Neural Network-Based Objectives Prioritization for Multi-Objective Economic Dispatch in Microgrids

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***Abstract*— In this paper we describe a neural network-based approach for automatic prioritization of objectives to solve the multi-objective economic dispatch (MOED) problem in the framework of smart microgrids. Four objectives are considered: energy cost, distance of supply, load balancing, and environmental impact. The proposed system tries to reproduce the preference function used by an expert to prioritize the objectives by assigning weights to the objectives themselves. To this aim, we use a multi-layer perceptron neural network whose inputs are four operating condition indicators sensed, with a regular time frequency, by the information network of the microgrid. Such indicators represent the current state of the microgrid. Learning has been performed by using a dataset composed of 150 samples, each one composed by a combination of the operating condition indicators, associated with a configuration of weights assigned to the objectives by an expert. Accuracies of 99.203% and 98.547% on the training and test sets, respectively, were achieved, with mean squared errors of $3.24 \cdot 10^{-4}$ and $6.59 \cdot 10^{-4}$ on the training and test sets, respectively.**

I. Introduction

A microgrid is an electricity distribution system consisting of interconnected loads and distributed energy resources [1]. A microgrid may be, e.g., a village, a part of a town, or an industry site; typical energy sources are solar panels on the roofs of buildings and small wind turbines. A microgrid may be either connected to the main power grid or islanded; when the microgrid is in islanded mode, an appropriate voltage control is needed [2] and load shedding policies may be necessary to satisfy the consumers' requirements [3]. A microgrid can thus be regarded as a smart self-managed localized grouping of energy consumers, producers and prosumers (i.e., customers that may both consume and produce energy). Within a smart microgrid three main aspects must be dealt with, namely, i) generation, distribution and regulation of the flow of electricity to consumers, and information management and transmission; ii) control of the degree of satisfaction of given objectives, such as cost minimization, pollution reduction, supply and demand balance, etc.; iii) reliability and security control. As far as previous point ii) is concerned, the implied control task consists in trying to simultaneously optimize more conflicting objectives. It is well-known that this type of problem, defined as multi-criteria decision making (MCDM) problem in the literature, does not admit a single solution able to simultaneously optimize all the objectives. In general, the methods aimed at solving MCDM problems can be divided into three major categories, namely, *a priori* methods, *a posteriori* methods, and *interactive* methods. These methods are characterized, respectively, by a priori specification of preferences, a posteriori specification of preferences, and no specification of preferences. In particular, in the first category of methods, which are by far the most frequently used, an expert is typically involved in the solution process to specify the relative importance of the considered objectives by associating, e.g., a weight with each objective.

In this paper we will deal with a multi-objective optimization problem [4] characterized by a priori specification of preferences. The problem is to solve the multi-objective economic dispatch (MOED) problem in smart microgrids taking four objectives into account, namely energy cost, distance of supply, load balancing, and environmental impact. We propose a neural network [5] purposely developed and trained to take the place of the human expert in specifying the weights that state the relative importance of the four objectives listed above. Since the expert makes his/her decision at regular time intervals based on information on the current state of the microgrid, we represent the state of the microgrid itself by defining four indicators related, respectively, to the cost of the available energy, the unbalancing of the loads, the available renewable energy, and the distance between generators and loads. The neural network takes the values of these indicators as inputs, and outputs the corresponding set of weights associated with the considered four objectives. We train the neural network with a set of pairs, each consisting of indicator values and related objective weights, collected during the operation of a simulated prototype microgrid. The results achieved in the experiments show the capability of the developed neural network to faithfully reproduce the reasoning process of the expert, by showing an error that is negligible on both the training and test sets.

The rest of this paper is organized as follows: in Section II we model a smart microgrid as a radial digraph; Section III contains the multi-objective optimization fundamentals; in Section IV we introduce the economic dispatch problem, the DC power model, the objectives we take into account, and we formalize the MOED problem in a smart microgrid; Section V contains an overview of artificial neural networks; in Section VI the proposed neural network-based automatic prioritization of objectives in the MOED problem is described, and the formal definition for the operating condition indicators is given; Section VII contains the results of the experiments we carried out to find out the best neural network architecture for automatic prioritization. Finally, in Section VIII we draw the conclusion of our work.

