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Distributed Energy Technologies Planning and Sizing in a Sample Virtual Power Plant Using Speedy Particle Swarm Optimization Algorithm

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Abstract

In modern power networks, once the restructuring of production units is done, traditional power plants will operate as virtual power plants (VPPs), which are actually a collection of distributed generation (DG) units and energy storage systems (ESSs) that form an integrated power plant. Commercial VPPs can replace the current traditional power plants in the near future, because they have many advantages such as organizing distributed energy resources (DER) and hydrogen and electricity storage systems. Considering that energy management and planning of DER resources in VPP have challenging issues, therefore, thoughts such as changes in instantaneous power generation, consumption, energy price and availability of system components should be taken into consideration, so that simulations and future research with problems will not accompanied. Since microgrids (MGs) have the ability to monitor and control real-time power in power grids, determining the number of DER resources in VPPs is deliberated essential in order to reduce planning costs. For this purpose, in this paper, the optimal sizing of DERs is done using speed particle swarm optimization (SPSO) algorithm. In proposed optimization algorithm, the coefficients c_1 and c_2 are not constant and is changing according to the number of iterations, which makes the search in the problem solving space more efficient and its convergence is improved by 26% compared to the traditional PSO algorithm. Consequently, the number and sizing of solar photovoltaic (PV), wind turbine (WT), fuel cell (FC), electrolyzer, hydrogen storage and battery resources in a 20-year time horizon will be achieved with the lowest cost.

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1. Introduction

Nowadays, the power grids around the world have faced to several concerns such as fossil fuel reduction, low energy efficiency, and environmental pollution [1,2]. These problems have increased the tendency to generate power at the distribution level [3,4]. Specific resources used in distribution networks side include wind turbines (WTs), photovoltaic (PVs), fuel cells (FCs), combined heat and power (CHP) systems, micro turbines (MTs) and a combination of these technologies. These types of power generations at the distribution level are called distributed generations (DGs). The reason for this naming is to differentiate between these sources and conventional power plants [5,6]. With DG integration in conventional power grids, the traditional distribution networks have become active distribution networks [7].

In recent years, a new architecture called the MG has been developed to maximize the potential of distributed energy sources [8,9]. MGs are a type of electrical system that uses renewable or non-renewable energies to meet the demand for local loads and can operate in islanding or grid-connected states, where in both modes, a coordination and balance of power generated and demands are controlled and managed [10,11]. MGs are small-scale and low-voltage (LV) power networks including renewable and non-renewable technologies to generate electrical and thermal power to provide heat and electrical loads such as domestic, commercial and industrial constructions [12,13]. Some differences between the conventional networks and MGs are as follows [14,15]:

The production resources in MGs have less capacity than the conventional generators used in upstream network.

In MGs, the generated power at the distribution voltage level is directly injected into the local loads, while in conventional power networks the generated power is transferred though transmission systems.

In MGs, the small DGs are installed near the customers, so that despite the conventional power networks, the thermal or electrical loads can be supplied without transmission line losses with the appropriate voltage profile and stable frequency.

A) An overview of MG optimization

In [16] an optimization Algorithm is proposed to optimize the VPP production scheduling. The results obtained by this algorithm have been validated by a similar operation based on the Particle Swarm Optimization (PSO) [17]. The outputs have represented that production costs are minimized as well as power losses are reduced along with power quality and reliability improvement of delivered power to the grid loads. The authors in [18] evaluate the role of VPPs in ancillary service improvement and their applicability. The presented model divides the tasks of transmission systems in incident management, reservation, reactive power control, execution of DRPs, etc. between two important parts of the network, namely transmission system operator (TSO) and distribution system operator (DSO). The framework proposed in [19] the formulation of risk and its effects on a VPP during the implementation of contingency management. Since the risk influences the behaviour of the market operator both mentally and objectively, thus choosing the right level of risk can increase the expected profit and minimize the power blackout. This paper deals with maximizing the objective function consisting of a constrained optimization and the risk function with additional variables. The additional variables included in the risk can greatly increase the role of the operator in the profitability of the system. The authors in [20] provide a definitive model and formulations for optimizing energy management in VPPs taking into account the reserve market laws. In this model, the flexibility indices refer to load controllability that can execute DRPs, while the uncertainties in the power system have also been solved with robust programming method considering the DG resources. Formerly, by improving the contingency planning, the output of these cases and the average amount of profit are compared.

B) Motivations

Human use of fossil fuels, despite the many benefits of fossil fuels, has caused excessive damage to the environment, as the release of pollutants such as climate change and greenhouse effects causing acid rain and etc. CO_2 gas is the main cause of climate change [21]. Since virtual power plants (VPPs) are a set of DG units, demand response programs (DRPs) and energy storage systems (ESSs) that are operated as a single unit, integrating them to the MGs can reduce CO_2 emissions and pollutions for the following reasons:

Simultaneous use of electricity and heat due to the proximity of production units and consumers increases the efficiency of MGs performance, results in CO_2 reduction.

The use of renewable energy producers that have little or no environmental pollution, such as PV units, WTs and etc.

Independent and coordinated control between DG sources, controllable loads and energy storage devices, performed by MG management units, are the main features of the VPPs. VPPs can be connected to the grid directly or indirectly. From the upstream network point of view, the VPP is seen as a controllable generator in the system which can be used as an auxiliary source to supply power to a part of the network in case of emergency (for e.g. peak load time) or safe case (for e.g. MGs). From the consumer's point of view, the VPPs are similar to a traditional LV distribution system that supply electrical and heating demands, as well as increasing their power supply reliability, reducing losses, improving power quality, and reduces energy prices. In fact, the purpose of operating a VPP is to use a set of DGs and loads that behave in a coordinated manner, instead of using many DGs that behave inappropriately and inconsistently [22]. Therefore the optimum sizing of DGs managed by a VPP is the main purpose of this research [23,24].

C) Research gap

One of the future achievements of restructuring has been the creation of a competitive environment in the electricity generation sector, in this regard, a set of small-scale production units with loads and a covered network managed by a certain entity is called a virtual power plant, which can have an active presence in the wholesale market of energy and rotating storage, but in this field, the existing articles have less discussed the planning and sensitivity analysis of the input parameters and have mostly limited themselves to VPP operation. Therefore, in this article, in addition to providing a comprehensive formulation for the planning of VPPs, with the approach of sensitivity analysis, different conditions are presented for the construction of a virtual power station.

