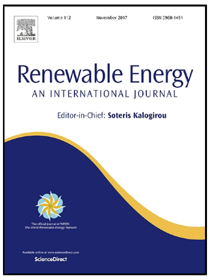

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Optimal Management of Renewable Energy Sources by Virtual Power Plant

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Abstract- In recent years, due to lack of sufficient quantity of fossil fuel, the need of Renewable Energy Sources (RESs) has become an important matter. In addition to the shortage of fossil fuel, global warming is another concern for many countries and companies. These issues have caused a large number of RESs to be added into modern distribution systems. Nevertheless, the high penetration of RESs beside the intermittent nature of some resources such as Wind Turbines (WT) and Photovoltaic (PV) cause the variable generation and uncertainty in power system. Under this condition, an idea to solve problems due to the variable outputs of these resources is to aggregate them together. A collection of Distributed Generators (DGs), Energy Storage Systems (ESSs) and controllable loads that are aggregated and then are managed by an Energy Management System (EMS) which is called Virtual Power Plant (VPP). The objective of the VPP in this paper is to minimize the total operating cost, considering energy loss cost in a 24h time interval. To solve the problem, Imperialist Competitive Algorithm (ICA), a meta-heuristic optimization algorithm is proposed to determine optimal energy management of a VPP with RESs, Battery Energy Storage (BSS) and load control in a case study.

Keywords: Virtual power plant, Renewable energy sources, Optimal energy management, Operating cost, Imperialist competitive algorithm.

1. Introduction

In recent years, major advances in the technology of DGs such as solar, wind, hydro and etc. have led them to be in the center of consideration more than before, because of need for lower cost, less environmental pollution, more flexibility, higher reliability, and better power quality. On the other hand, due to lack of fossil fuel that leads to increase in energy prices and the gradual rise in the global temperature, many industrialized countries have been compelled to alter the focus of their energy policy towards different kinds of energy supplies and deployment of RESs. Since RESs cannot yet supply levels of return on investment similarly to fossil fuels [1], various encouraging plans for RES have been initiated. These contain discount in tariff plan, discount in premium plan and the quota plan. Due to this fact, wind power and photovoltaic are considered more than other sources. In the year 2015, the worldwide wind power capacity reached 433 GW with an annual growth rate of 15% [2], while the installed solar photovoltaic (PV) in the same year reached a cumulative capacity of 233 GW, with an annual growth rate over 30% [3]. For a large number of RESs, it is troublesome to control their output, mainly when the output of the generators such as wind power and photovoltaic fluctuate quickly and are intermittent. A solution to this problem is to aggregate the RESs, so that they emerge generally like a conventional generator with relatively stable output. One of the aggregation approaches is to create a VPP.

VPP is a combination of renewable sources, Energy Storage System (ESS), small conventional power plants and interruptible loads that can supply market actions as a single power plant [4]. However, Hybrid systems in different locations of any country could be controlled by a VPP. In order to participate in the VPP structure and provide a virtual hybrid system, there is an aggregator that makes contracts with each DG owner. Thus, the aggregator acquires the chance of contributing in the electricity market with a reliable power quality. Because of the uncertainty and intermittent nature of PV and WT powers, it is usually possible that the actual values of these variables are different from the corresponding schemed values. Therefore, grid operators attempt to have a definite level of reserve in the grid. Thus, they would be capable of compensating for the uncertainty in the output power of these sources to protect the system security [5-6]. In order to compensate the uncertainty of wind and PV powers, Pumped Hydro Energy Storage (PHES), Compressed Air Energy Storage (CAES), flywheel energy storage, Super conducting Magnetic Energy Storage (SMES), super capacitor energy storage and battery energy storage are used [7]. The storage units have two major benefits: first, these are loads with limited abilities, and second they can turn into generators. Nowadays, many papers have concentrated on VPP and different associated aspects and concept of their interactions with the power system. In [8-9] the VPP is considered as a centralized entity, including some micro Combined Heat and Power (CHP) units connected to a low voltage distribution system. An optimal operation approach of a VPP composed of CHP units is offered based on a decentralized control strategy [10]. In [8–10], however, the optimal utilization of CHP units has been specified as the main aim but the important role of electrical storages and demand response resources was not considered. The impact of demand response on power system operation is assessed in [11]. In [12], a robust optimization tool is demonstrated by self-scheduling of VPPs with power markets uncertainty. A method for utilization of the thermal mass of a building to defer power consumption from electric space heating using of interruptible load in the distribution system is presented in [13]. In [14] optimum operation of a wind-hydro VPP considering the day-ahead scheduling of VPP components using mixed integer linear programming (MILP) is presented. In the mentioned study, the energy prices of market and the deviations of wind power were considered with a risk strategy on bidding prices. In [15], a control method of VPP, which includes photovoltaic panels and controllable loads, is solved by using a mixed integer programming so that the power output of the VPP can be set in a wide range flexibly. In [16], the VPP attempts to maximize its expected turn over via participating in both the day-ahead and the balancing markets using a two-stage stochastic mixed integer linear programming model. A heuristic game theory based virtual power market model for security restricted unit commitment strategy was proposed in [17]. A price-based unit commitment method allowing a VPP to exchange energy with upstream network for day-ahead market sale/purchase bids was employed in [18]. In [19] an optimal scheduling of a micro grid, including PV, WT, Fuel cell (FC) in an isolated load area has been formulated for a 24-hour period and 1h time interval each. Likewise, in [20] the scheduling of DERs in an isolated grid has been investigated that the optimization problem has been solved by Branch and Bound technique and then used by an Artificial Neural Network (ANN) to better manage the DER. In [21], an optimization algorithm is used to solve bi-level optimal dispatch in VPP considering the uncertain factors number. A methodology is considered in [22] to control the emissions from a group of generation sources installed in laboratories aggregated in a VPP. In [23], a combined wind and pumped storage VPP is presented in an island system. In [24] the weekly scheming of a VPP comprising of intermittent renewable sources, energy storage device and a conventional power plant for maximizing their total profit is considered. In [25-26] a VPP bidding strategy in an unbalanced model based on price-based unit commitment is presented to contribute in energy and spinning reserve markets. In [27], an energy management method is investigated for VPPs and the cost and emission impacts of VPPs formation and electric vehicle penetration are analyzed. In [28], a modified particle swarm optimization method has been specified aiming at minimization of VPP costs in the day-ahead. A new algorithm has been suggested in [29] in order to optimize electrical and thermal scheduling of a large scale VPP, including cogeneration systems and energy storage systems, but no specific model for RESs and their corresponding uncertainties has been proposed.

