{k,t} - \lambda_{k,t} * x_{k,t}\} \tag{11}$$

Therefore, three objective functions have emerged. The first aims to minimize the cost of energy imported from the main grid. The second aims to minimize the total fuel cost of the conventional generator and the third aims to maximize the financial benefit of the microgrid management company. Thus, the final objective function $Obj_{total}(t)$ is the following:

$$Obj_{total}(t) = z_1 * [fun_1(t) + fun_2(t)] + z_2 * fun_3(t) \tag{12}$$

where, z_1, z_2 are the weights associated with the constituent objective functions.

B. Solving Strategy

Equal function weights z_1, z_2 are selected, $z_1 = z_2 = 0.5$. This essentially reflects that we attribute equal importance to minimizing costs for the consumer (z_1) and for maximizing benefits for the utility company (z_2). It would, of course, be possible to run different scenarios by adjusting the values of the weights (so long as they sum to 1), to examine cases where the consumer is valued higher than the utility company. It should be noted that the costs associated with the consumer are essentially related to the environmental impact of the operation, hence increased values for z_1 would correspond to scenarios where environment protection is the critical issue.

The analysis is performed for the period of one day (24 h) and the decision variables for each hour of the day are the active output power of the wind turbine P_{WG}, the active output power of the photovoltaic array P_{PV}, the exchange power between main grid and microgrid P_{trans}, the output power of the conventional generator P_{gen}, the reduction power in response to the demand constraint for each consumer x_1, x_2 and the amount each consumer will receive as payment for the power reduction achieved, y_1, y_2.

C. Data Selection

i. PV Array Power Prediction Data

Solar data was calculated by the Photovoltaic Geographic Information System (PVGIS) which provides open access to solar data for any area of the earth, for interconnected and autonomous grid systems for different types of technologies. In our case, we dimension the nominal power of the array at 30 kW. The solar radiation database used is PVGIS-SARAH. The data are calculated in hourly average values, and we choose to install the park in the area of Thessaly, with latitude 39.371°, longitude 22.812° and altitude 216 m. System losses are set at 14%. The hourly values of photovoltaic power for the day 17 August 2016 are presented in Table 1.

Table 1. PV Power prediction data.

Time (Hours)	PV Power (KW)	Time (Hours)	PV Power (KW)
1	0	13	19.48
2	0	14	16.41
3	0	15	11.74
4	0	16	6.04
5	0.24	17	1.25
6	0.39	18	0
7	10.06	19	0
8	15.24	20	0
9	18.9	21	0
10	21.1	22	0
11	22.06	23	0
12	21.47	24	0

ii. Wind Turbine Power Prediction Data

The wind power generation data were adjusted to have a nominal value of 22 KW, based on [32] and are presented in Table 2.

Table 2. WG Power prediction data.

Time (Hours)	Wind Power (KW)	Time (Hours)	Wind Power (KW)
1	17.56	13	21.02
2	16.5	14	20.05
3	16.25	15	20.67
4	17.48	16	20.98
5	18.48	17	19.37
6	19.42	18	19.61
7	19.82	19	19.7
8	19.35	20	18.72
9	20.08	21	17.21
10	19.01	22	16.75
11	20.04	23	16.03
12	21.68	24	16.9

iii. Total Initial Consumer Demand

The total average value per hour of the initial hourly load demand of the two consumers is presented in Table 3.

Table 3. Total initial demand.

Time (Hours)	Demand Power (KW)	Time (Hours)	Demand Power (KW)
1	31.83	13	39.67
2	31.4	14	41.7
3	31.17	15	42.1
4	31	16	41.67
5	31.17	17	40.7
6	32.1	18	40.07
7	32.97	19	38.63
8	34.1	20	36.4
9	37.53	21	34.1
10	38.33	22	32.8
11	40.03	23	32.5
12	41.17	24	32

iv. Hourly Values of λ

The value λ is defined as the "power outage" cost for the utility company and can be determined by optimal power flow techniques [30]. Table 4 shows the hourly values of λ in relation to the total average hourly demand, which were adjusted by [32] and we consider to be common to both consumers.

Table 4. Hourly values of λ.

Time (Hours)	λ (€/KW)	Time (Hours)	λ (€/KW)
1	0.157	13	0.73
2	0.14	14	0.78
3	0.22	15	0.85
4	0.376	16	0.71
5	0.45	17	0.68
6	0.47	18	0.63
7	0.504	19	0.58
8	0.535	20	0.42
9	0.67	21	0.38
10	0.616	22	0.301
11	0.638	23	0.253
12	0.682	24	0.142

v. Conventional Generator

Table 5 shows the fuel cost coefficients of the conventional Diesel generator, the corresponding maximum and minimum value of its generated power, as well as the maximum rates of increase and decrease of production, based on [28].

Table 5. Conventional generator data.

$P_{gen,min}$ (KW)	$P_{gen,max}$ (KW)	k_i	m_i	Max Increase Rate (KW)	Max Decrease Rate (KW)
0	9	0.04	0.3	8	8

vi. Commercial Consumer

For the two commercial consumers, the data of consumer type, daily power interrupt limits and cost coefficients for each consumer, are presented in Table 6, based on [29].

Table 6. Consumer type, daily power interrupt limits and cost coefficients for each consumer.

