An optimal energy management system for islanded Microgrids based on multi-period artificial bee colony combined with Markov Chain

Mousa Marzband, Fatemeh Azarinejadian, Mehdi Savaghebi, Member, IEEE, and Josep M. Guerrero, Fellow, IEEE

Abstract—Optimal operation programming of electrical systems through minimization of production cost and market clearing price (MCP) as well as better utilization of renewable energy resources has attracted the attention of many researchers. To reach this aim, energy management systems (EMS) has been studied in many research activities. Moreover, demand response (DR) expands customer participation to power systems and results in a paradigm shift from conventional to interactive activities in power systems due to the progress of smart grid technology. Therefore, modelling of consumer characteristic in DR is becoming so important issues in these systems. The customer information as the registration and participation information of DR is used to provide additional indices for evaluating customer response, such as consumer’s information based on the offer priority, DR magnitude, duration, and minimum cost of energy (COE). In this paper, a multi-period artificial bee colony (MABC) optimization algorithm is implemented for economic dispatch considering generation, storage and responsive load offers. The better performance of the proposed algorithm is shown in comparison with the modified conventional energy management system (MCEMS) and its effectiveness is validated experimentally over a Microgrid (MG) Testbed. The obtained results show cost reduction (by around 30%), convergence speed increase as well as remarkable improvement of efficiency and accuracy under uncertain conditions. An artificial neural network (ANN) combined with Markov-chain (MC) (ANN-MC) approach is used to predict non-dispatchable power generation and load demand considering uncertainties. Furthermore, other capabilities such as extendibility, reliability and flexibility are examined about the proposed approach.

Index Terms—artificial bee colony, demand response, microgrid, Optimum energy management, optimum scheduling of DG, responsive load demand, uncertainty.

NOMENCLATURE

<table>
<thead>
<tr>
<th>Acronyms</th>
<th>Variables</th>
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<tbody>
<tr>
<td>ABC</td>
<td>the supply bids by A (€/kWh)</td>
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<tr>
<td>ANN</td>
<td>A ∈ {WT, PV, MT, ES-, ES+, UP, EGP, &amp; EWH}</td>
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<td>DR</td>
<td>$\lambda^A_t$ MCP</td>
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<td>DSM</td>
<td>MCP at each time $t$ in MCEMS (€/kWh)</td>
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<td>EMS</td>
<td>$\lambda^A_t$ MCP</td>
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<td>ES</td>
<td>MCP at each time $t$ in EMS-MABC (€/kWh)</td>
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<tr>
<td>EWH</td>
<td>$P^A_t$ available power of A in MCEMS (kW)</td>
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<td>MG</td>
<td>$P^A_t$ available power of A in EMS-MABC (kW)</td>
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<tr>
<td>LEM</td>
<td>real power set-points of A in MCEMS (kW)</td>
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<td>MABC</td>
<td>real power set-points of A in EMS-MABC (kW)</td>
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<tr>
<td>MCEMS</td>
<td>$P^A_t$ available power of A (kW)</td>
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<td>MC</td>
<td>$P^A_t$ non-responsive load (NRL) demand (kW)</td>
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<tr>
<td>MCP</td>
<td>$SOCC_t$ battery SOC in MCEMS (%)</td>
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<tr>
<td>MLP</td>
<td>$SOCC^*_t$ battery SOC in EMS-MABC (%)</td>
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<tr>
<td>MINLP</td>
<td>$P, \bar{P}$ limit of power (kW)</td>
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<td>MPE</td>
<td>$E, \bar{E}$ limit of energy (kWh)</td>
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<td>MT</td>
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The contributions of the paper are as follows:

1) development of an intelligent algorithm based on ABC within a real MG towards supporting real time applications;
2) presentation of an algorithm based on artificial neural network (ANN) combined with Markov chain to consider system uncertainties;
   a) prediction of wind speed in a very short-time (adequate for real-time optimization);
   b) reduction of prediction error and uncertainty of predictions;
   c) significant reduction in calculation time which is considered very critical in real-time applications.
3) experimental implementation of the proposed smart algorithm demonstrating some benefits including flexible multi-device support, fast development with a running time proper for real-time applications.