In this paper one probabilistic methodology based on 2m Point Estimate Method (PEM) is proposed to consider the uncertainties of hourly load demand, available output power of solar and wind and market price. The VPP, which is considered here includes different renewable energy sources such as wind turbine (WT), photovoltaic (PV), micro turbine (MT), fuel cell (FC) and a battery as storage device. The objective function of the problem is modeled as the total operating cost of the VPP considering energy loss cost that is optimized for 24h time period. The optimal operation problem is modeled as an optimization problem and it is solved by using Imperialist Competitive Algorithm (ICA) under technical constraints.

The rest of the paper is organized as follows: In Section 2, the definition of VPP is presented. In Sections 3, the objective function and the related constraints are discussed. In Section 4, the 2m PEM is proposed as an approach to model the uncertainties. In Section 5, the ICA is introduced and explained completely as an optimization method. In Section 6, the simulation results and comparison of different methods are shown. Finally, the conclusion is presented in Section 7.

2. Virtual power plant

VPP is a combination of dispersed generator units, controllable load and ESS, participating at power market as an independent power plant for the purpose of trading their electrical energy for minimizing the cost. When the electricity price in the power market is low, the VPP can buy power for the power market and charge power into the energy storage systems. But when the electricity price in the power market is high, the VPP decreases the power obtained from the controlled load and discharge power from the energy storage systems. The generators of VPP could use fossil fuels and renewable energy sources. The EMS is the core of the VPP, and it coordinates the output energy of all generators, the energy storage system's capacity, and the load demand. The VPP concept and its possibility in the system operation have been identified in some recent researches.

The generators that are used in distributed systems are generally based on RES and have a low output power. Because of the fluctuating power of some RESs such as wind turbine and photovoltaic, accurate forecast of both the capacity and the moment in which the energy will be generated, is not straightforward. For that reason, such generators cannot be appropriate in deregulated power systems for two reasons, first they are not able to suggest the bids for effective capacity, and second they do not receive the grid requirements for maintaining the systems security. Such economical and security constraints can be done if these generators are place together to create a VPP structure. One of the principal features of a VPP is that each part of the VPP is linked directly to the EMS, so that the central control unit can get their latest status data. Hence, it is important to provide the connection among units. The aim of the EMS is trading electrical energy with the main grid and electricity market to achieve energy balance between generation and consumption for minimizing the operating cost at different hours of the day. The VPP components and interaction with power market are shown in Fig. 1.

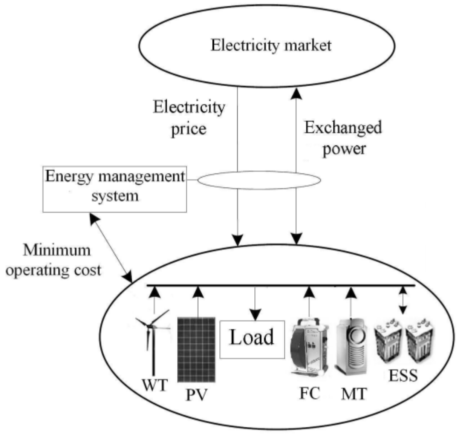

Fig. 1. VPP and trading of electrical energy with electricity market.

3. Problem formulation

The objective function and the corresponding constraints of the optimal operation management are described in this section.