D) Contributions

The main contributions of this research are:

- Energy optimization in VPPs including several scenarios such as wind speed variation, converter loss increment and so on.
- Determining the number of DERs and optimal capacity of them in the virtual power plant.

While list measurable outcomes and objectives that are expected to in this paper achieve are listed below:

- Modelling and coding the smart grid resources and loads in MATLAB software.
- Using speedy particle swarm optimization (SPSO) algorithm to optimize the objective function including the costs of distributed energy resources (DERs) installation costs, operation and maintenance and so on.
- Investigating the effects of battery efficiency on best solutions of DERs optimization.

E) Paper organization and structure

This paper is organized as follows: in Section 1 the main introduction to VPPs, the benefits, contributions and motivations are mentioned. The VPP structures and energy management advantages in it is expressed in Section 2. Section 3 describes the problem formulations including the main DERs and modelling of power exchanges. The proposed PSO algorithm used in this optimization problem to achieve the best solution of DER numbering and sizing is introduced in Section 4. The simulation results consist of several case studies are presented in Section 5 and finally, the conclusion is shown in Section 6.

2. VPP structures

The concept of the VPP was first introduced in 1994 with the goals of utilizing DGs, providing a suitable interface for local operators, activating distributed control strategies, and managing these facilities as shown in Figure (1) [25]. The VPP structures can be divided into two important categories [26]:

- Commercial VPP (CVPP) type
- Technical VPP (TVPP) type

VPPs always sell the electricity generated by internal sources to the upstream electricity grid and make money by uniform managing of all DG units. It should be noted that the cost of power flowed in transmission lines should also be reduced from the revenue earned.

A) CVPP structures

The highest aim of CVPP structures is to generate revenue and gain profit from the electricity market. In these VPPs, the main focus of the network operator is on optimizing the size of resources, storages, selling more power to the upstream network and reducing operating costs. Such problems in these areas are usually solved with intelligent algorithms and cost constraints are involved. The use of probabilistic and stochastic methods to model and solve nonlinear behaviours of WTs and PVs are also inevitable. There are several papers that have investigated about optimizing CVPP integrating DERs structures and have tried different optimization methods [27,28].

B) TVPP structures

This structure of the VPPs deal with technical issues in safe operation and load balancing, such as: network monitoring, debugging and fault detection, telecommunication protocols, connecting and disconnecting to MG, protection systems, cyber and infrastructure attacks, telecommunication hacking, etc. This issue has been investigating in numerous literatures [29,30].

C) Comparison between CVPP and TVPP structures

The electricity price in these two structures is different, which is determined by the energy management module (EMM).The discussion about price and load forecasting in the first structure shows itself more and looks at the electricity market as a stock market.In the CVPP structure, the price bidding is set by the producers, while in the TVPP structure the electricity price will be determined by the network operator according to the technical constraints of the network.The TVPP structure is more secure and shows more stability against intentional and unintentional events. Uncertainty of resources in the TVPP structure can be modelled, which helps to facilitate the operation. However, in CVPP structure, unpredictable resource models are not easily implemented and the solutions obtained will not be accurate.

D) Energy management in VPPs

Authors in [31] investigate the effect of flexible loads such as demand response (DR) in VPP and their effect on the market clearing price and energy efficiency. The data mining method based on DR incentive programs can generate an applicable platform between the VPP energy management system and the users. The data mining in this paper has mentioned the categorization of available demand by price, which can facilitate the optimal selection in production.

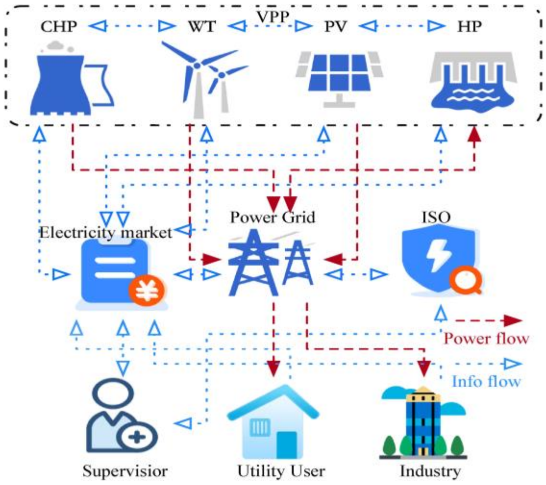

Fig. 1. A sample of VPP considering DGs [27]

In [32] the authors examine the availability of VPP in the presence of time transferable loads. In this paper, flexible loads are distributed in several modes. The control strategies used for VPP in this paper have been compared with similar references and the comprehensiveness of the proposed method has been determined. The introduced objective function includes wind, solar, storage and diesel generator sources. It also includes the effect of load flexibility index and DR.

The operational scheduling based on industrial VPPs has been evaluated in [33], which also take advantage of using wind energy to generate power. The objective function is to maximize the combined profit of production units considering VPP efficiency. In VPP, the net profit is the difference between revenue (selling of power to the network through DR, PVs and WTs) and costs (production costs, load shedding and shortcomings caused by uncertainty of the units).

In [34] the authors deal with VPP optimization using the deterministic and interval hybrid optimization algorithm. This paper states that due to the uncertainty of resources in VPP, economic load dispatch cannot be done by probabilistic and robust methods. The proposed combined method not only estimates the deterministic benefit of VPP under the several scenarios, but also extremely maximizes social welfare to overcome uncertainties. The proposed method, by providing appropriate weighting coefficients, performs the optimization among the DGs such as CHP, electric vehicles, PV and upstream network.

The authors in [35] study on the behaviour of DR programs in MG including VPP, in which the main focus is on commercial buildings and the participation of DGs. The objective function (including wholesale market, heating, ventilation, and air conditioning (HVAC) systems and DERs) is going to be optimized based on linear programming, which leads to the following results: Improving VPP profit by increasing the influence of DERs penetration, reducing electricity bills by optimizing the consumption of HVAC systems and increase the efficiency of commercial buildings by using DRPs.