II. ALGORITHMS IMPLEMENTATION FOR EMS

The EMS proposed in this paper is depicted in Fig. 1. It comprises different units, namely ANN-MC, EMS and LEM units. As shown in Fig. 1, four different algorithms are presented for implementing EMS based on LEM by using heuristic techniques or without using any optimization method. Flexibility, good accuracy, speed in decision making and plug and play abilities of LEM unit, MCEMS, EMS-MINLP (EMS based on mixed integer non-linear programming) and EMS-PSO (EMS based on particle swarm optimization) algorithms are discussed in detail in the previous studies [1], [14], [15]. Therefore, these are not addressed in the present paper and only EMS-MABC algorithm is described.

A. EMS-MABC algorithm

This algorithm encompasses ANN-MC, MABC and LEM units as illustrated in Fig. 1. Since LEM unit is explained in detail in [1] and [15], only ANN-MC and MABC units are discussed bellow.

1) ANN-MC unit: In this study, MC method is applied for obtaining long-term trends in wind speed data. Thus, a simple ANN structure with the minimum number of input variables and data regulations is required for training and the over-training problem can be solved with the proposed structure. As the MC method keeps the signals long-term behavior in the memory, the error obtained from the extrapolated prediction is also reduced. As another solution for extrapolation problem, the artificial samples covering the entire range are drawn as much as possible based on the existing knowledge about the proposed problem then used for ANN initializing to ensure that most of the future prediction involves interpolation. The outline of the proposed model is shown in Fig. 2. A set of wind speed data 2.5s in a 175min period is used to improve the model accuracy for predicting wind speed up to 7.5s ahead (total of 4200 wind speed data). In Fig. 2, TPM is transition probabilities matrix for the primary prediction, forward neighborhood indices (FNIs) and Backward neighborhood indices (BNIs) are two upper/lower states and their corresponding probabilities, respectively. \( \hat{v}_{t-k} \) is the real speed data at time \( t-k \), and \( \hat{v}_{t-k|i} \) is the predicted wind speed data for \( t+k \) and \( i \) states an index of the model \( i^{th} \) vector used in ANN-1. Also, \( \hat{v}_{t-1}, \hat{v}_{t-2}, \cdots, \hat{v}_{t-n} \) are considered as wind real speed data which are used for forming TPM by MC. In the proposed model, two ANNs are used for prediction. The first ANN (ANN-1) is applied for primary prediction and short-term obtaining of wind speed signal, where 10 real-time speed data from \( t \) to \( t-10 \) are used as input variables. Primary prediction can take place by ANN-1 for different time horizon. For training, 30 sets of data with 10 measured wind speed in each set are selected. After primary prediction, the provided TPS for the values and four other indices with primary predictions are fed as input variables to the second ANN (ANN-2). At the end, the implemented model based on two ANNs and MC method can be utilized for predicting different time horizons. Multi-layer perceptron (MLP) is used for ANN-1 which includes an input layer, a hidden layer and an output layer. In the output layer, only one neuron is used as \( \hat{v}_{t-k|i} \) in which \( k \) is the time step and \( \hat{v} \) is the anticipated wind speed at time \( t+k \) (calculated at time \( t \)). Because the number of neurons in each layer have an effect on the speed and network stability, sensitivity analysis shows that the structure of ANN-1 with the least mean absolute percentage error (MAPE) is equal to 5, 2 and 1 neurons for input, hidden and output layers with 30 training vectors and 0.01-0.08 learning rates. Based on the wind speed data histogram, wind speed states have become compatible with the 1m/s upper and lower limit difference of the wind speed for reaching high accuracy at an acceptable time. Based on the state matrix, it is possible to find the number of transitions from the two previous states during wind speed data sequence to the next state at time \( t+k \). Finally, TPM is calculated. TPM is formed by using 600 wind speed data and the calculated matrix is used as primary prediction values (Fig. 2). At the beginning, Markov state is calculated for the primary prediction values by ANN-1 for one step ahead. Then, according to TPM, the probability of predicted value is calculated during the next step. This process is carried out for all of the primary predictions. It must be noted that the prediction values of the previous step are generated by ANN-1. For the final prediction, MLP has been used for ANN-2. The number of neurons in the input layer is selected by considering the calculation of time and error (maximum prediction error (MPE) and MAPE). Since ANN-2 has six input and one output
variables, the number of neurons in each layer must be located in the range of variables and the best structure for ANN-2 with the least MAPE is estimated as 3,0 and 1 neuron for the input, hidden and output layers with 10 training vector and learning rate between 0.01-0.05. In Fig. 3, the proposed model is shown for ANN-MC unit.