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II. Radial digraph model

We model a microgrid as a radial directed graph [6] whose nodes are identified by integer numbers. Arcs are denoted by using ordered pairs of nodes. A node of a microgrid can be active or passive. A node is active if it provides energy, otherwise, if it absorbs power, the node is passive. A *dispatcher* (in Fig. 1 a circle with a white label) is a node which neither consumes nor produces energy. Its task consists in dispatching the power available in the active nodes to the passive nodes. Each dispatcher is connected to a *central controller* (a ring in Fig. 1) through an outgoing arc and an incoming arc. Central controllers neither produce nor consume energy, and they are connected to the main grid at the point of common coupling. A *producer* (a circle with a unique outgoing arc in Fig. 1) is an active node characterized by the distance from the dispatcher it is connected to, the amount of suppliable power, the resource it uses to generate energy (e.g., fossil fuels, biomass, etc.), the quantity of pollutants released into the environment to produce a kWh of energy, and the cost per kWh of energy produced. A *consumer* (in Fig. 1 a circle with a unique incoming arc) is a passive node. A consumer has a distance from the dispatcher, and a nominal power. Within a microgrid, a consumer can be *sensitive*, *adjustable* or *shedable*. In the following, a consumer will be also referred to as a *load*. A sensitive load cannot stop working, so it continuously requires the nominal power to work properly. Adjustable loads can work at different levels of power, that is, their power consumption can be changed according to power availability. In fact, adjustable loads are often managed by the smart microgrid to reduce the global power consumption during peak periods. Finally, shedable loads only work at their nominal power, but their switching on can be delayed depending on the energy pricing convenience. A *prosumer* (represented in Fig. 1 as a filled circle with a pair of arcs connecting it to a dispatcher) is a node which produces or consumes electricity, depending on the instant in time. A prosumer is characterized by all the attributes of producers and consumers. Prosumers generate electricity by exploiting renewable sources, so they have a zero environmental impact. Each producer or consumer is connected to a dispatcher with an arc whose direction is compatible with the power flow. Also, each prosumer is connected to a dispatcher via a pair of arcs: one directed to the dispatcher, the other directed to the other side. Microgrids are composed of *feeders*. A feeder consists of all the nodes (except the central controller) that are connected to a given dispatcher, including the dispatcher itself. In Fig. 1 the dashed circle delimits a feeder.

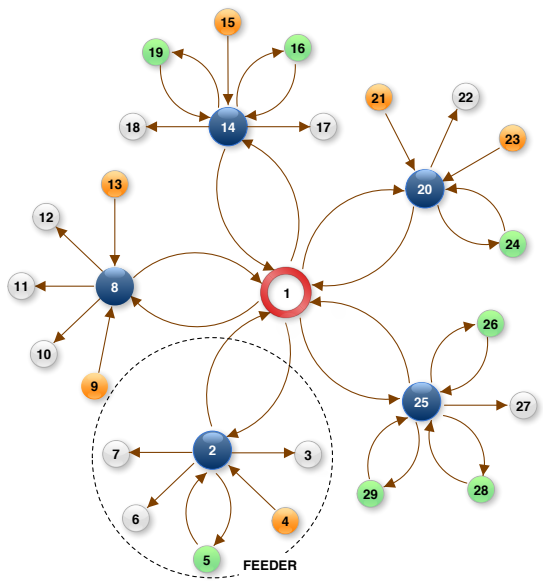

Fig. 1. A smart microgrid represented as a radial directed graph.

III. Multi-objective optimization

A. Overview

In multi-objective optimization (MOO) problems multiple objective functions are optimized at the same time. Formally, an MOO problem is

$$\text{Minimize} \quad \mathbf{f} = [f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_k(\mathbf{x})] \tag{1}$$

subject to:

$$g_i(\mathbf{x}) \leq 0, \quad i = 1, \ldots, m \tag{2}$$

$$h_j(\mathbf{x}) = 0, \quad j = 1, \ldots, n \tag{3}$$

where $k \geq 2$ is the number of objectives, m and n are, respectively, the number of inequality and equality constraints, that define the feasible region X. The global objective function $\mathbf{f} : X \to \mathbb{R}^k$ is a vector-valued function defined as $\mathbf{f}(\mathbf{x}) = [f_1(\mathbf{x}), \ldots, f_k(\mathbf{x})]^T$, containing all the objective functions to be optimized. Each element $\mathbf{x} \in X$ is a feasible solution. Since, in general, no feasible solution that simultaneously minimizes all the objective functions exists, the concept of *Pareto-optimal solution* is introduced, i.e., a particular feasible solution that cannot be improved with respect to any objective without degrading at least one of the other objectives. The set of Pareto-optimal solutions is called the *Pareto front*.