The authors in [36] focus on the performance area of VPPs on the P-Q plane and the limitations of active and reactive power. This paper states that practically, each DG has many power generation limitations and it is not possible to extract power from each source up to its maximum nominal capacity. It goes on to illustrate the limitations of power generation in VPPs by presenting the operating range of diesel generators, batteries and PV systems. The useful activity ranges of DG units for power generation and expressing the difference between flexibility and feasibility is one of the most important results of this paper.

3. Problem Formulations

Figure (2) represents the structure of a VPP that exchanges electrical power to the upstream electricity market. As it is observed, the system under consideration includes WT units, PV units, electrolyzers, hydrogen storage tanks (HSTs), FCs, batteries, DC-AC inverters, DC-DC converters, AC-DC converters and several local loads. The power generated by solar units and WTs are injected to the DC bus, where some part of that is stored in the battery, directly, the remained part will energize the electrolyzer or transfer to the DC-AC inverter for supplying the local loads and selling to the upstream network if possible.

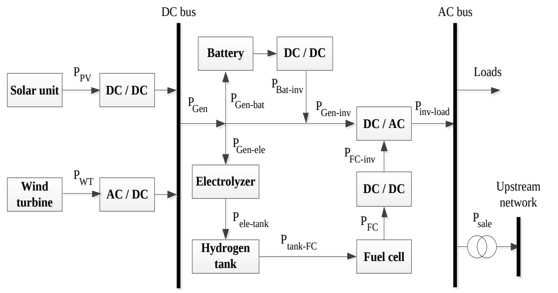

Fig. 2. Structure of the VPP under consideration [14]

A) Solar Unit

The solar cells generate electrical power after absorbing the sun's irradiation. Given that the irradiance power used in this paper is shown in Figure (3) over a year (8760 hours), so that the output active power of PV cells would be calculated using the following equation [37].

$$P_{\mathrm{PV}} = \frac{G}{1000} P_{\mathrm{PV,rated}} \eta_{\mathrm{PV,conv}} \tag{1}$$

where in equation (1), the parameter G represents the irradiance power received to the array surface normally in (W/m2) as shown in Figure (3) and $P_{PV,rated}$ is the rated power of every single array, that is gotten using PV catalogues. $\eta_{PV,conv}$ stands for the total efficiency of PV cells with the equivalent model of DC-DC converter connected to the PV source and the consistent node. Since the vertical and horizontal components of the irradiance power can be divided from each other, for every instant, the effective power can be received (vertically) to the surface of PVs with the constructed angle of θ_{PV} is considered in line with equation (2):

$$G(\mathrm{t},\theta_{\mathrm{PV}})=\mathrm{G}_V(t)\cos(\theta_{\mathrm{PV}})+\mathrm{G}_H(t)\sin(\theta_{\mathrm{PV}}) \tag{2}$$

Where parameters $G_V(t)$ and $G_H(t)$ are the model of vertical and horizontal components of irradiance power received in (W/m2), correspondingly.

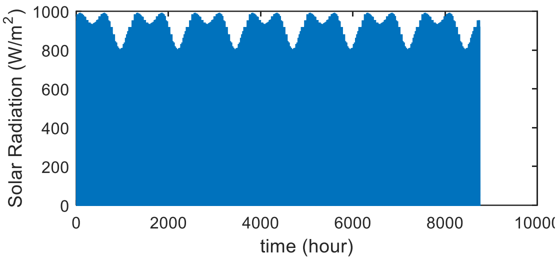

Fig. 3. The solar radiation used in this study [37]

B) Wind Turbine Unit

In recent decades, due to the growing need for demand and energy shortages around the world, efforts have been made to generate electricity from renewable energy sources. The only source of renewable energy that is economically comparable to fossil fuels is wind energy. This is because the energy received is mechanical and easily converted into electrical energy with minimal conversions and losses. The behavior of power-velocity characteristic of the wind turbine is usually provided by the manufacturer company of turbines which expresses the real power flow from the turbine to the DC node. The parameter (P_{WT}) or output power can be found by changing the wind speed (v_W) in equation (3) where the velocities v_{cutin}, v_{cutout} and v_{rated} are low cut-in, high cut-off and rated velocity (m/s) of the wind rotating the turbine, respectively. The maximum output power of the turbine is modelled by $P_{WT,max}$ (kW) while the output power at high cut-off speed is represented by P_{furl}. In this research, the constant *m* is measured to be equal to 3.12. The wind data used in this study is shown in Figure (4).

$$P_{WT} = \begin{cases} 0 & ; v_w \le v_{cutin}, v_w \ge v_{cutout} \\ P_{WT\,max} \times \left(\dfrac{v_w - v_{cutin}}{v_{rated} - v_{cutin}}\right)^m & ; v_{cutin} \le v_w \le v_{rated} \\ P_{WT\,max} + \dfrac{P_{furl} - P_{WT\,max}}{v_{cutout} - v_{rated}} \times (v_W - v_{rated}) & ; v_{rated} \le v_w \le v_{cutout} \end{cases} \tag{3}$$

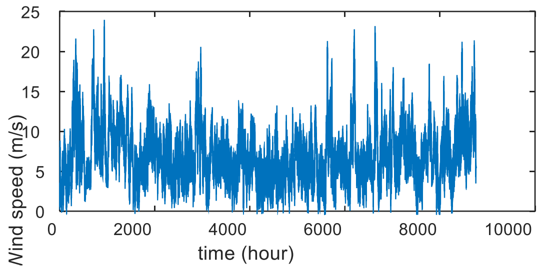

Fig. 4. The wind speed data used in this study [26]

C) Electrolyzer Unit

One of the most essential elements for the operation of fuel cells is hydrogen. This required hydrogen can be provided in various ways, the most important of which is: extracting hydrogen from fossil fuels or obtaining it from the electrolyte. The electrolyte process of water is the only possible way to obtain the constituents of water without the use of fossil fuels. The hydrogen obtained from the water electrolyte can be stored in a very compact form and has a very high purity. Of course, the amount of this purity varies depending on the type of electrolyzer used. The compressor-free design reduces energy consumption, although the software developed is very flexible and the compressor model can be easily added to process. The electrochemical interactions in the water electrolyzer are as follows [38]:

$$H_2O \to \frac{1}{2}O_2 + 2H^+ + 2e^- \tag{4}$$

To model the electrolyzer in power system of VPP, the efficiency is an input parameter that plays an important role. With the present knowledge, we know that an electrolyzer is an electrochemical device that behaves inversely to the function of a fuel cell, because it produces hydrogen when an electric current enters, during a chemical reaction. But the rate of hydrogen production by the electrolyzer, according to Faraday law, is directly related to the transfer of electrons. The following equation shows the relationship between the electrolyzer current and the rate of hydrogen production: (5).The number of H_2 generated to transfer to the HSTs is calculated in (6).