Step 1
TPM calculation based on 600 data points of wind speed;

Step 2
Design of ANN-1 for primary prediction by using 300 other points of wind speed data:
- Calculation of MAPE and MPE

Step 3
Implementation of MC model for testing ANN-1 and designing ANN-2 (another 100 data set):
- finding non-dispatchable and load demand data state
- evaluation of different states transition
- TPM calculation
- TPM accumulation

According to Fig. 3, ANN-1 designed in the previous step is applied for the primary prediction. Then, the TPM calculated in step 1 is used to calculate the required coefficients. ANN-2 provides six input variables of primary wind speed prediction, their transition probability values, FNI-1 and FNI-2 of the current predicted states and BNI-1 and BNI-2 of previous predicted states.

Step 4
Design of ANN-2 for secondary prediction by using ANN-1 and TPM.
Both ANNs and TPM obtained are applied steps for the final prediction.

All the above steps must be applied for different prediction time horizons.

2) MABC unit: The flowchart of MABC unit is shown in Fig. 4. The highlighted areas in this Figure are the modifications made to ABC algorithm in order to adapt it in MG application. Each response of the optimization problem has \( D \) variables. In this paper, \( D = 7 \) is considered including WT \( (P_t^{\text{WT}}) \), PV \( (P_t^{\text{PV}}) \), MT \( (P_t^{\text{MT}}) \), charging and discharging power ES \( (P_t^{\text{ES}^+} \) and \( P_t^{\text{ES}^-}) \), EWH \( (P_t^{\text{EWH}}) \) and DR \( (P_t^{\text{DR}}) \) variables. The proposed algorithm is trying to find the optimal values for the design variables that minimize the objective function. Therefore, \( X_t \) is defined as \( X_t = x_t^1, x_t^2, \ldots, x_t^7 \) vector. The elements are \( x_t^i = P_t^{i,\text{WT}}, x_t^2 = P_t^{i,\text{PV}}, x_t^3 = P_t^{i,\text{MT}}, x_t^4 = P_t^{i,\text{ES}^+}, x_t^5 = P_t^{i,\text{ES}^-}, x_t^6 = P_t^{i,\text{EWH}} \) and \( x_t^7 = P_t^{i,\text{DR}} \). These variables are divided into two categories of dependent \( (P_t^{i,\text{MT}}, P_t^{i,\text{ES}^+}, P_t^{i,\text{ES}^-}, P_t^{i,\text{EWH}} \) and \( P_t^{i,\text{DR}} \)) and independent \( (P_t^{i,\text{WT}} \) and \( P_t^{i,\text{PV}} \)) variables. Since WT and PV are non-dispatchable resources which are affected by weather conditions, MT and ES powers can be varied depending on the power generated by WT and PV and energy consumed by load. To begin, independent variables must be made considering ANN-MC unit output. It is necessary to involve target population members in program planning, implementation and evaluation of objective function. It must be checked during optimization process if the generated population members satisfy constraints or not. Then, by using valid values for these independent variables and associated constraints, dependent variables can be generated randomly. Furthermore, after selecting a food source, the onlooker bee generates a new food source. MABC unit is illustrated by a
Algorithm 1 MABC UNIT