	θ	Max Limit/Day (KW)	K_1	K_2
Consumer 1	0.5	50	0.108	0.132
Consumer 2	0.6	60	0.184	0.164

D. Constraints

A central feature of our implementation is the explicit deployment of constraints that guide the application of the PSO algorithm in finding the optimal solution. All constraint formulae refer to parameters that can be set for each run of the implementation, thus enabling experimentation with different sizes of, microgrid and number of consumers, different power capacity for the generation units, different utility company incentives budgets and policies towards consumers of different profiles, and so on. The constraints employed are, in detail, as follows:

- For each hour t of the day, the system must be in power balance. The total power produced by the wind turbine, the photovoltaic array, the conventional generator and the main grid should be equal to the total required power of the two consumers. Mathematically this condition is expressed through the following constraint:

$$P_{gen}(t) + P_{PV}(t) + P_{WG}(t) + P_{trans}(t) = TD(t) - \sum_{k=1}^{k=2} P_{curtail,k}(t) \tag{13}$$

where, $TD(t)$ is the total requested power of the consumers and $P_{curtail,k}(t)$ is the reduced power of the consumer k, $(where\ k = 1,2)$.

- For each hour of day t, the power output of both the wind turbine and the photovoltaic array should be within acceptable limits:

$$0 \le P_{PV}(t) \le P_{PV,\ max} \tag{14}$$

$$0 \le P_{WG}(t) \le P_{WG,\ max} \tag{15}$$

- The maximum active power exchanged between the main grid and the microgrid must be within the specified limits, in accordance with the following condition:

$$|P_{trans}(t)| \le P_{trans,\ max} \tag{16}$$

- Production of the conventional generator must be within limits:

$$P_{gen,\ min} \le P_{gen}(t) \le P_{gen,\ max} \tag{17}$$

- About the rate of change of the output power of the generator, an increase or decrease from time t to time t + 1 of requested production may not be instantaneous, but must be within certain limits, according to the condition:

$$-P_{limit,\ min} \le \Delta P_i \le P_{limit,\ max} \tag{18}$$

where, $\Delta P_i = P_{gen}(t+1) - P_{gen}(t)$, $P_{limit,\ max}$ is the upper limit of increase of the generated power and $P_{limit,\ min}$ is the lower limit of its decrease.

- The utility company knows the coefficients of the cost function K_1, K_2 of each customer and sets a daily budget $Total\ y_{cost}$ regarding the daily total compensation to be paid for both customers, which is set at 150€. The corresponding condition is the following:

$$\sum_{t=1}^{t=24}\sum_{k=1}^{k=2} y_{t,k} \leq Total\ y_{cost} \tag{19}$$

- The utility company also knows each of the two consumers' maximum ability to reduce their daily power $Max\ Limit/Day$, which helps it in determining the parameter θ for each customer. For each customer the maximum capacity to reduce his daily power must be at most equal to the total reduced power it achieves for each hour of the day, in which case the following condition is formed:

$$Max\ Limit/Day_k \geq \sum_{t=1}^{t=24} x_{k,t},\ k = 1,2 \tag{20}$$

- Finally, for the pricing of the exchange power between the main grid and the microgrid, the value 0.12 €/kWh is used [33].

3. Results

The initial curve of total hourly demand of the two commercial consumers of the program is presented in Figure 7. It is noteworthy that the peak of demand appears between the hours 10 a.m.–7 p.m., which may be due to increased commercial needs the two consumers are required to cover during that time.

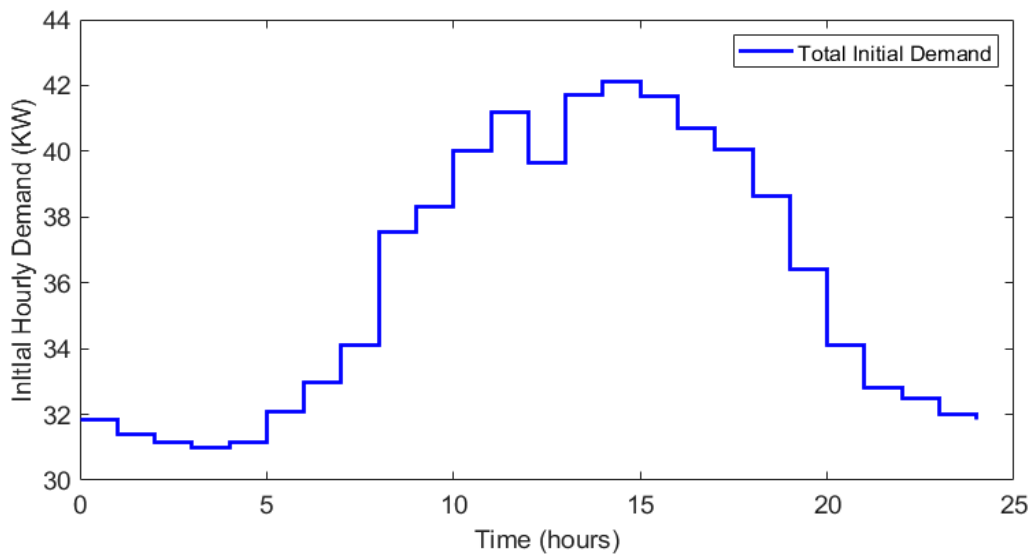

Figure 7. Initial total demand.

3.1. Conventional Generator Power

Table 7 and Figure 8 show the optimum hourly power produced by the conventional microgrid diesel generator for the period of 24 h, with the generator presenting a continuous operation at all hours.

Table 7. Conventional generator power.