$$P_{elec,min} \le P_{elec}(t) \le P_{elec,max} \tag{5}$$

$$N_{H_2} = \frac{\eta_{PV,conv} P_{elec}(t)}{N_H} \tag{6}$$

D) Hydrogen storage tank unit

To reduce the system cost, the maximum pressure of the hydrogen tank is assumed equal to the electrolyzer operating pressure. The energy that has been stored in the tank ($E_{tank}(t)$) can be calculated for each time step from (7) [37].

$$E_{\text{tank}}(t) = E_{\text{tank}}(t) + P_{elec-\text{tank}}(t)\Delta t - \frac{P_{FC-\text{tank}}(t)\Delta t}{\eta_{storage}} \quad (7)$$

In equation (7), $P_{elec-tank}$ shows the transfer power from the electrolyzer to the hydrogen tank, Δt is the length of each time step and $P_{FC-tank}$ represents the transfer capacity from the hydrogen tank to the fuel cell. The parameter $\eta_{storage}$ also represents the efficiency of the storage system, which can indicate leakage or pumping losses.

The maximum quantity of hydrogen stored in a tank, is considered equal to its nominal capacity. It also assumed that not all stored hydrogen in tank, can be extracted due to some problems, including pressure drop inside the tank. The hydrogen in the tank will always have a high ($E_{tank}(t)_{max}$) and low ($E_{tank}(t)_{min}$) range.

$$E_{\text{tank},\,min} \leq E_{\text{tank}}(t) \leq E_{\text{tank},max} \quad (8)$$

E) Fuel Cell Unit

Fuel cells are devices that convert the chemical energy of a fuel directly into electricity by electrochemistry. A fuel cell is similar to a battery in many ways, but it can provide electricity for a longer period of time. This is because the fuel cell is constantly supplied with fuel (or oxygen) from an external source, while a battery contains only a limited amount of fuel and oxidants that can be used to discharge it. . That's why fuel cells have been used for decades in space probes, satellites and manned spacecraft. Thousands of fixed fuel cell systems have been installed in primary power plants, hospitals, schools, hotels and office buildings for primary and backup power around the world. Many waste treatment plants use fuel cell technology to power the methane gas produced by waste decomposition. Each fuel cell has an electrolyte that transfers electrically charged particles from one electrode to another and is a catalyst that accelerates reactions at the electrodes. Hydrogen is the main fuel, but fuel cells also need oxygen. One of the great attractions of fuel cells is that they generate electricity with very little pollution - most of the hydrogen and oxygen used to generate electricity eventually combine to form a harmless by-product, water. The purpose of fuel cells is to generate an electric current that can be directed out of the cell to do the work, such as powering an electric motor or turning on a light bulb. Due to the behaviour of electricity, this current returns to the fuel cell and completes an electrical circuit. The chemical reactions that produce this flow are the key to how fuel cells work. PEMs have a relatively fast dynamic response, about 1 to 3 seconds. The power output of these fuel cells can be calculated as a function of the input power of the hydrogen as well as its efficiency (η_{FC}), which can be assumed to be constant. Therefore, the output power extracted from fuel cell stacks ($P_{tank-FC}$) could be represented with (9) in which $P_{tank-FC}$ is gross productive power of fuel cells [39].

$$P_{FC-inv} = P_{\text{tank}-FC}\eta_{FC} \quad (9)$$

F) Energy Storage (Battery) Unit

Batteries and fuel cells have a similar function in terms of generating electrical power, and both obtain this power through chemical reaction. In the battery, chemical reactants are stored in the battery and these materials are used during the reactions and the battery must be recharged or discarded if the battery is not rechargeable. But in a fuel cell, the reactors or the same fuels are stored outside the cell, so electricity generation will continue until the fuel is supplied. For example, a fuel cell car needs refuelling instead of recharging. The battery source in VPP is used to provide the load in the absence of renewable energy sources. The difference between the power produced and the load power required indicates whether the battery should be charged or discharged. The amount of charge of the battery bank is obtained in time horizon t using the following [37]:

$$E_{bat}(t) = E_{bat}(t) + P_{gen}(t)\Delta t\eta_{bat} - \frac{P_{bat-inv}(t)\Delta t}{\eta_{dis}} \quad (10)$$

where, $E_{bat}(t)$ represents the amount of battery electric energy at time t. Δt is the time step, P_{gen} shows the received power from DC bus and $P_{bat-inv}$ is the power transferred from battery to inverter. By the way, η_{bat} and η_{dis}, are the charge and discharge efficiency of the battery bank, respectively. It is worth mentioning that in batteries, the chemical reactions in the battery are stored and used during the reaction operations, and if the battery is rechargeable, this operation is performed again, and if it is not rechargeable, it is discarded. But in fuel cells, the reactors, or in other words, the same fuels are stored outside the cell, due to this issue, the production of electricity continues until the required fuel is supplied.

G) Objective function

Life cycle cost analysis evaluates the costs of covering all processes experienced during the activity period. The net present cost (NPC) is used as the charge of the system life cycle. The NPC includes initial installation costs, replacement costs, operation and maintenance of the equipment and the revenue of selling electrical power to the grid. In NPC calculations, the costs are considered positive and earnings are considered negative. The main challenge in relation to new and renewable energies is the entry of a large number of such low-capacity products into the current network. The virtual power plant has provided a way to integrate this type of production. In this complex, while implementing a virtual power plant by distributed generation, the concept of decentralized energy management has been used to feed local consumers of the virtual power plant and optimize energy consumption; so that by setting priorities for the units in the VPP, the connection of the units with the national network have been minimized. By implementing a virtual power plant with a distributed management system, the load is fed completely locally by local controllers, and each unit feeds its scattered load, otherwise, according to the implemented logic, communication with adjacent units and the network is established. In this case, due to the reduction of the connection between the distributed generation units of the virtual power plant, energy consumption will be saved and energy loss will be prevented to a large extent.