Require: PV, WT and load demand profile of the MG, the initial SOC of ES and the characteristic of system.
Initialize control parameters/ the problem specific parameters

for $t = 0 : m$ do
$\triangleright m$: the number of time periods
Generate the initial population by

$$X_{t}^{i,j} = x^{i,j} + \rho \times (\overline{x}^{j} - \underline{x}^{j})$$  \hspace{1cm} (1)

$\triangleright X_{t}^{i,j}$: $j^{th}$ variable from the $i^{th}$ response at time $t$,
$i \in \{1, 2, \ldots, N_{P}\}, \ j \in \{1, 2, \ldots, D\} \triangleright \overline{x}^{j}$ and $\underline{x}^{j}$: upper and lower of component $x \triangleright \rho$: random number in [0, 1] interval

Evaluate (Eq.(7))

$\text{cycle} = 1$

while $\text{cycle} < \text{MCN}$ do
$\triangleright$ MCN: maximum cycle number

Employed bee Generates $x_{t}^{n,i,j}$ by

$$x_{t}^{n,i,j} = x_{t}^{i,j} + \rho' \times (x_{t}^{i,j} - x_{t}^{k,j})$$  \hspace{1cm} (2)

$\triangleright k \in \{1, 2, \ldots, N_{P}\}, k \notin i \triangleright x_{t}^{n,i,j}$: new food source in the neighborhood of $x_{t}^{i,j}$ position

Evaluate and apply the greedy selection process

Onlookers Calculate $P_{t}^{i}$ for $x_{t}^{i,j}$ by

$$P_{t}^{i} = \frac{f t_{i}}{\sum_{j=1}^{N_{P}} f t_{j}^{i}}$$  \hspace{1cm} (3)

$\triangleright f t_{i}^{i}$: fitness value of $i^{th}$ response at $t$

Generates $x_{t}^{n,i,j}$ based on $P_{t}^{i}$

Evaluate and apply the greedy process

Scout Determine the abandoned $x_{t}^{i,j}$ if exist

Update it by Eq.(7)

Update the best solution acquired so far

end while

Return optimal power set-points

end for

III. MODIFIED ABC ALGORITHM

Several attempts, employing classical ABC were made in the past for solving unit commitment. However, ABC algorithm is good at exploration but poor at exploitation. These drawbacks become more prominent in case multimodal problems having several optima. This paper presents a modified ABC algorithm for optimization problems to improve the exploitation capability of the ABC algorithm and to further improve its performance. In this paper, to improve exploitation process of classic ABC, a different probability function modifying searching mechanism has been applied to the original ABC algorithm. Probability value of selecting a food source determines the exploitation rate. In order to improve the exploitation mechanism of onlooker bees, a modified probability function has been proposed in this paper (Eq. (2)). In addition, to increase the population diversity, avoid the premature couverture as well as to improve the exploitation of classic ABC algorithm, a second modification has been proposed by using a new searching mechanism (Eq. (1)). In the first modification, the worst fitness valued solution has the best chance to local search then algorithm uses the best solution in the current population to mutate parameters in the second modification. Generally, these modifications are based on reducing the colony size; maintaining the perturbation scheme; and using a rank selection strategy for maintaining diversity. In the proposed MABC, binary numbers 1 and 0 are used to indicate the status of generating units ON/OFF whereas the economic dispatch is solved using the real coded ABC. Whereas classical ABC algorithm is essentially a real-coded algorithm, thus, some modifications are needed to deal with the binary-coded optimization problem. In the proposed ABC, the relevant variables are interpreted in terms of changes of probability. The onlookers produce a modification in the position selected by it using (Eq. (1)) and evaluate the nectar amount of the new source. Improving strategy through by constraint based management in MABC whenever the commitment status for each time interval is generated randomly or by the modification of employed/onlooker bee’s position, dispatchable constraint must be checked as follows:

Step 1: If dispatchable resources constraints are met, then go to Step 3. Otherwise, go to next step.
Step 2: The less expensive units which are shut OFF can be identified and should be turned ON. Then go to Step 1.