3.1. Objective function

This paper presents an energy management scheme in a VPP including renewable and conventional DGs. The objective function is to minimize the VPP operational cost by the control of the local production as well as the interactive relationship with the grid. In fact, the VPP will try to supply its consumers locally. However, if the total power produced by DGs is not enough or too expensive to cover the supplying loads, then energy is bought from the grid (as the upstream network) and will be sold to the consumers or stored in the storage devices. Consequently, it can be concluded that the objective cost consists of the power that exchange between the VPP and grid, the fuel cost for DGs, and the start up or shut down cost of the power sources used in the VPP. The objective function is similar to [30], but the principal difference is the cost of the energy loss reduction occurred into distribution system lines.
This function is stated as follows:

$$\left[Min\ f = \sum_{t=1}^{T} Cost = \sum_{t=1}^{T} \left(\begin{array}{l} P_{Grid}(t) \times C_{Grid}(t) \\ + U_{WT}(t) \times P_{WT}(t) \times C_{WT}(t) \\ + U_{PV}(t) \times P_{PV}(t) \times C_{PV}(t) \\ + U_{FC}(t) \times P_{FC}(t) \times C_{FC}(t) \\ + U_{MT}(t) \times P_{MT}(t) \times C_{MT}(t) \\ \sum_{j=1}^{N_s} U_j(t) \times P_{Sj}(t) \times C_j(t) \\ + \sum_{i=1}^{N_g} S_{Gi} \,|U_i(t) - U_i(t-1)| \\ + \sum_{j=1}^{N_s} S_{Sj} \,|U_j(t) - U_j(t-1)| \\ - \Delta P(t) \times C_{\Delta P}(t) \end{array} \right) \right] \tag{1}$$

$$\sum_{t=1}^{T} \Delta P(t) = \sum_{t=1}^{T} (P_{original\ losses}(t) - P_{new\ losses}(t)) \tag{2}$$

$$P_{final\ losses}(t) = \sum_{t=1}^{T} \sum_{i=1}^{Nbr} R_i \times \left| I_i(t) \right|^2 \tag{3}$$

Where $C_{WT}(t), C_{PV}(t), C_{FC}(t), C_{MT}(t)$ and $C_j(t)$ are the bids of the wind turbine, photovoltaic, fuel cell, micro turbine and storage devices at hour t respectively. $S_{Gi}(t)$ and $S_{Sj}(t)$ are the start-up or shut-down costs for *i*th DG and *j*th storage respectively, $P_{Grid}(t)$ is the active power which is bought (sold) from (to) the utility at time t and $C_{Grid}(t)$ is the bid of utility at time t. N_g and N_s represent the total number of generation and storage units respectively, $U_{WT}(t)$, $U_{PV}(t)$, $U_{FC}(t)$, $U_{MT}(t)$ and $U_j(t)$ represent the ON or OFF states of all units at hour t of the day. Also $\Delta P(t)$, $C_{\Delta P}(t)$, R_i and I_i are the difference between the original losses and the new losses of feeders and it's cost at hour t and the resistance and the actual current of the i^{th} branch respectively [31].

3.2. Constraints

- Power Balance in each time period t

$$\sum_{t=1}^{T}\begin{pmatrix} P_{Grid}(t)+P_{WT}(t) \\ +P_{PV}(t)+P_{FC}(t) \\ +P_{Battery\,discharge}(t) \end{pmatrix}=\sum_{t=1}^{T}\begin{pmatrix} Load(t) \\ +P_{Battery\ charge}(t) \\ +P_{Loss}(t) \end{pmatrix} \tag{4}$$

- Wind turbine generation limitation in each time period t

$$P_{WT\min}(t)\le P_{WT}(t)\le P_{WT\max}(t);\quad t=1,\dots,T \tag{5}$$

- Photovoltaic generation limitation in each time period t

$$P_{PV\min}(t)\le P_{PV}(t)\le P_{PV\max}(t);\quad t=1,\dots,T \tag{6}$$

- Fuel cell limitation in each time period t

$$P_{FC\min}(t)\le P_{FC}(t)\le P_{FC\max}(t);\quad t=1,\dots,T \tag{7}$$

- Micro turbine limitation in each time period t

$$P_{MT\min}(t)\le P_{MT}(t)\le P_{MT\max}(t);\quad t=1,\dots,T \tag{8}$$

- Utility limitation in each time period t

$$P_{Grid\min}(t)\le P_{Grid}(t)\le P_{Grid\max}(t);\ t=1,\dots,T \tag{9}$$

- Storage battery limitation in each time period t

$$P_{Sj\min}(t)\le P_{Sj}(t)\le P_{Sj\max}(t);\ t=1,\dots,T \tag{10}$$

Due to restriction on charge and discharge rate of storage devices during each time period the following equation and constraints can be considered:

$$W_{ess}(t)=W_{ess}(t-1)+\eta_{charge}P_{charge}\Delta t-\frac{1}{\eta_{discharge}}P_{discharge}\Delta t \tag{11}$$

$$W_{ess\min}\le W_{ess}(t)\le W_{ess\max}\ ;\quad t=1,\dots,T \tag{12}$$

$$P_{charge}(t)\le P_{charge\max}.X(t)\ ;\quad t=1,\dots,T;\ X\in\{0,1\} \tag{13}$$

$$P_{discharge}(t)\le P_{discharge\max}.Y(t)\ ;\quad t=1,\dots,T;Y\in\{0,1\} \tag{14}$$

- Storage battery cannot charge and discharge at the identical time

$$X(t)+Y(t)\le 1;\ t=1,\dots,24;\ \ X\ and\ Y\in\{0,1\} \tag{15}$$

where $W_{ess}(t)$ and $W_{ess}(t-1)$ are the quantities of energy storage inside the battery at hour t and $t-1$ respectively, P_{charge} and $P_{discharge}$ are the allowed rates of charge and discharge through a definite period of time $(\Delta t = 1h)$, η_{charge} and $\eta_{discharge}$ are the charge and discharge efficiency.