Time (Hours)	P_{gen} (KW)	Time (Hours)	P_{gen} (KW)
1	6.68	13	1.18
2	6.9	14	6.17
3	6.92	15	1.02
4	5.52	16	8.95
5	8.69	17	7.29
6	8.44	18	7.21
7	5.26	19	6.93
8	0.69	20	5.68
9	6.21	21	8.89
10	4.42	22	8.05
11	2.89	23	8.47
12	1.43	24	7.1

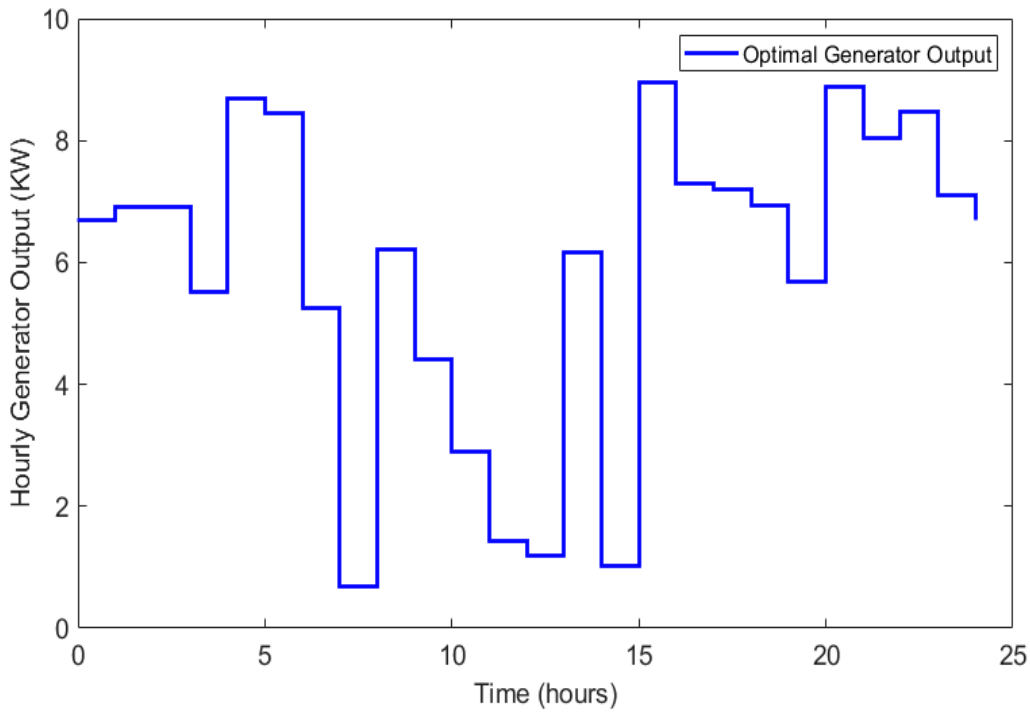

Figure 8. Optimal hourly output power of the conventional generator.

3.2. Exchange Power between Main Grid and Microgrid

The optimal hourly exchange between the main grid and the microgrid, as a results of the simulation of our algorithm taking into consideration a specific scenario in terms of parameters and the imposed constraints, is presented in Table 8 and Figure 9.

Table 8. Exchange power between main grid and microgrid.

Time (Hours)	P_{trans} (KW)	Time (Hours)	P_{trans} (KW)
1	4	13	−4
2	4	14	−4
3	4	15	4
4	3.99	16	−4
5	4	17	4
6	4	18	4
7	4	19	4
8	4	20	4
9	−4	21	4
10	−4	22	4
11	−4	23	4
12	−4	24	4

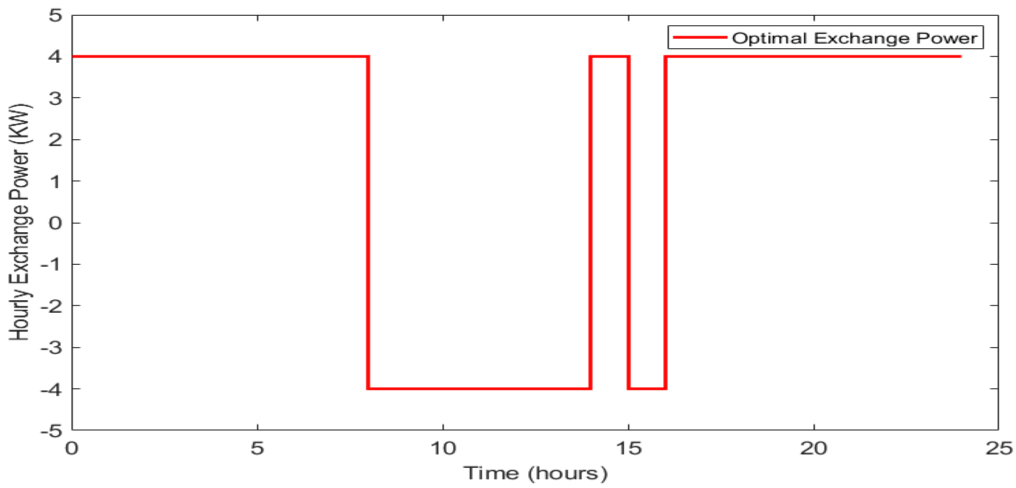

Figure 9. Optimal hourly exchange power.

3.3. *Wind Turbine Generated Power*

Figure 10 shows the variation of the hourly produced power from the wind turbine.