Step 3: If dispatchable resources constraint is satisfied, then the maximum and minimum operating times constraints are checked for each unit. If there is any violation in the minimum up or down time constraint then a repair scheme is performed to overcome the violation.

Step 4: The modified scheme for Step 3 can effect on the dispatchable resources constraint. If the reliability level is sufficient, then return the feasible solution. Otherwise go to Step 1.

IV. PROBLEM FORMULATION

The problem formulation is divided into two parts which are closely connected and dependent on each other. The first part is related to the prediction error of uncertainty model and the other include MG constraints.

A. Error criteria for uncertainty consideration

The prediction error of a model is classically defined as the difference between the measured and predicted values. A horizon dependent model error \( e_{t+\Delta t}^t \) is given by

\[
e_{t+\Delta t}^t = P_{t+\Delta t}^X - \hat{P}_{t+\Delta t}^X
\]

where \( X \) denotes non-dispatchable resources and load demand entries. \( P_{t+\Delta t}^X \) is the measured X power at time \( t+\Delta t \), \( \hat{P}_{t+\Delta t}^X \) is the power prediction for X computed at time \( t \). The most commonly used evaluation criterion is the MAPE defined as follows [24].

\[
MAPE_k = \frac{1}{N} \sum_{t=1}^{N} \left( \frac{|e_{t+\Delta t}^t|}{P_{t+\Delta t}^X} \times 100 \right)
\]

where \( \Delta t \) and \( N \) describe the prediction horizon and number of prediction, respectively. It is very important to reduce MPE because a large prediction error and consequently wrong control commands may cause an unstable condition for non-dispatchable resources. MPE is calculated as [24].

\[
MPE_{\Delta t} = max \left| \frac{e_{t+\Delta t}^t}{P_{t+\Delta t}^X} \right| \times 100; t = 1, \ldots, N
\]

B. MG mathematical modeling

The system under study is considered as an islanded MG including non-dispatchable (WT and PV in this study) and dispatchable generation resources (MT in this study) and ES supplying some responsive (EWH and DR in this study)/non-dispatchable loads (NRL). The optimization problem is defined as the following cost function:

\[
\min \sum_{t=1}^{m} \left( C_t^g + C_t^{g'} + C_t^{ES-} - C_t^{ES+} + \Omega_t \right) \times \Delta t
\]

where \( m \) is the number of the simulation periods in time interval \( t \), \( C_t^g \) and \( C_t^{g'} \) are the cost of the energy generated by non-dispatchable and dispatchable resources, respectively, \( C_t^{ES+} \) and \( C_t^{ES-} \) are the energy generation cost by ES unit during charging and discharging operation modes, respectively, \( C_t^\ell \) is the cost of the energy consumed by responsive load demand (RLD) (EWH and DR are respectively termed as shiftable and controllable loads in this study) and \( \Omega_t \) is the penalty cost resulting from undelivered power (UP) during the time period \( t \). The objective of economic dispatch problem is in fact minimizing the total production cost while satisfying generation resources constraints. \( \Omega_t \) is included in the objective function as a penalty cost for the MG operator to avoid undelivered power to the NRL. Each one of these costs can be calculated as follows

\[
C_t^g = \sum_{k=1}^{n^g} \alpha_{t,k}^g \cdot P_t^{k,g}
\]

\[
C_t^{g'} = \sum_{k=1}^{n^{g'}} \alpha_{t,k}^{g'} \cdot P_t^{k,g'}
\]

\[
C_t^\ell = \sum_{k=1}^{n^\ell} \alpha_{t,k}^\ell \cdot P_t^{k,\ell}
\]