All costs and expenses are assessed at a fixed interest rate throughout the year. In this type of assessment, in order to inflation rate (ir) in calculations at the end of the process of analysis and review of the system, it should be applied to the NPC [40]. The NPC value of each equipment can be calculated according to the following equation:

$$NPC_i = N_i(CC_i + RC_iK_i + OMC_iPWA) \tag{11}$$

The problem is formulated and solved in the form of a correct mixed linear programming. In the proposed model, the main goal is to manage energy resources for the coming years. The energy sources of the virtual power plant include various types of distributed generation sources such as dispatchable units and non-dispatchable units such as PVs and wind turbines and responsive loads. The virtual power plant is also able to exchange energy with the main network; Therefore, the operator of the virtual power plant is able to provide loads by using the generation capacity of distributed generation sources, discharging batteries and purchasing power from the main network. It can also sell surplus power to the main network. This is planned in such a way that the profit of the virtual power plant is maximized. In the above statement, N is the number of each equipment or capacity (kW or kg), CC_i is initial capital cost ($/unit), RC_i stands for replacement cost, $O\&MC_i$ is annual operation and maintenance cost of each equipment ($/unit-yr) at R project lifetime (in this study is 20 years). PWA and K are respectively the annual and constant payments current value, which are defined as follows [41]:

$$PWA(ir, R) = \frac{(1+ir)^R - 1}{ir(1+ir)^R} \tag{12}$$

$$K_i = \sum_{n=1}^{y_i} \frac{1}{(1+ir)^{n \times L_i}} \tag{13}$$

where y and L are the number of replacements and useful life of the equipment, respectively.

H) Power Selling Revenue

Since the main goal of DG sizing is to minimize the planning costs of objective function, we introduce negative revenue from the trade of electricity to the upstream network in the calculations. The NPC of electricity sold to the upstream network is [41]:

$$NPC_{sale} = \sum_{t=1}^{8760} \begin{matrix} (P_{sale}(t) \times \\ C_{sale}(t) \times PWA(ir, R)) \end{matrix} \tag{14}$$

where Csale is the electricity costs (kW/hr), while it depends on the time of the power exchange and the price of energy at that period. Given the costs and income mentioned above, the objective function is defined as (15).

$$J = min_x \left\{ \sum_i NPC_i - NPC_{sold} \right\} \tag{15}$$

where, i represents the desired equipment and X is a vector of optimization variables. This equation can be extended to equation (16).

$$J = \min_{N_{PV}, N_{FC}, N_{Bat}, N_{WT}, M_{HST}, N_{Electrolyzer}} \left\{ \begin{matrix} \sum_{i=1}^{N_{PV}} NPC_{PV,i} + \sum_{j=1}^{N_{FC}} NPC_{FC,j} + \sum_{r=1}^{N_{Bat}} NPC_{Bat,r} \\ \sum_{k=1}^{N_{WT}} NPC_{WT,k} + \sum_{m=1}^{M_{HST}} NPC_{HST,i} \\ + \sum_{n=1}^{N_{Electrolyzer}} NPC_{Electrolyzer,n} - NPC_{sold} \end{matrix} \right\} \tag{16}$$

I) Constraints

At any given interval, the total production capacity of the hybrid production system should be equal to the total demand which is calculated by the following equation [41]:

$$\sum P_{DGs,inv}(t) = \frac{P_{sold}(t) + P_{load}(t)}{\eta_{inv}} \tag{17}$$

Accordingly, $P_{load}(t)$, $P_{sold}(t)$ and $P_{DGs,inv}(t)$ represent the total demand, the power sold to the upstream network and the power transmitted from DGs to battery and the DC-AC inverter, respectively. In this case, the power capacity to be sold to the upstream network should not exceed a certain limit, which is determined by prior agreements [41]:

$$P_{sold}(t) \leq P_{sold,max} \quad (t) \tag{18}$$

The proposed formulation is optimized using the PSO algorithm. The capacity of DGs is constant while the number of DGs is variable. In the other words our variables that should be optimized are the number of DGs using the PSO.

4. Optimization Algorithm

The PSO algorithm and how to use it in optimization problems is presented in this chapter. In order to validate the proposed algorithm, several mathematical problems will be solved using different methods and the final solutions will be compared with the PSO algorithm. It is then observed that the PSO algorithm, regardless of the complexity of the mathematical optimization methods, finds the global optimal answer in certain iterations with an acceptable error. The search process based on the above concepts can be described as a group of particles in a community seeking to optimize a specific objective function. Every particle in this community knows the best solution to their history and current position (P_{best}). In addition, everyone is aware of the best answer in the history (G_{best}). The modified position vector for each particle can be obtained from the following equation [42]:

$$v_i^{k+1} = w_i v_i^k + c_1.rand.(P_{best,k} - x_i^k) + c_2.rand.(G_{best,k} - x_i^k) \tag{19}$$

Where v_i^k and v_i^{k+1} are the velocity vector of the i^{th} particle in the k^{th} and $(k+1)^{th}$ iterations, $rand$ is a random number between 0 and 1, x_i^k represents the current position of i^{th} particle in the k^{th} iteration, w_i is the weight coefficient for the velocity vector of the i^{th} particle, calculated in (19), and c_1 and c_2 are the PSO algorithm coefficients which are often choses as 2 [42]. Using the above equation, the new position of the particle which is specifically going to be closed to P_{best} and G_{best}, can be calculated in (21).

$$w = w_{max} - \frac{w_{max} - w_{min}}{i_{max}} i \tag{20}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{21}$$

Where w_{max} and w_{min} are the maximum and minimum of weight coefficient of velocity and i_{max} represents the maximum number of iterations. The modification in PSO is done as shown in equation (22) to ignore the initial negative effects of c_1 and c_2 on the convergence.

$$\begin{aligned} c_1 &= c_1(i) = {c_1}^{old}(1 - \frac{i}{i_{max}} e^{-i}) \\ c_2 &= c_2(i) = {c_2}^{old}(1 - \frac{i}{i_{max}} e^{-i}) \end{aligned} \tag{22}$$

These modifications case the PSO (new algorithm is called speedy PSO or SPSP) converges faster to 26% than conventional PSO.