4. Imperialist competitive algorithm

Imperialist competitive algorithm (ICA) is a new algorithm that has been proposed by Atashpaz-Gargari and Lucas based on the human's socio political in different fields of engineering. The random initial population in this method is called countries. Some countries with the less cost are chosen to be imperialist, and the others are considered colonies of these imperialists. The countries are arrays that their dimension depends on the dimension of the optimization and each of them is defined by:

$$Country = [P_1, P_2, P_3, \ldots, P_N] \tag{16}$$

Where, P_i are regarded as the variable values that should be optimized. The cost of each country can be found by evaluation of the cost function (f) by the following equation:

$$C_i = f(country_i) = f(P_1, P_2, P_3, \ldots, P_N) \tag{17}$$

The algorithm begins with initial population of size N and N_{imp} is selected as the country with minimum cost in order to create the empires [32]. The remaining of the population (N_{col}) will be the colonies that each of them belongs to one of the empires.
For dividing amongst the imperialist, some of these colonies proportional to their power are transferred to each imperialist.
For proper division of the colonies amongst the imperialists, we define the normalized cost of an imperialist by:

$$C_n = \max(c_i) - c_n \tag{18}$$

C_n and c_n are normalized cost and cost of n-th imperialists, respectively. After determining the normalized cost of all imperialists, the normalized power of each imperialist is determined according to the following equation:

$$P_n = \left| \frac{C_n}{\sum_{i=1}^{N_{imp}} C_i} \right| \tag{19}$$

In the other words, the normalized power of an imperialist is the part of colonies that should be possessed by that imperialist [33]. Afterward, the primary number of colonies for n-th empire will be defined by following:

$$NC_n = round\{P_n . N_{col}\} \tag{20}$$

Where, NC_n is primary number of colonies belonging to the n-th imperialists and N_{col} is the total number of remaining colonies in the primary countries crowds.

After this stage, operators of ICA must be accomplished. There are three operators in ICA: Assimilation, Exchange and Imperialistic Competition. They are exhibiting as follows:

4.1. Assimilation

Imperialist states try to attract their colonies to move themselves toward the direction of different socio-political axis such as social welfare. This process is called assimilation policy. By moving all the colonies in the direction of the imperialist, the assimilation policy is planed in ICA. This movement is shown in Fig. 2.

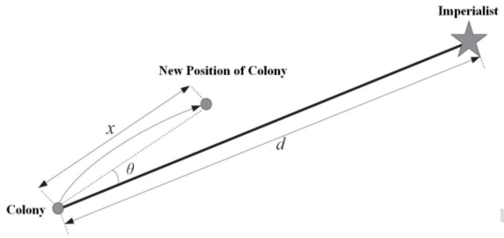

Fig. 2. Motion of colonies toward their imperialist

In order to search different parts around the imperialist, a random quantity of deflection is added to the direction of colony motion toward its imperialist.
In the above figure, x is a random variable with uniform distribution that is defined by:

$$x \sim U(0, \beta \times d) \quad (21)$$

Where, β is a number between one and two and near to two. d is distance between colony and imperialist and θ is a parameter with uniform distribution.

$$\theta \sim U(-\gamma, \gamma) \quad (22)$$

Where, γ is a significance parameter that its rising causes increase in searching region around imperialist and decrease of its value brings colonies near to the vector of connection between colony and the imperialist.

4.2. Exchange

A colony may reach to a location with lower cost than imperialist when moving toward the imperialist. In this condition, the imperialist and the colony alter their locations. Then, the algorithm will continue with the new location of the imperialist and thus the imperialist in its new location will assimilate the colonies.

4.3. Imperialistic competition

It is obvious that all empires attempt to get the ownership and control the colonies of other empires. In ICA, imperialistic competition is modeled by picking one of the feeblest colonies of the feeblest empire and cause a competition among all the empires to get this colony. To begin the competition, first total power of an empire is computed.
The total power of an empire is influenced by the power of imperialist country, while the colonies power of an empire has a negligible effect upon the total power of that empire. The total cost of each imperialist is calculated as below:

$$TC_n = Cost(imperialist_n) + \xi \, mean\{Cost(colonies\,of\,empire_n)\} \tag{23}$$

In the above equation, TC_n is the total cost of the n-th impire and ξ is a number between zero and one that indicates the influence of the colonies in value of the power of each imperialist [33].

After calculation of the total power of an empire, a colony of the feeblest empire is chosen and then the amount of power of each empire is found by ownership probability that is proportional to the total power of the empire. Then, the normalized total cost is determined by the following:

$$NTC_n = \max\{TC_i\} - TC_n \tag{24}$$

Where, TC_n is total cost n-th empire and NTC_n is the normalized cost of that n-th empire. Having the normalized total cost, the ownership probability of each empire is given by:

$$P_{pn} = \left| \frac{NTC_n}{\sum_{i=1}^{N_{imp}} NTC_i} \right| \tag{25}$$

Where, P_{pn} is the ownership of the n-th empire. Each empire which has greater power can take more colonies.