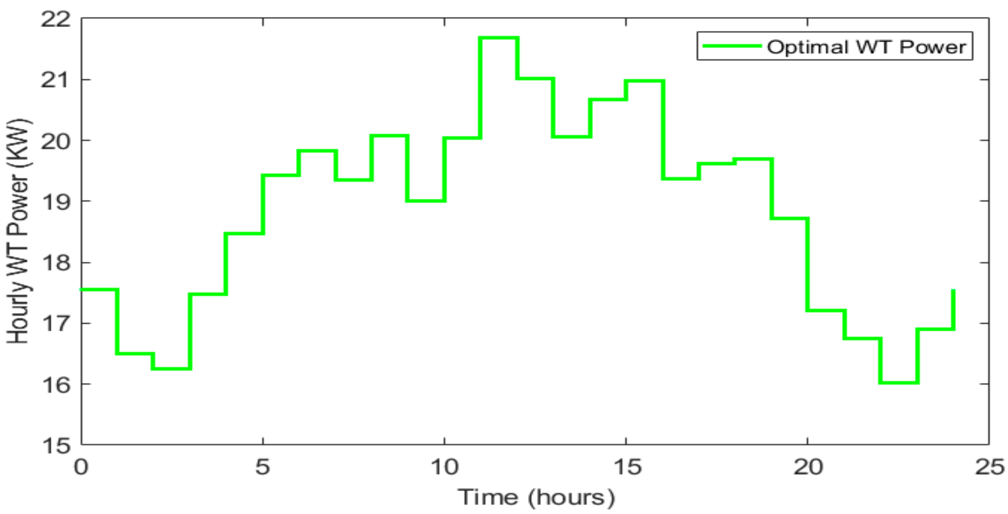

Figure 10. Optimal hourly WG power.

3.4. *PV Generated Power*

Figure 11 shows the variation of the hourly produced power from the PV array.

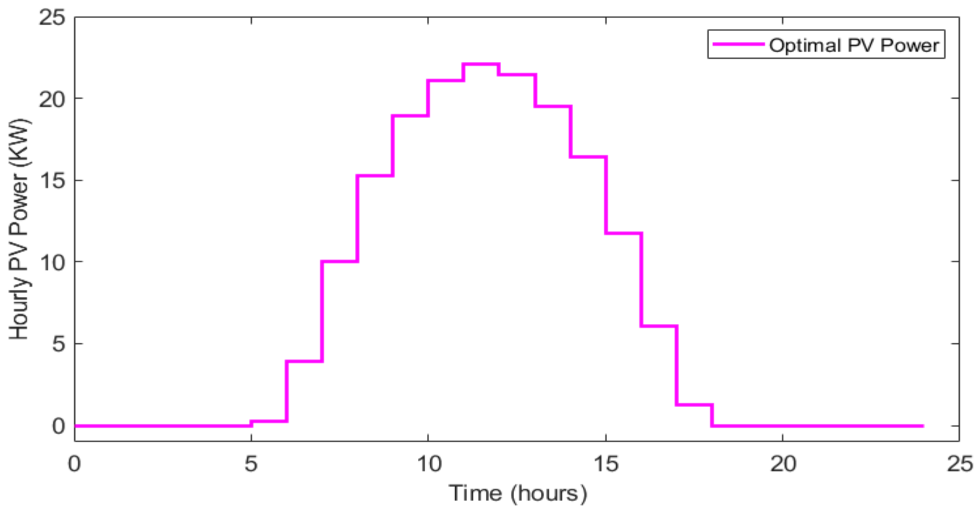

Figure 11. Optimal PV Generated Power.

3.5. Optimal Hourly Consumer Reduction Power

The optimal hourly values of the power reduction of the two consumers of the system because of their participation in the Demand Response program are presented in Table 9 and in Figure 12 respectively. Essentially load shifting occurs because a customer defers his consumption to a different time period beyond the 24 h window that we examine. Within this window power reduction actually refers to load shedding. As a result of such shifting and load coverage at a different time consumers enjoy some financial reward, which results from some incentive tariffs. For example, the utility company may reward shifting load from off peak periods at a certain low rate (e.g., 10% off the normal price), shifting load from mid peak periods at a medium rate (e.g., 20% off the normal price) and shifting load from on peak periods at a high rate (e.g., 30% or more off the normal price). A utility company may be offering a flat incentive to all customers, or a customised one for valued customers, based on the time of consumption and customer profile information.

Table 9. Optimal hourly power reduction per consumer.

Time (Hours)	Consumer 1 (KW)	Consumer 2 (KW)	Time (Hours)	Consumer 1 (KW)	Consumer 2 (KW)
1	0	3.58	13	0	0
2	0	4	14	0	0
3	4	0	15	0	0
4	0	4	16	4	0
5	0	0	17	3.99	0
6	0	0	18	4	4
7	0	0	19	4	4
8	0	0	20	4	4
9	0	0	21	4	0
10	0	0	22	4	0
11	0	0	23	4	0
12	0	0	24	0	4