\[
C_t^{ES+} = \sum_{k=1}^{n^{ES+}} \alpha_{t,k}^{ES+} \cdot X_t^{ES} \cdot P_t^{k,ES+}
\]

\[
C_t^{ES-} = \sum_{k=1}^{n^{ES-}} \alpha_{t,k}^{ES-} \cdot (1 - X_t^{ES}) \cdot P_t^{k,ES-}
\]

\[
\Omega_t = \pi_{t,U}^{UP} \cdot P_t^{U_t}
\]

where \( \pi_{t,k}^g \) and \( \pi_{t,k}^{g'} \) are the \( k \)th non-dispatchable and dispatchable resources, \( P_t^{k,g} \) and \( P_t^{k,g'} \) are the output power generated by the \( k \)th non-dispatchable and dispatchable resources, \( n^g \) and \( n^{g'} \) are the number of non-dispatchable and dispatchable units installed in the MG system, \( \Delta_t \) is duration of the period \( t \), \( \pi_{t,k}^{ES} \) is the offer price by \( k \)th RLD, \( P_t^{k,\ell} \) is the output power consumed by \( k \)th RLD during the time period \( t \), \( \pi_{t,U}^{UP} \) is the offer price when the system is encountered UP and \( P_t^{U_t} \) is the amount of power is not supplied by MG. \( X_t^{ES} \) is status of ES operation mode (i.e. \( X_t^{ES}=0 \) when ES is in the discharging mode and \( X_t^{ES}=1 \), otherwise).

Equality and unequally constraints are formulated in the following:

- Power balance

\[
\sum_{k=1}^{n^g} P_t^{k,g} + \sum_{k=1}^{n^{g'}} P_t^{k,g'} + \sum_{k=1}^{n^{ES}} (1 - X_t^{ES}) \cdot P_t^{k,ES-} + P_t^{U_t} = P_t^{NRL} + \sum_{k=1}^{n^\ell} P_t^{k,\ell} + \sum_{k=1}^{n^{ES}} X_t^{ES} \cdot P_t^{k,ES+}
\]

- non-dispatchable resources

\[
0 \leq \sum_{k=1}^{n^g} P_t^{k,g} \leq \bar{P}^g
\]
where $P_{tg}^g$ is the maximum power generated by non-dispatchable generation units during the time period $t$.

- dispatchable resources [15]
  - electricity generation unit boundaries
  - ramp-up and ramp-down limits
  - maximum and minimum operating times
- ES constraints [15], [26]–[28]
  - energy storage limits;
  - maximum charge/discharge power limit;
  - maximum charge/discharge energy stored limit;
  - energy balance in ES;
  - SOC limit;
  - ES limit.
- RLD constraints

\[ P_{t}^{RLD} = P_{t}^{RLD} \quad (16) \]

\[ \sum_{t} P_{t}^{DR} = \sum_{t} P_{t}^{UP} \quad (17) \]

\[ P_{t}^{EGP} = X_{t}^{ES} \cdot P_{t}^{ES+} + X_{t}^{DR} \cdot P_{t}^{DR} + P_{t}^{EWH} \quad (18) \]

\[ \sum_{t} P_{t}^{EGP} = \sum_{t} X_{t}^{ES} \cdot P_{t}^{ES} + \sum_{t} X_{t}^{DR} \cdot P_{t}^{DR} + \sum_{t} P_{t}^{EWH} \quad (19) \]

where $X_{t}^{DR}$ is a binary variable indicating DR status (i.e. 1 if the request is in service and 0 otherwise). Eq. (17) guarantees that the total consumed power by DR should be equal to the total $P_{t}^{UP}$ during daily operation system, whereas EGP at each interval can be supplied for charging of ES, DR and EWH as formulated in Eq. (18). In addition, the summation of consumed power by these customers should be equal to the summation of EGP during a daily operation system as shown mathematically in Eq. (19).