In order to divide the mentioned colonies among the empires, vector P is formed as follows:

$$P = [P_{p1}, P_{p2}, P_{p3}, \ldots, P_{PN_{imp}}] \tag{26}$$

Then, the vector R should be created with the same size as vector P. The arrays of this vector are random number with uniform distribution between zero and one.

$$R = [r_1, r_2, r_3, \ldots, r_{N_{imp}}] \tag{27}$$

Then, the vector D is formed by subtracting R from P.

$$D = P - R = [P_{P1} - r_1, P_{P2} - r_2, \ldots, P_{PN_{imp}} - r_{N_{imp}}] \tag{28}$$

Referring to vector D, it will hand the mentioned colonies to an empire so that relevant index in vector D is bigger than the others. The imperialistic competition will gradually result in a growth of the power of great empires and a decrease in the power of weaker ones. Powerless empires will disintegrate in the imperialistic competition and their colonies will be divided among other empires.

For execution of ICA to performance of optimal management of RESs by a VPP, The implementation steps are summarized below:

Step 1: Generate initial countries, each country displaying operating cost for a 24-hour period (objective function).

Step 2: Sort the initial countries based on the lowest operating cost.

Step 3: Select the imperialist cases (the countries with the less operating cost) and divide colonies among them to contribute the empires.

Step 4: Move colonies toward their relevant imperialist and apply assimilation. Again, compute the objective function for each country.

Step 5: If a colony in an empire has lower operating cost than of imperialist, exchange the location of that imperialist and the colony.

Step 6: Compute the operating cost of an empire.

Step 7: Pick the feeblest colony from the feeblest empire and assign it to the empire that has the most probability to possess it.

Step 8: If there is an empire with no colony, eliminate the empire.

Step 9: If there is only one empire, stop condition if not, go to the step 4.

5. Uncertainty modeling

There are three main methods to consider the uncertainty effect [34, 35]: the first one is Mont Carlo Simulation (MCS) that has some defects such as complicated computation. The second one is the analytical techniques that can satisfy MCS fault, but they need some mathematical assumptions to make the problem much more easier. The third one is approximate method [36] that can overcome the defects of both previous methods. The 2m point estimate method (PEM), as an approximate method, is a proper and straightforward method to model the uncertainty in investigated problem. This paper implements the 2m PEM to model the uncertainty in market prices, load demand, and available output power of PV and WT units.

5. 2m point estimate method

The 2m PEM is a modified version of the original point estimate method [37]. The normal distribution function is used to model uncertain variables. With the utilization of 2m PEM, each random variable in the uncertain problem is substituted by two deterministic points on both sides of the mean value of the distribution function. Then, for each random variable, the problem is solved for above and below mean value. The mathematical formulation is as described below:

$$\begin{aligned} &S = F(Z) \\ &Z = [z_1, z_2, ..., z_m] \end{aligned} \qquad (29)$$

Where set of input variables is shown by Z and S as output variables. In order to, for each uncertain variable (z_l), a probability function (f_{zl}) is considered. This method utilizes three points of f_{zl} as sample points to substitute them with two probability ones. Therefore, for m random input variables, 2m PEM will solve Eq. (26) 2m times. The probabilistic description of 2m PEM is shown in Fig. 3.

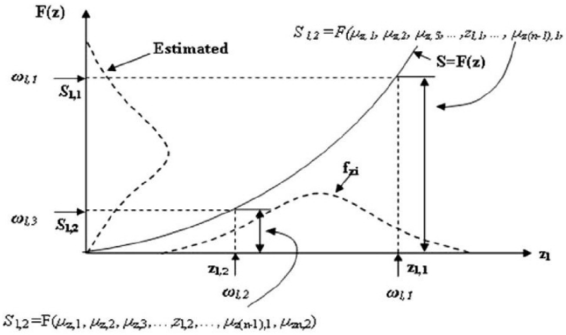

Fig. 3. The conceptual idea of 2m PEM

As it is shown in the above figure, the input data $Z_{l,1}$ & $Z_{l,2}$ are mapped to the output data $S_{l,1}$ & $S_{l,2}$, respectively. Two weighting factors are supposed $\omega_{l,1}, \omega_{l,2}$ for both $S_{l,1}$ & $S_{l,2}$ estimations. The location $(Z_{l,k})$ and weighting factor $(\omega_{l,k})$ can be considered as one pair $(Z_{l,k}, \omega_{l,k})$. Here $(Z_{l,k})$ can be formulated as follows:

$$Z_{l,k} = \mu_{zl} + \xi_{l,k} . \sigma_{zl} \,; k = 1,2 \qquad (30)$$

The standard location is named as $\xi_{l,k}$ in Eq. (27) can be evaluated as below:

$$\xi_{l,k} = \frac{\lambda_{l,3}}{2} + (-1)^{3-k}\sqrt{m - \left(\lambda_{l,3}^{2}\big/2\right)^{2}} \quad ;k = 1,2 \tag{31}$$

In Eq. (28), $\lambda_{l,3}$ as the third central moments of Z_l can be computed as follows:

$$\lambda_{l,3} = \frac{E\left[(Z_l - \mu_{Zl})^3\right]}{(\sigma_{Zl})^3} \tag{32}$$