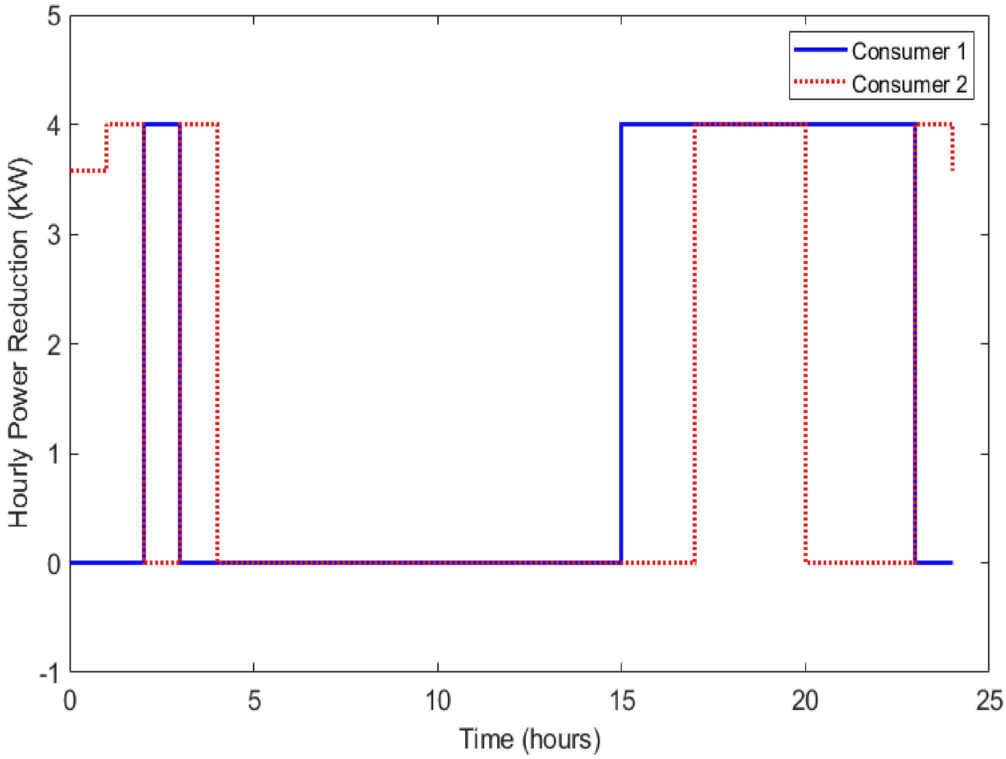

Figure 12. Hourly power reduction for each consumer.

As can be seen from Table 9, consumer 1 shifts a total of approximately 36 KWh and consumer 2 shifts a total of approximately 28 KWh.

3.6. Hourly Incentive Payment

The hourly amounts that the two consumers receive as compensation for their participation in the Demand Response program and the reduction of their consumption are presented in Table 10 and in Figure 13.

Table 10. Hourly inventive payment per consumer.

Time (Hours)	Consumer 1 (€)	Consumer 2 (€)	Time (Hours)	Consumer 1 (€)	Consumer 2 (€)
1	0	2.6	13	0	0
2	0	3.22	14	0	0
3	1.99	0	15	0	0
4	0	3.22	16	1.99	0
5	0	0	17	1.99	0
6	0	0	18	1.99	6
7	0	0	19	6	3.21
8	0	0	20	1.99	3.22
9	0	0	21	6	0
10	0	0	22	6	0
11	0	0	23	1.99	0
12	0	0	24	0	3.21

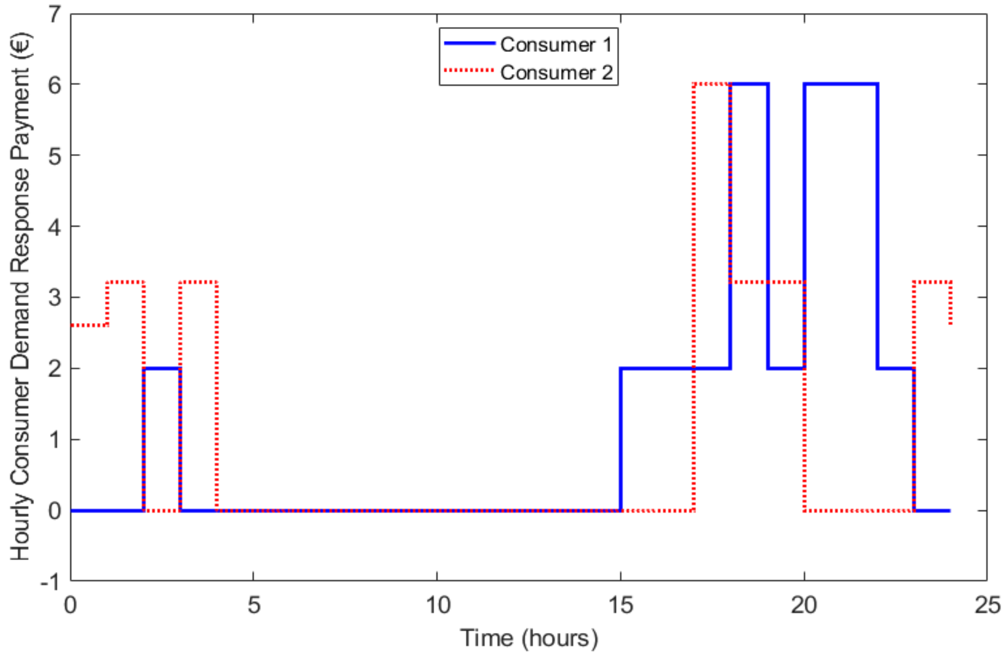

Figure 13. Hourly consumer payment.

4. Discussion

The results of the implementation present interesting data regarding the behavior of the microgrid and its cooperation with the main grid. According to Figure 14, the conventional diesel generator operates almost uninterruptedly throughout the 24 h, except at 8 o'clock where it presents almost zero output but does not reach its nominal operating value at any point in time, because power demands are partly covered by the RES. It is observed that during the hours when there is lack of solar energy and therefore the PV shows zero output, the presence of the conventional generator is more intense, reaching up to an output power equal to 8.95 kW. The stronger presence of Renewable Energy Sources reduces the presence of conventional form of production, which is desirable. However, during low penetration of RES the Demand Response plays a critical role and is most used in order to balance load demand and generation.