A) SPSO Validation

To prevent premature convergence of algorithm and improve the precision of solution, a modified particle swarm optimization algorithm based on velocity update mechanism is introduced in this paper. One of the weaknesses of the PSO algorithm is that it has more search ability at the beginning of the execution, but in the final stages, the local search ability decreases. Therefore, in solving problems that have many local optima, it is likely that PSO will be caught by local optima in the final stages of execution. Of course, there is also a possibility that if the PSO parameters are not selected correctly, this algorithm will converge to local optima in the very early stages of execution and will suffer leading convergence. Therefore, speed of convergence and prevention of falling into local minima are two attractive goals in improving the PSO algorithm. Consequently, the coefficients of the algorithm should be selected small at first, and after several iterations, their weighting coefficients are weakened and return to the conventional PSO algorithm. For this purpose, the authors have included the coefficients of the algorithm according to the changes of the iterations, which has achieved better results. Several case studies selected according to mathematic benchmarks, conducted out as below:

B) Case 1:Minimizing $f_1(x)$:

$$f_1(x) = \frac{1}{400}(x_1^2 + x_2^2) - cos\left(\frac{x_1}{\sqrt{1}}\right) cos\left(\frac{x_2}{\sqrt{2}}\right) + 1$$

s.t.:

$g_1(x) = x_1 - 3 = 3$

$h_1(x) = 2 - x_2 < 0$

$-10 < x_i < 10\ , i = 1,2$

After 150 iterations, SPSO reaches 0.0065, but PSO reaches 0.0265.

C) Case 2:Minimizing $f_2(x)$:

$$f_2(x) = \frac{-sin(2\pi x_1)^3 sin(2\pi x_2)}{x_1^3(x_1 + x_2)}$$

s.t.:

$h_1(x) = x_1^2 - x_2 + 1 < 0$

$h_2(x) = 1 - x_1 + (x_2 - 4)^2 < 0$

$0.1 < x_1 < 10\ , 0 < x_2 < 10$

After 150 iterations, SPSO reaches 0.00287, but PSO reaches 0.0943.

D) Case 3:Minimizing $f_3(x)$:

$$f_3(x) = x_1^2 + x_2^2$$

s.t.:

$g_1(x) = x_1 - 3 = 3$

$h_1(x) = 2 - x_2 < 0$

$-10 < x_i < 10\, , i = 1,2$

After 150 iterations, SPSO reaches 12.978, but PSO reaches 12.946.

5. Simulation Results with SPSO

The simulation of the mathematical models presented for DG resources mentioned in part 3 is implemented in MATLAB software and then the energy optimization will be done using the SPSO algorithm in this chapter. The validity of the SPSO algorithm was fully proven in chapter 4, and in this part of the paper, the results of DER sizing optimization in a VPP are presented.

A) Base case scenario

Suppose that to build a new MG, we need to provide a certain demand of 500 kW. Therefore, the General Manager of the Electricity Network asks us to supply the desired demand power using renewable energies. To this end, building a VPP consisting of DERs is much more cost-effective than construction of a traditional fossil power plant. Therefore, the main goal is to spend the minimum cost for the purchase, installation and maintenance of the VPP components, and in return, the demand is fully provided. Since the sources considered in this paper are PV, WT, FC, HST, Battery and Electrolyzer, so first we perform the first simulation according to the initial values given in Table (1) and call it "base case". Table (2) also represents the wind turbine speed characteristics in the operation range. The converter efficiency is also assumed to be 90%. Other simulations and analyses will be compared with this mode to be evaluated.

The simulation results in this case are assumed to be acceptable after 300 iterations as the convergence diagram is shown in Figure (5) and the results are shown in Table (3). The convergence diagram represents that after about 130 iterations, the optimal solution is obtained, which is equal to $ 5.46158e7 as can be seen visually. The number of iterations has been set to 300 to ensure that the optimal solution would not change and to prevent the algorithm from getting stuck at local optimal points. It is worth noting that the initial population is 50 particles, which this can be generalized to all scenarios. The cost of buying the converters and extra power for selling to the upstream network which is assumed to be 0.4 $/kWh are calculated in MATLAB code.

Altogether, the total cost of building a VPP with miscellaneous costs is precisely equal to $ 5.46158e7. The ability to sell power to the upstream network is available but it depends on operation condition which is not considered in planning. Since it is assumed that the capacity of the converter is equal to all DER sources to be able to convert their generated DC electricity to AC, so that according to the SPSO outputs, the cost of purchasing converters is also equal to $ 5.2610e+05.

Table.1.
Data used for DERs sizing

DERs	*Nominal Power*	*Capital Cost ($)*	*RC ($)*	*O&M Cost ($)*	*Life ime (years)*
PV	2 kW	8000	6000	20	20
WT	7.5 kW	19400	15000	75	20
FC	2 kW	3000	2500	175	4.5
HST	1 kg	1300	1200	15	20
Battery	9.64 kW/h	1250	1100	30	4
Electrolyzer	1 kW	2000	1500	20	7
Converter	1 kW	800	800	0	15

Table.2.
Wind speed data

Parameters	*Value (m/s)*
Cut-in speed	3.1
Cut-off speed	25
Rated speed	11

Table.3.
Number of DERs in base case

DER	*WT*	*PV*	*El.*	*HST*	*FC*	*Bat.*
No.	9	596	5008	272	61	804
Cost($)	1.4e6	9.7e6	1.7e7	1.9e6	1.1e7	2.9e6

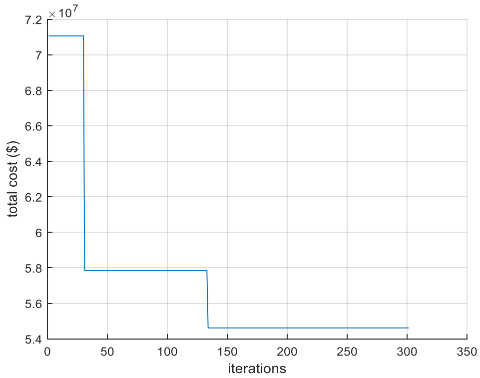

Fig. 5. The SPSO algorithm convergence diagram of base case

B) Wind speed change scenario

In this scenario, the cut-in speed of the wind is assumed to increase from 3.1 m/s used in the base case to 5 m/s. The output results in this scenario are given in Table (4). Comparing it with the base case, it turns out that the total cost is calculated at $ 6.71193e+07, which is more than the base case. But overall, the number of wind turbines and PVs has decreased, indicating a less interest in generating power at low wind speeds and using irradiation power more than previous. This has led to increase in the number of electrolyzers and hydrogen. In this case, the cost of buying converters is calculated at $ 5.2610e+05 obtained from the SPSO algorithm. The convergence diagram of this case is also shown in Figure (6), which indicates that the total costs in converged after about 40 iterations.