In Eq. (29), the expected value is shown by E and Z_l is expressed as the standard deviation for output data and it can be calculated as follows:

$$\begin{aligned} &\sigma = \sqrt{Var(S_i)} = \sqrt{E\left(S_i^2\right) - \left[E(S_i)\right]^2} \\ &E\left(S_i^j\right) = \sum_{l=1}^{m}\sum_{k=1}^{2}\left(\omega_{l,k} \times S_i^j\left(\mu_{Z1}, \mu_{Z2}, \ldots, Z_{l,k}, \ldots, \mu_{Zm}\right)\right) \\ &\omega_{l,k} = \frac{1}{2m} \end{aligned} \tag{33}$$

In this paper, the uncertainty associated with the load demand forecast error, market price changes and PV and WT output power changes are modeled in the problem. For example, suppose that the *l*th load value $P_{L,l}(t)$ should be modeled by the PEM. By assuming the normal distribution function for all the load amounts, the PEM will solve this problem for two times. To simulate this uncertainty, it is supposed that the value of $P_{L,l}(t)$ is placed on the mean value of the load $\mu_{P_L(t)}$, then after that, according to the Eq. (27), two new points are generated to replace $P_{L,l}(t)$ as $Z_{l,k} = \mu_{P_L(t)} + \xi_{l,k}.\sigma_{P_L(t)};\ k = 1,2$. As it can be seen in Eq. (28), also the amount of the $\xi_{l,k}$ can be calculated. The optimal management problem should be solved for two new load amounts separately. Modeling the other uncertain variables can be implemented, similarly. Finally, the optimal solutions are aggregated to determine the expected amount of the objective function.

6. Simulation results

In order to verify the effectiveness and generality of the proposed ICA for the optimal energy management problem, it is implemented on a low voltage case study. This system consists of several types of RESs such as WT, PV, FC, MT and also one storage device such as NIMH-Battery. The single diagram of the system is shown in Fig. 4. The system complete data is extracted from [30]. As it can be seen, the system includes an industrial area for the supplement of a workshop, a residential area and a light commercial customer. The analysis is implemented for a 24 h time interval to see the performance of each power unit better. It is assumed that all the DGs generate active power at unit power factor. In addition, the heat load demand is not considered in the proposed system. Moreover, there is a power exchange link between the VPP and the utility in order to trade energy at any hour in the day.

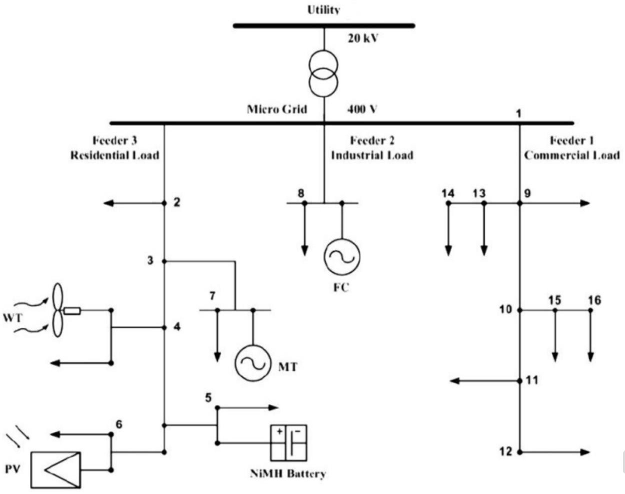

Fig. 4. Single line diagram of the test system

The maximum and the minimum generation limit and bids information for each of the DGs are shown in Table 1. As it can be seen from this table, although the WT and PV do not require any fuel for power generation, their bid is higher than the other DGs. This event is because of their high capital cost. The higher bid of these RESs offers to return the extra capital cost as well as to pay for renewal and maintenance costs. Also the cost of startup/shut-down for each unit in cent of Euro (€ct) per kilo-Watt hour (kWh) are given in Table 1. The total load demand during a 24 h time interval equals 1695KW as shown in Fig. 5. The hourly forecasted market prices for the examined period are considered as Table 2. The forecasted PV and WT power generation for each hour are plotted in Fig. 6. In order to better understanding our study, three different scenarios are considered. In the first scenario, all the DGs are dispatched regarding their real constraints. In the second scenario, all DGs are allowed to start up or shut down and the battery initial charge is zero. In fact, the battery should be charged in the first hours to be able to discharge at later hours and the third scenario, the utility is assumed as an unconstraint unit that can exchange energy with VPP without any restriction.

Table1
The limitations and bids of RESs and the utility

ID	Type	Min power (KW)	Max power (KW)	Bid (€ct/KWh)	Start up/ Shut down cost(€ct)
1	MT	6	30	0.457	0.96
2	FC	3	30	0.294	1.65
3	PV	0	25	2.584	0
4	WT	0	15	1.073	0
5	Battery	-30	30	0.38	0
6	Utility	-30	30	-	-