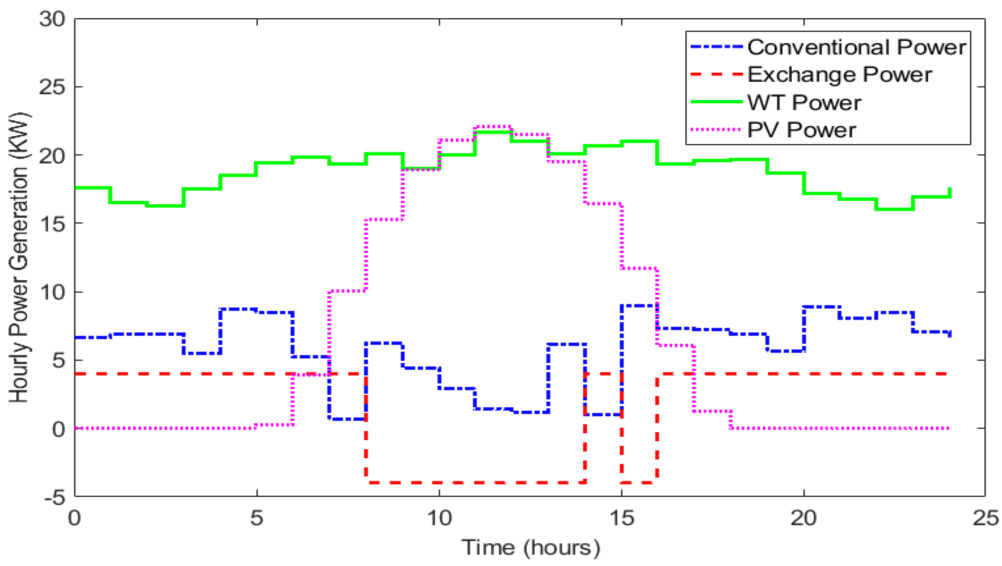

Figure 14. Total hourly power generation of all sources.

Of particular interest is the curve of exchanged active power between main grid and microgrid. When it is positive, then the microgrid purchases power from the main grid and when it is negative it sells excess power to it. According to Figure 14, in the first 8 h the microgrid purchases energy to meet consumer demands. Then for a period of 8 h, the microgrid can sell energy back to the main grid, until the solar power becomes zero and then the need to buy energy for the rest of the day emerges again. When the RES is in full load flow, there is power available for sale in the main grid, especially when the photovoltaic array is fully operational.

As can be noticed above, wind and solar power are the basic sources of the microgrid and the goal is to operate them 24 h a day, as it happens.

Regarding the participation of customers in the DR program, studying the form of Figure 12, it is observed that both consumers are forced to reduce their demand when the PV array produces zero or relatively little power, because the sum of the wind turbine output power and the input power from the main grid are unable to meet the initial total hourly demand.

The total energy reduction of the consumption of the two consumers and the total monetary reward that each customer will receive depending on λ are presented in Table 11. The Table also shows savings that arise from load shifting from on to off peak periods, due to participation of the consumer to the demand response program which offers him as incentive a 30% return of the total compensation.

Table 11. Total energy reduction and total compensation for each consumer.

	Energy Reduction (KWh)	Total Compensation (€)	Incentive Saving (€)
Consumer 1	35.99	29.95	8.985
Consumer 2	27.58	24.70	7.410
Total	63.57	54.65	16.395

Both consumers are forced to reduce their consumption, without however having to reach the upper limits, as agreed with the rule's administrator of the program. Thus, the system can respond to and handle unpredictable conditions of lack of electricity, which is a goal of the large-scale and advanced Smart Grids [34]. This fact is encouraging as it creates backup conditions in emergencies, such as the case of damage to the photovoltaic array for some hours of the day. The parameters θ are almost the same for the two consumers, which in turn contributes to the formation of the total final reduction power and respectively to the monetary compensation for each one.

5. Conclusions

This paper discusses an implementation of an incentive-based Demand Response program, which employs the PSO algorithm to induce customers to reduce their energy consumption. Beyond the obvious benefits afforded by the replacement of conventional power produced with RES, as illustrated by the implementation, the main contribution of this work to the broader area of Demand Side Management lies in the modelling, and specifically in the constraints that are incorporated explicitly in the implementation.

All the values specified in constraint formulae are parameterized, thus enabling experimentation from the perspective of the customer as well as from the perspective of the utility company. Indirectly, the customer perspective is related to the environmental impact of power generation, and such experimentation can be particularly useful to policy makers, for example to decide appropriate values for the tariffs used in incentives, or to decide the number of RES that can be employed if some particular environmental target values must be met (e.g., net zero by 2050).

Furthermore, a utility company may offer bespoke incentives to customers based on their past demands, the revenue they generate for the main grid, and the periods of consumption that they tend to concentrate their activities (on/mid/off peak).

In the future we intend to apply the model and experiment with varying numbers of consumers, varying consumer profiles, varying incentive tariffs, and varying availability of RES depending on geographical location which affects climate conditions. We hope, thus, to contribute to the creation of a testbed for other incentive-based demand response programs. The purpose of Demand Response is typically to level the demand curve, and often as a result power generation cost reduction is achieved both for the supplier and the consumer, as well as lower emissions. Studies in [35,36] use PSO in a similar manner with specific target values in mind. In our approach rather, we discover potential target values, and whether these are achievable can be determined with further experimentation using our implementation.