V. APPLICATION TO TEST GRID

EMS-MABC algorithm is implemented and validated experimentally over the IREC’s MG. In this MG, all the microsources with any characteristic can easily be emulated by digital signal processing. This MG is used to investigate various concepts such as control design and implementation of EMS [1], [15], [28]. A general scheme of this system including emulators is shown in Figs. 5 and 6. This MG has two non-dispatchable resources (PV and WT), a dispatchable resource (MT), and ES integrated with some responsive (EWH and DR) and NRL. Emulators specifications are presented in the previous papers [1]. Furthermore, the system has a controller that EMS-MABC algorithm should be loaded in that. To begin, the central controller receives data including generated power and load demand ($P_{t}^{WT}$, $P_{t}^{PV}$ and $P_{t}^{n}$) provided by ANN-MC unit, SOC, and bid offers. Then, all optimal power set-point of each microsource will be dispatched to them at each time interval based on EMS algorithm. WT, PV and load demand profiles are shown respectively in Figs. 7(a)-7(c) [1].

The ability of the proposed algorithm under several scenarios is considered for optimal scheduling and operation of resources, minimizing the generation cost as well as applying demand side management.

The following scenarios are studied:
- Scenario ♯1: Normal operation
- Scenario ♯2: Sudden load increase
- Scenario ♯3: Plug and play ability

VI. RESULTS AND DISCUSSION

In this section, the results of experimental evaluation of the proposed algorithm over IREC’s MG are presented.

SOC and ES power during the 24 hour system operation are shown in Figs. 8 and 9, respectively. As it is observed in Fig. 8, during 00:00-06:00 period, SOC′ is almost always decreasing and at the end of this operation interval reached to SOC. However, in EMS-MABC a part of the power needed for charging the ES is provided by MT. As a result, SOC′ is reached about to 70% at the end of this time interval. More SOC causes the increase of the ability for supplying the loads during the rest of the system daily operation. During 06:00-12:00 period, MCEMS has already used ES for supplying a part of power shortage, while in EMS-MABC, ES is operated in the charging mode and continuing to reach SOC′. It is still clamped until the end of this interval. Scenarios
Fig. 7: the power generated by the emulators WT, PV and load demand

(a) WT emulator

(b) PV emulator

(c) Load emulator

Fig. 8: SOC during system operation (Solid light-gray line indicates MCEMS algorithm. Also, dash black line with circle marker type represent output of EMS-MABC algorithm)

Fig. 9: Charging/discharging power of ES emulator during system operation

EGP power are shown in Fig. 10. As it is observed in both algorithms, MG is not able to supply the power required by all consumers in scenarios ♯2 and ♯3 during 12:00-18:00. UP in MCEMS is more than EMS-MABC and ES is fully discharged.

It is noticeable that in this time interval, $P_{ES}^{E-}$ is about 30% more than its value in EMS-MABC. Therefore, more penalty cost due to lack of delivery of the power required by consumers should be paid. In these time intervals, $\lambda_{MCP}$ is about 0.3 €/kWh, but when UP exists, MCP is about 0.9 €/kWh. On the other hand, EMS-MABC has significantly reduced the electricity cost by curtailting a number of consumers (when MCP is relatively high) and feeding them at other hours with cheaper MCP. EWH is mainly supplied in the afternoon for both algorithms.

For experimental evaluation, the proposed algorithms are implemented in C environment on a PC with i5-3320 M, 4 GB RAM, 2.6 GHz. Table I shows the experimental results of proposed algorithm including computation time and total generation cost which is compared with the conventional PSO method. It is clearly seen in this table that EMS-MABC
algorithm got the minimal total generation cost around 35.35 € and needed shorter computation time than PSO algorithm. Also, the nearest value of objective function compared to realistic method (MINLP) is achieved in MABC algorithm.