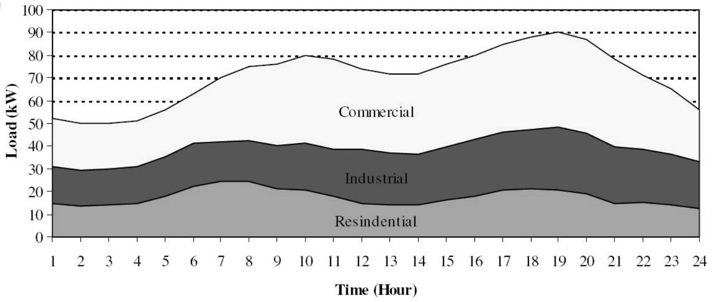

Fig. 5. Daily load curve of the test system

Table2
The real-time market

h	Price (€ct/KWh)
1	0.23
2	0.19
3	0.14
4	0.12
5	0.12
6	0.2
7	0.23
8	0.38
9	1.50
10	4.00
11	4.00
12	4.00
13	1.50
14	4.00
15	2.00
16	1.95
17	0.60
18	0.41
19	0.35
20	0.43
21	1.17
22	0.54
23	0.30
24	0.26

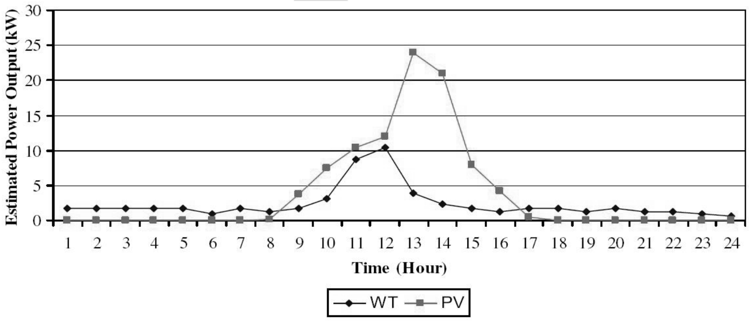

Fig. 6. Forecasted power output from WT and PV

6.1. First scenario

In the first scenario, it is supposed that all the units with related characteristics generate electricity and surplus of energy or additional demand inside of the grid is exchanged with the utility from the point of common coupling. All the units including the utility can operate just within their power limits while satisfying the required restrictions. The simulation results for the first scenario are presented in Table 3. As it can be seen from this table, the ICA has much better performance than the other algorithms. Comparison of results in the case of the best and the worst solutions for objective function indicates that the ICA not only demonstrates a better performance but also presents a faster convergence characteristic. The output power of the DGs in the first scenario are shown in Table 4.

As it can be seen from this table, at the early morning hours of a day a large part of the load is supplied by the FC and the utility because their bids are lower in comparison with other DGs. Due to the increasing of demand and bids of utility during the next hours of the day, DGs increase their output powers according to priority in lower cost. It should be also noted that the battery charging process has done at the first hours of the day when the prices are low but the discharge process will be done at midday when the load curve achieves peak values.

6.2. Second scenario

In the second scenario, the DGs can switch between the ON/OFF modes but the initial charge of the battery is zero. It means that the discharge amount of battery is limited by the amount of energy that is charged in the last hours. Table 5 shows the comparison results from the performances of the different algorithms. Similarly, the results of economic power dispatch using the proposed approach are shown in Table 6.

Table3

Comparison of total cost for first scenario

Type	Best solution (€ct)	Worst solution (€ct)	Mean (€ct)
GA [30]	162.9469	198.5134	179.6502
PSO[30]	162.0083	180.2282	171.2103
FSAPSO[30]	161.5561	175.5402	168.2442
CPSO-T[30]	161.0580	165.3110	162.9845
CPSO-L[30]	160.7708	163.5512	162.1614
AMPSO-T[30]	159.9244	160.4091	160.2368
AMPSO-L[30]	159.3628	159.6813	159.5143
ICA	151.4229	151.4253	151.4241

Table4

Economic dispatch using ICA (first scenario)

Time (h)	DG sources					
	MT	FC	PV	WT	Battery	Utility
1	6	30	0	0	-14	30
2	6	30	0	0	-16	30
3	6	30	0	0	-16	30
4	6	30	0	0	-15	30
5	6	30	0	0	-10	30
6	6	30	0	0	-3	30
7	6	30	0	0	4	30
8	6	30	0	0	9	30
9	30	30	0	1.785	30	-15.785
10	30	30	7.528	3.09	30	-20.615
11	30	30	9.225	8.775	30	-30
12	30	30	3.59	10.41	30	-30
13	30	30	0	3.915	30	-21.915
14	30	30	9.63	2.37	30	-30
15	30	30	0	1.785	30	-15.785
16	30	30	0	1.305	30	-11.305
17	30	30	0	0	30	-5
18	6	30	0	0	30	22
19	6	30	0	0	24	30
20	6	30	0	0	30	21
21	30	30	0	1.3005	30	-13.3005
22	30	30	0	0	30	-19
23	6	30	0	0	-1	30
24	6	30	0	0	-10	30

Table5

Comparison of total cost for second scenario

Type	Best solution (€ct)	Worst solution (€ct)	Mean (€ct)
GA [38]	334.8694	345.0211	336.2912
PSO[38]	327.7211	340.3123	331.2102
FSAPSO[38]	326.4291	335.4931	331.4301
θ- PSO[38]	318.6401	332.9012	322.9102
SAM- θ- PSO [38]	299.4124	299.9012	299.4124
ICA	299.1013	299.1042	299.1027

As it can be seen Table 6, the battery is charged in the first hours of day (hours 1-8), even by buying energy from MT. This event indicates that it is more economical to charge the battery by the use of MT to reduce the utility power generation at later times. During the high price period (hours 9-16), the battery is discharging at heavy load times to supply the utility by selling energy to it. In addition, at hours 23-24 the MT is forced to decrease its power to reduce the total cost. This event leads the MT to shut down at hour 24.