Author Contributions: Conceptualization, V.M.L.; Data curation, V.M.L. and A.I.A.; Formal analysis, V.M.L. and D.B.; Investigation, V.M.L., D.B. and A.D.; Methodology, V.M.L. and D.B.; Project administration, D.B., A.D. and L.H.T.; Resources, V.M.L. and A.I.A.; Software, V.M.L.; Supervision, D.B., A.D. and L.H.T.; Validation, V.M.L., D.B. and A.D.; Visualization, V.M.L. and A.I.A.; Writing—original draft, V.M.L.; Writing—review & editing, V.M.L., D.B., A.D. and L.H.T. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data used in this study are openly available at https://ec.europa.eu/jrc/en/pvgis (accessed on 15 July 2021).

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations and mathematical symbols are used in the manuscript.

$C_{gen}(t)$	Cost of Conventional Generator
$C_{trans}(t)$	Transfer Power Cost between Main Grid and Microgrid
$C(\theta, x)$	Cost function of the consumer
DR	Demand Response
DSM	Demand Side Management
P_{PV}	Power of the Photovoltaic Array
P_{wind}	Power of the Wind Turbine
RES	Renewable Energy Sources
SG	Smart Grid
SR	Spinning Reserve
TOU	Time of Use
V_1	Benefit Function of a Consumer
V_2	Utility company Benefit Function

References

1. Keles, C.; Alagoz, B.B.; Kaygusuz, A. A note on demand side load management by maximum power limited load shedding algorithm for smart grids. In Proceedings of the 3rd International Istanbul Smart Grid Congress and Fair (ICSG), Istanbul, Turkey, 29–30 April 2015; pp. 1–5. [CrossRef]
2. Viel, F.; Augusto, S.L.; Leithardt, V.R.Q.; De Paz Santana, J.F.; Celeste, R.G.T.; Albenes, C.Z. An Efficient Interface for the Integration of IoT Devices with Smart Grids. *Sensors* **2020**, *20*, 2849. [CrossRef]
3. Prieto, G.L.; Fensel, A.; Gómez, B.J.M.; Popa, A.; de Amescua Seco, A. A Survey on Energy Efficiency in Smart Homes and Smart Grids. *Energies* **2021**, *14*, 7273. [CrossRef]
4. Miceli, R. Energy Management and Smart Grids. *Energies* **2013**, *6*, 2262–2290. [CrossRef]
5. Chen, X.-T.; Zhou, Y.-H.; Duan, W.; Tang, J.-B.; Guo, Y.-X. Design of intelligent Demand Side Management system respond to varieties of factors. In Proceedings of the CICED, Nanjing, China, 13–16 September 2010; pp. 1–5.
6. Hossain, M.M.; Zafreen, K.R.; Rahman, A.; Zamee, M.A.; Aziz, T. An effective algorithm for demand side management in smart grid for residential load. In Proceedings of the 4th International Conference on Advances in Electrical Engineering (ICAEE), Dhaka, Bangladesh, 28–30 September 2017; pp. 336–340. [CrossRef]
7. Zhang, N.; Ochoa, L.F.; Kirschen, D.S. Investigating the impact of demand side management on residential customers. In Proceedings of the 2nd IEEE PES International Conference and Exhibition on Innovative Smart Grid Technologies, Manchester, UK, 5–7 December 2011; pp. 1–6. [CrossRef]