TABLE I: Run time and total generation cost for case study corresponding to 100 iteration

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<tr>
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<th>MABC</th>
<th>PSO</th>
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<tr>
<td>Execution time (S)</td>
<td>10.14</td>
<td>27.35</td>
</tr>
<tr>
<td>Total generation cost (€)</td>
<td>35.35</td>
<td>36.42</td>
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<tr>
<td>Error (%)</td>
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<td>4.32</td>
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</tbody>
</table>

MCP during daily operation system of shown in Fig. 11. \( \lambda^MCP \) and \( \lambda_t^{MCP} \) during the day are respectively 0.52 €/kWh and 0.32 €/kWh that shows a 39% reduction in EMS-MABC. The maximum value of \( \lambda^MCP \) (1.33 €/kWh) is observed during scenario 2, while the maximum value of \( \lambda_t^{MCP} \) is 0.90 €/kWh and is obtained during scenarios 2 and 3. The minimum value of \( \lambda^MCP \) and \( \lambda_t^{MCP} \) are respectively 0.2 €/kWh and 0.13 €/kWh which are obtained for both algorithms during 00:00-06:00. MCP values during 24 hours of system operation are listed in Table II for both algorithms. As observed, MCPs in both algorithms are minimum during 00:00-06:00, so it is proper to supply more number of RLD and ES loads in this time interval. During this period, the supplied RLD and ES in EMS-MABC algorithm are totally about 46% more than their values in MCEMS. As a result, these consumers are supplied with lower price. During 06:00-12:00, in both algorithms, MT is placed in service and with attention to its higher offer in comparison with other generation sources, MCP is significantly increased. Hence, RLD and ES is supplied in EMS-MABC for a proportionately less time (about 85%). During 12:00-18:00, PV is started to generate power when the sun is starting to rise and MT is gone out of service. Since PV offer is less than MT, MCP is drastically reduced. Furthermore, in this time interval, about 6% more of RLD and ES loads are supplied in MCEMS in comparison with EMS-MABC. During 18:00-24:00, MCP is maximum in both algorithms, so it is beneficial that the loads with less offers are supplied in this time interval. Only ES with higher offer is charged in MCEMS while EWH is also fed in EMS-MABC. EWH has proposed minimum offer and as a result, consumers are considerably less cost-effective for feeding their loads.

TABLE II: The average value of MCP during system operation

<table>
<thead>
<tr>
<th></th>
<th>00:00-06:00</th>
<th>06:00-12:00</th>
<th>12:00-18:00</th>
<th>18:00-24:00</th>
</tr>
</thead>
<tbody>
<tr>
<td>MCP</td>
<td>0.62</td>
<td>0.49</td>
<td>0.56</td>
<td>0.57</td>
</tr>
<tr>
<td>( \lambda^MCP )</td>
<td>0.50</td>
<td>0.43</td>
<td>0.35</td>
<td>0.52</td>
</tr>
</tbody>
</table>

VII. CONCLUSIONS

In this paper, modeling of consumers’ information has been addressed by using EMS-MABC to present RLD characteristics in a DR program as well as to estimate the participation quality and commitment in a LEM structure with the aim of reducing MCP. In addition, a new concept for the virtual generation sources derived from demand resources has been introduced to estimate the optimal scheduling of generation resources and DR in an isolated MG. The DR constraints are expressed with various status flags, the information of other consumers and the excess power generated has been modeled to obtain the minimum total generation cost and less market clearing price. These points have been considered for modeling the limiting conditions for
the consumers participating in a demand response program. The optimal programing for generation scheduling combined with DR has been performed to minimize the operation cost of MG linked to customer information. This combined programming has been evaluated over a MG Testbed. Since renewable resources such as WT and PV have intermittent characteristic, approaches to analyze economic dispatch in MGs would be stochastic rather than deterministic. To take the uncertainties into account, ANN-MC method according to artificial neural network combined with Markov-chain concept is implemented.

The obtained experimental and simulation results show the reduction of the total operation cost (about 30%) also significant reduction of MCP in each time interval with adequate and real time control of DR in the proposed algorithm. The proposed approach shows more decrease in the objective function than EMS-PSO algorithm while reducing computation time.

REFERENCES


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