Table6

Economic dispatch using ICA (second scenario)

Time (h)	DG sources					
	MT	FC	PV	WT	Battery	Utility
1	20.215	30	0	1.785	-30	30
2	18.215	30	0	1.785	-30	30
3	18.215	30	0	1.785	-30	30
4	19.215	30	0	1.785	-30	30
5	24.215	30	0	1.785	-30	30
6	30	30	0	0.915	-27.915	30
7	30	30	0	1.785	-21.785	30
8	30	30	0.2	1.305	-16.505	30
9	30	30	3.75	1.785	30	-19.535
10	30	30	7.525	3.09	30	-20.615
11	30	30	10.45	8.775	28.775	-30
12	30	30	11.95	10.41	21.64	-30
13	30	30	23.9	3.915	14.185	-30
14	30	30	21.05	2.37	18.58	-30
15	30	30	7.875	1.785	30	-23.66
16	30	30	4.225	1.305	30	-15.53
17	30	30	0.55	1.785	-7.335	30
18	30	30	0	1.785	-3.785	30
19	30	30	0	1.302	-1.302	30
20	30	30	0	1.785	-4.785	30
21	30	30	0	1.3005	30	-13.3005
22	30	30	0	1.3005	0.232	9.4675
23	6	30	0	0.915	-1.915	30
24	0	30	0	0.615	-4.615	30

6.3. Third scenario

In this scenario, it’s assumed that all DGs act within their power limits but the utility behaves as an unconstraint unit and exchanges energy with the VPP without any restriction. Similar to the previous cases, the comparison results of performances are implemented to solve the economic dispatch problem and the simulation results are gathered correspondingly as shown in Table 7. The best optimal power dispatch using ICA for a day ahead and in terms of cost objective is also tabulated in Table 8.

Table7
Comparison of total cost for third scenario

Type	Best solution (€ct)	Worst solution (€ct)	Mean (€ct)
GA [30]	91.3293	127.7625	105.2070
PSO[30]	90.7629	112.8628	99.8493
FSAPSO[30]	90.6919	108.7761	99.7340
CPSO-T[30]	90.5545	102.1001	96.3273
CPSO-L[30]	90.4833	100.8786	95.6809
AMPSO-T[30]	89.9917	90.6221	90.3119
AMPSO-L[30]	89.9720	90.0431	90.0080
ICA	65.8273	65.8284	65.8295

Table8
Economic dispatch using ICA (third scenario)

Time (h)	DG sources					
	MT	FC	PV	WT	Battery	Utility
1	6	3	0	0	-30	73
2	6	3	0	0	-30	71
3	6	3	0	0	-30	71
4	6	3	0	0	-30	72
5	6	3	0	0	-30	77
6	6	3	0	0	-30	84
7	6	4	0	0	-30	90
8	6	30	0	0	-30	69
9	30	30	0	1.7855	30	-15.7855
10	30	30	7.5279	3.0854	30	-20.6133
11	30	30	10.4412	8.7724	30	-31.2136
12	30	30	11.964	10.413	30	-38.377
13	30	30	0	3.9228	30	-21.9228
14	30	30	21.0493	2.3766	30	-41.4259
15	30	30	0	1.7855	30	-15.7855
16	30	30	0	1.3017	30	-11.3017
17	30	30	0	0	30	-5
18	6	30	0	0	30	22
19	6	30	0	0	-30	84
20	6	30	0	0	30	21
21	30	30	0	1.3017	30	-13.3017
22	30	30	0	0	30	-19
23	6	30	0	0	-30	59
24	6	3	0	0	-30	77

As it can be seen Table 8, the utility takes the lead in supplying the load inside the grid during the first hours of the day while purchasing energy in large quantities from the VPP during the peak times. Regarding objective function, PV and WT start-up when shortage of power generation happens inside the grid or there is a need for more energy to the utility. The other DG units such as FC and storage battery generate electricity at their maximum rates during the most hours of the day while MT holds the maximum power level during a period of time from 9-17.

7. Conclusion

In this paper, an ICA method is introduced and applied to solve the optimal management of RESs such as WT, PV, FC and MT and one storage device like a battery that 2m PEM was implemented to cover the uncertainties in load demand, market price and available output power of the WT and PV units for a 24 h time interval. To investigate the performance of the proposed algorithm three different scenarios have been proposed and the simulation results in each scenario have been collected truly. The numerical results showed that proposed optimization method reduced the operation cost fairly well in comparison to the other methods.

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1- Integrated operation of wind turbine, photovoltaic panel, fuel cell, micro turbine, energy storage systems and controllable loads by virtual power plant.

2- Consider uncertainties related to forecasted values for load demand, market price, output power of wind and photovoltaic.

3- Investigating the application of methodology to reduce the operational cost with considering energy loss cost under three scenarios for a 24-hour period.

4- Optimal management is formulated by one optimization meta-heuristic algorithm, Imperialist Competitive Algorithm (ICA).