8. Palensky, P.; Dietrich, D. Demand Side Management: Demand Response, Intelligent Energy Systems, and Smart Loads. *IEEE Trans. Ind. Inform.* **2011**, *7*, 381–388. [CrossRef]
9. Tur, M.R.; Selim, A.Y.; Erduman, A.; Shobole, A.; Wadi, M. Impact of Demand Side Management on Spinning Reserve Requirements Designation. *Int. J. Renew. Energy Res.* **2017**, *7*, 946–953.
10. Jang, M.; Jeong, H.-C.; Kim, T.; Joo, S.-K. Load Profile-Based Residential Customer Segmentation for Analyzing Customer Preferred Time-of-Use (TOU) Tariffs. *Energies* **2021**, *14*, 6130. [CrossRef]
11. Andruszkiewicz, J.; Lorenc, J.; Borowiak, W.; Michalski, A. Time of use tariff design for domestic customers integrating the management goals of efficient energy purchase and delivery. In Proceedings of the 12th International Conference on the European Energy Market (EEM), Lisbon, Portugal, 19–22 May 2015; pp. 1–5. [CrossRef]
12. Muzmar, M.A.R.; Abdullah, M.P.; Hassan, M.Y.; Hussin, F. Time of Use pricing for residential customers case of Malaysia. In Proceedings of the IEEE Student Conference on Research and Development (SCOReD), Kuala Lumpur, Malaysia, 13–14 December 2015; pp. 589–593. [CrossRef]
13. BintoBintoudi, A.D.; Bezas, N.; Zyglakis, L.; Isaioglou, G.; Timplalexis, C.; Gkaidatzis, P.; Tryferidis, A.; Ioannidis, D.; Tzovaras, D. Incentive-Based Demand Response Framework for Residential Applications: Design and Real-Life Demonstration. *Energies* **2021**, *14*, 4315. [CrossRef]
14. ENCORP. Available online: http://encorp.com/demand-response/ (accessed on 15 July 2021).
15. Paterakis, N.G.; Erdinç, O.; Catalão, J.P.S. An overview of Demand Response: Key-elements and international experience. *Renew. Sustain. Energy Rev.* **2017**, *69*, 871–891. [CrossRef]
16. Albadi, M.H.; El-Saadany, E.F. A summary of demand response in electricity markets. *Electr. Power Syst. Res.* **2008**, *78*, 1989–1996. [CrossRef]
17. Shafie-khah, M.; Heydarian-Forushani, E.; Osório, G.J.; Gil, F.A.S.; Aghael, J.; Barani, M.; Catalão, J.P.S. Optimal Behavior of Electric Vehicle Parking Lots as Demand Response Aggregation Agents. *IEEE Trans. Smart Grid* **2016**, *7*, 2654–2665. [CrossRef]
18. Shewale, A.; Mokhade, A.; Funde, N.; Bokde, N.D. An Overview of Demand Response in Smart Grid and Optimization Techniques for Efficient Residential Appliance Scheduling Problem. *Energies* **2020**, *13*, 4266. [CrossRef]
19. Matthews, B.; Craig, I.K. Demand Side Management by Load Shifting a Run-of-Mine Ore Milling Circuit. *IFAC Proc. Vol.* **2012**, *45*, 84–89. [CrossRef]
20. Singh, S.; Chandra, S. Energy Efficiency and Demand Side Management. *Int. Adv. Res. J. Sci. Eng. Technol. (IARJSET)* **2015**, *2*. Available online: https://iarjset.com/upload/2015/si/ncree-15/IARJSET%2090%20P170.pdf (accessed on 15 July 2021).
21. Dharani, R.; Balasubramonian, M.; Babu, T.S.; Nastasi, B. Load Shifting and Peak Clipping for Reducing Energy Consumption in an Indian University Campus. *Energies* **2021**, *14*, 558. [CrossRef]
22. Abir, H.J.; Teh, J.; Ishak, D.; Abunima, H. Impact of Demand-Side Management on the Reliability of Generation Systems. *Energies* **2018**, *11*, 2155. [CrossRef]
23. Kong, X.; Zhang, S.; Sun, B.; Yang, Q.; Li, S.; Zhu, S. Research on Home Energy Management Method for Demand Response Based on Chance-Constrained Programming. *Energies* **2020**, *13*, 2790. [CrossRef]
24. Ullah, K.; Ali, S.; Khan, T.A.; Khan, I.; Jan, S.; Shah, I.A.; Hafeez, G. An Optimal Energy Optimization Strategy for Smart Grid Integrated with Renewable Energy Sources and Demand Response Programs. *Energies* **2020**, *13*, 5718. [CrossRef]
25. Laitsos, V.M.; Bargiotas, D. Impact of Demand Side Management Methods on Modern Power Systems. In Proceedings of the 56th International Universities Power Engineering Conference (UPEC), Middlesbrough, UK, 31 August–3 September 2021; pp. 1–6. [CrossRef]
26. Muqeet, H.A.; Munir, H.M.; Javed, H.; Shahzad, M.; Jamil, M.; Guerrero, J.M. An Energy Management System of Campus Microgrids: State-of-the-Art and Future Challenges. *Energies* **2021**, *14*, 6525. [CrossRef]
27. Bonyadi, M.R.; Michalewicz, Z. Particle swarm optimization for single objective continuous space problems: A review. *Evol. Comput.* **2017**, *25*, 1–54. [CrossRef]
28. Tazvinga, H.; Zhu, B.; Xia, X. Energy dispatch strategy for a photovoltaic–wind–diesel–battery hybrid power system. *Sol. Energy* **2014**, *108*, 412–420. [CrossRef]
29. Shayeghi, H.; Asefi, S.; Shahryari, E.; Dolatabad, R.D. Optimal management of renewable energy sources considering split-diesel and dump energy. *Int. J. Tech. Phys. Probl. Eng. (IJTPE)* **2018**, *10*, 34–40. Available online: https://www.researchgate.net/publication/321006362_OPTIMAL_MANAGEMENT_OF_RENEWABLE_ENERGY_SOURCES_CONSIDERING_SPLIT-DIESEL_AND_DUMP_ENERGY (accessed on 15 July 2021).
30. Fahrioglu, M.; Alvarado, F.L. Designing incentive compatible contracts for effective demand management. *IEEE Trans. Power Syst.* **2000**, *15*, 1255–1260. [CrossRef]
31. Willems, B.; Zhou, J. The Clean Energy Package and Demand Response: Setting Correct Incentives. *Energies* **2020**, *13*, 5672. [CrossRef]
32. Nwulu, N.I.; Xia, X. Optimal dispatch for a microgrid incorporating renewables and demand response. *Renew. Energy* **2017**, *101*, 16–28. [CrossRef]
33. PPC, S.A. Business Tariffs. Available online: https://www.dei.gr/Documents2/TIMOLOGIA/07-10-2020-TIMOLOGIA/TIMOK-XT-2020-G21-OCT2020.pdf (accessed on 15 July 2021).
34. Sestrem, O.I.; Augusto, S.L.; de Mello, G.; Garcia, N.M.; de Paz Santana, J.F.; Quietinho, L.V.R. A Cost Analysis of Implementing a Blockchain Architecture in a Smart Grid Scenario Using Sidechains. *Sensors* **2020**, *20*, 843. [CrossRef]

35. Aghajani, G.R.; Shayanfar, H.A.; Shayeghi, H. Demand side management in a smart micro-grid in the presence of renewable generation and demand response. *Energy* **2017**, *126*, 622–637. [CrossRef]
36. Hassan, M.A.S.; Chen, M.; Lin, H.; Ahmed, M.H.; Khan, M.Z.; Chughtai, G.R. Optimization modeling for dynamic price based demand response in microgrids. *J. Clean. Prod.* **2019**, *222*, 231–241. [CrossRef]