C) Investment cost of PV decrement

In this scenario, it is assumed that the cost of PV investment will reduce from $ 8000 to $ 6000. This means that we are actually buying cheaper PVs, which directly influence in PV capital cost. A summary of the output results is shown in Table (5) that states that the total cost is $ 4.84408e+07, which is desirable compare to base case. The decreasing cost of investing in PVs has led to an increase in the number of solar arrays compared to base cases. This means that more power is produced by PVs. Then the cost of the converters is calculated at $ 5.2610e+05. The convergence diagram of the in this case that has been obtained after about 50 iterations is shown in Figure (7).

Table.4.
Number of DERs in scenario of cut-in speed = 5 m/s

DER	***WT***	***PV***	***El.***	***HST***	***FC***	***Bat.***
No.	5	561	9406	1738	6	112
Cost($)	8.1e5	9.2e6	3.e7	1.2e7	1.1e6	4.1e5

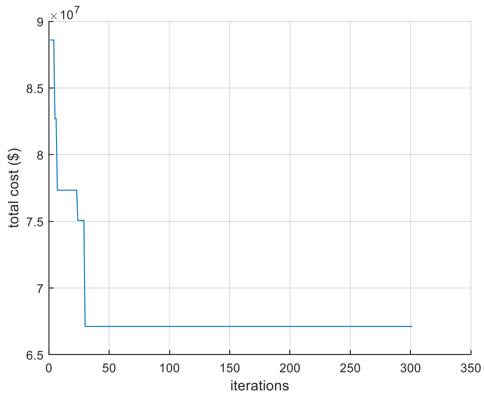

Fig. 6. The SPSO algorithm convergence diagram in scenario of cut-in speed = 5 m/s

Table.5.
Number of DERs in scenario of PV capital cost increment

DER	***WT***	***PV***	***El.***	***HST***	***FC***	***Bat.***
No.	7	1091	2017	1396	7	1609
Cost($)	1.0e6	1.3e6	1.3e7	1.0e7	1.3e6	5.9e6

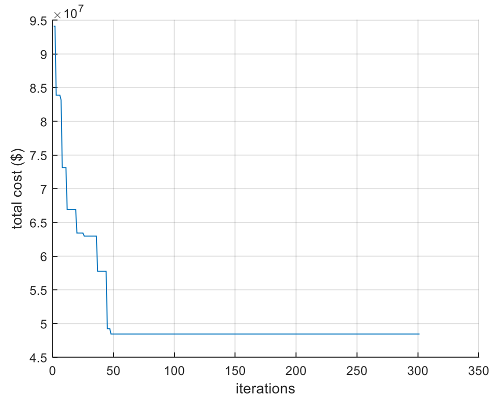

Fig. 7. The SPSO algorithm convergence diagram in scenario of PV capital cost increment

D) Electrolyzer efficiency increment

In this scenario, we increase the efficiency of the electrolyzer from 0.9 to 0.95. The output results shown in Table (6) show that the interest in using them increases. Therefore, the total cost of planning is equal to $ 3.68314e+07, which is increased compared to the base case. The reason is to buy higher quality and more efficient electrolyzer equipment. The optimization results show that increasing the efficiency of electrolyzers reduces the number of PVs and WTs, which will decrease the planning cost as obtained in the SPSO outputs, correspondingly. This indicates that the construction of VPP with existing equipment and electrolyzers with higher efficiency is economically viable. The cost of buying converters is $ 5.2610e+05. The convergence diagram in this case is represented in Figure (8) in which implies that only after about 40 iterations, the optimal solutions are achieved.

E) FC efficiency increment

At this part, we increase the efficiency of the fuel cell from 0.9 to 0.95. The output results shown in Table (7) represent that, as before, the interest in using them increases. Therefore, the total cost of planning is equal to $ 4.75944e+07, which is again decreased compared to the previous cases. Overall, increasing equipment efficiency reduces the cost of purchasing VPP components, which is also evident in the output of optimization results. Therefore, this mode is desirable and the base case does not provide better results. The cost of buying converters is $ 5.2610e+05. The convergence diagram in this case study is shown in Figure (9), where the convergence is obtained after about 60 iterations.

F) Battery charging efficiency increasing

In this scenario, we increase the battery charge efficiency from 0.8 to 0.9 to take into account the impact on the number of other sources. The simulation results presented in Table (8) show that the tendency in using high-efficiency batteries grows up. Therefore, the desired load can be provided with a more number of batteries due to loss reduction. Consequently, the total cost of planning is equal to $ 4.53407e+07, which is still lower than the base case. The cost of purchasing the converters is $ 5.2610e+05. The convergence in this case is obtained rapidly after about 30 iterations in which the diagram is represented in Figure (9).

G) Demand increasing

To provide the required power of the virtual power plant, it is assumed that in the basic state, the maximum power will increase by 20% (600 kW), so in this case, the number of production resources will be as described in the table below. In this case, the total costs increases to $ 7.15429e7.

Table.6.
Number of DERs in scenario of electrolyzer efficiency increment

DER	***WT***	***PV***	***El.***	***HST***	***FC***	***Bat.***
No.	4	11	463	1626	46	1321
Cost($)	6.1e5	1.8e5	1.6e6	1.1e7	8.4e6	4.8e6

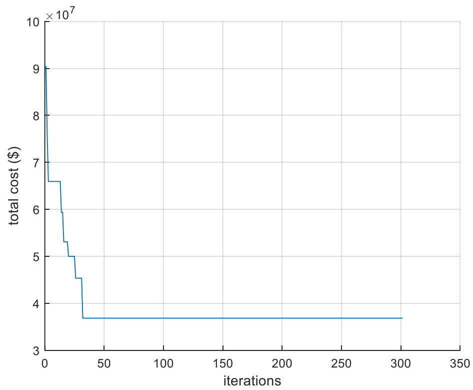

Fig. 8. The SPSO algorithm convergence diagram in scenario of electrolyzer efficiency increment

Table.7.
Number of DERs in scenario of FC efficiency increment

DER	***WT***	***PV***	***El.***	***HST***	***FC***	***Bat.***
No.	3	22	2998	1819	67	313
Cost($)	5.7e5	3.6e5	1.0e7	1.3e7	1.2e7	1.1e6

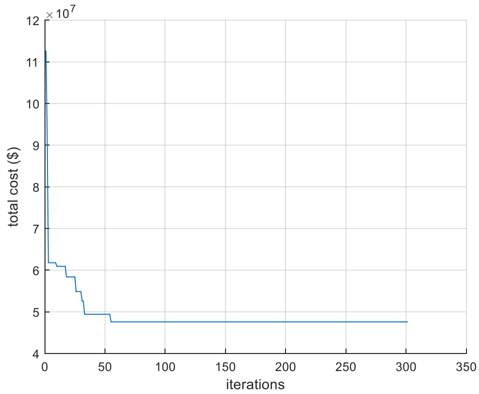

Fig. 9. The SPSO algorithm convergence diagram in scenario of FC efficiency increment

Table.8.
Number of DERs in scenario of battery charging efficiency increment

DER	***WT***	***PV***	***El.***	***HST***	***FC***	***Bat.***
No.	14	76	6811	89	19	1092
Cost($)	2.1e6	1.2e6	2.4e7	6.4e5	3.5e6	4.0e4

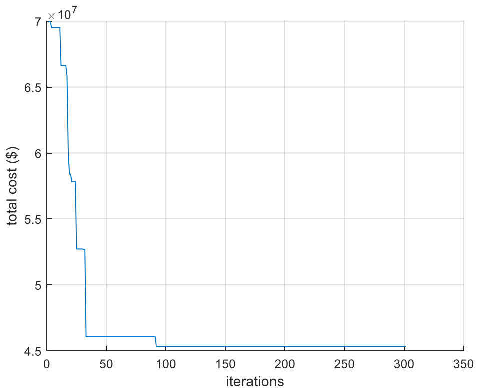

Fig. 10. The SPSO algorithm convergence diagram in scenario of battery charging efficiency increment

Table.9.
Number of DERs in scenario of PV capital cost increment

DER	***WT***	***PV***	***El.***	***HST***	***FC***	***Bat***
No.	9	1142	2283	1498	16	1823
Cost($)	1.6e6	1.9e6	1.8e7	1.8e7	1.9e6	6.8e6

6. Discussion

The concept of virtual power plant was first presented in 1994 with the goals of visibility of distributed production resources, providing a suitable interface for local components, activating distributed control strategies and optimal use of existing capacity. The set of scattered production units, responsive loads and energy storage systems that are operated as a single entity is called a virtual power plant. Due to the advantages of distributed generation resources, responsive loads and energy storage system, a virtual power plant can be a suitable alternative to conventional fossil power plants. The need to modify, change, and relocate electrical energy consumption has drawn attention to load response as an efficient solution. Responsive load pursues network security objectives such as balancing, system reliability and risk management by reducing or increasing demand in a short period of time and reducing the development of additional generation and transmission capacity in a long period of time. The use of responsive loads is proposed as a solution to increase the penetration and integration of scattered production sources in the power system in the form of a virtual power plant and as a tool to facilitate energy management to overcome the challenges caused by the random nature of renewable energy sources.

Energy management is a general and very broad concept and includes all measures that are planned and implemented to ensure the consumption of the minimum amount of energy in various activities. Business, industry and organizations have been under a lot of economic and environmental pressure in the last two decades. Economic competition in the global market and increasing environmental laws and standards in order to reduce air pollutants have been the most important factors included in the investment and operation costs of all organizations. Energy management is an important tool in helping various organizations to reduce costs in order to meet these necessary goals in order to survive and succeed in the long term.

The energy management of the virtual power plant faces fundamental challenges that make this issue complicated. Among these challenges, we can mention the uncertainty in the amount of production and consumption, the price of energy and the availability of network components. Smart grids increase the ability of the energy management system in the fields of overcoming uncertainty, aggregating renewable resources, load response, and network monitoring and control. By continuously monitoring and measuring the state of network operation, the smart network provides users with valuable real-time information about the state of the network, such as the amount of production and consumption, the power of lines, and the availability of network components. Therefore, by establishing a two-way communication between the energy management system and microgrid users such as producers and energy applicants, it provides a suitable platform for more effective use of the virtual power plant. Meanwhile, in this article, the appropriate sizing of DJ resources in a VPP has been analysed, in which the cost of establishing a virtual power plant has been considered in the case studies. Considering these issues, sensitivity analysis has been done for many variables in this network and they have been specified with input parameters, system cost and the number of production resources. Determining the best case in this situation is not possible, because a compromise must always be made between the costs paid and the quality of the equipment. Hence, for example, the higher the efficiency of the battery, the higher its cost; But their number will decrease, because casualties are reduced and this is desirable. Therefore, this article states what kind of network can have the best productivity according to the budget and the available conditions and equipment.

7. Conclusions

From the studies conducted out, the following results can be concluded briefly as following:

One of the main solutions to the problem of energy uncertainty is the use of supportive production systems or ESSs, in which the battery and hydrogen tank are used as the storage systems in order to provide optimal energy availability.

Combining different ESSs for those energies that have complementary production characteristics (such as wind and sun) are considered as a convenient and inexpensive way to improve system reliability. The proposed grid has such a structure to overcome the above problems.

Using high the capacity batteries as ESSs in a VPP system would increase the planning costs by increasing the system's ability to track the load. The results show that simultaneous use of FCs as a storage medium in the hybrid system, in addition to reducing costs, also increases the system's ability to track the load. Selling additional power to the upstream network will reduce the costs in a VPP. Increasing the battery charge efficiency increases the number of batteries and consequently has reduced the total cost. Since increasing the cut-in wind speed of increases the total cost, it is not recommended to use turbines with higher cut-in speed. Decreasing the investment cost of PVs has reduced the number of batteries, which will increase the total cost. Increasing the efficiency of electrolyzers, converters and FCs has led to an increase in the use of large numbers of electrolyzers, converters and FCs, respectively, which increases the total cost and is not desirable. As shown in the case studies conducted out, the convergence of the SPSO algorithms usually is achieved in a few iterations, so that this algorithm is very useful in scientific optimization problems.

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