B. Classification of MOO methods

As previously stated, MOO methods are divided into *a priori*, *a posteriori* and *interactive* [4]. A priori methods require an expert to preliminarily prioritize objectives, e.g., through a set of weights. On the contrary, with a posteriori methods, the optimization process begins generating an approximation of the Pareto front. Then, the decision maker is required to choose the solution that best represents his/her preferences. Finally, interactive methods cooperate with the decision maker, who progressively controls the optimization process.

C. Normalized weighted sum

Normalized weighted sum (NWS) is the most common approach to multi-objective optimization [4]. NWS is an a priori method, which requires an expert to express a set of weights $\mathbf{w} = (w_1, \ldots, w_k)$, each related to one of

the objective functions, obtaining the aggregate objective function:

$$F(\mathbf{x}) = \sum_{i=1}^{k} w_i f_i(\mathbf{x}). \tag{4}$$

If all the weights are positive, then minimizing (4) provides a Pareto-optimal solution to the problem [4].

IV. Multi-objective economic dispatch in smart microgrids

A. Economic dispatch: an overview

The energy dispatch problem in a power system includes two successive steps, namely, unit commitment (UC) and economic dispatch (ED). Within a microgrid, generators are split into *dispatchable* and *non-dispatchable*. Dispatchable generators are characterized by a deterministic production level, while non-dispatchable generators are influenced by stochastic fluctuations of the produced power, since they are based on renewable sources like sunlight, wind, etc. UC selects the dispatchable generators (referred to as *scheduled generators*) that have to be active in a given time slot of the day after to meet the forecasted load demand for such time slot. ED is a short-term optimization process aimed at determining the power output of the one day-ahead scheduled generators and the non-dispatchable generators, in order to minimize a cost objective function, under operational constraints. More advanced formulations of ED include network constraints [7]. Also, multi-objective formulations have been proposed to optimize further objectives at the same time, e.g., transmission loss and fuel cost [8], risk and operation cost [9], cost and emissions [10], and energy cost of renewable sources [11].

B. DC model with piecewise approximation of losses

Considered an AC transmission line (i, j) connecting two nodes i and j of a microgrid modeled as a radial directed graph, active and reactive power flows are, respectively,

$$p_{i\to j} = V_i^2 g_{i\to j} - V_i V_j (g_{i\to j}\cos\theta_{i\to j} + b_{i\to j}\sin\theta_{i\to j}) \tag{5}$$

$$q_{i\to j} = -V_i^2 b_{i\to j} - V_i V_j (g_{ij}\sin\theta_{i\to j} + b_{i\to j}\cos\theta_{i\to j}), \tag{6}$$

where V_i and V_j are the voltage magnitudes at node i and node j, respectively, $g_{i\to j}$ is the conductance of the line, $b_{i\to j}$ is the susceptance of the line, and $\theta_{i\to j}$ is the phase angle difference between the nodes, where the subscript $i \to j$ denotes the direction of the power flow from node i to node j DC models are approximated models for transmission lines considering voltages and voltage angles measured in per-unit (p.u.), i.e., fractions of a base unit quantity. DC models are based on the concept that active power flow tends to be significantly higher than reactive power flow: for this reason, DC models are only based on active power flows. Further, voltage magnitudes are considered close to 1 p.u., and small voltage phase angle differences are assumed. Therefore, in DC models, $\sin\theta_{i\to j} \approx \theta_{ij}$ and $\cos\theta_{i\to j} \approx 1$, then Equation (5) is simplified as follows:

$$p_{i\to j} \approx b_{i\to j}\theta_{i\to j} = \frac{\theta_{i\to j}}{x_{i\to j}}. \tag{7}$$

Taking into consideration two directly connected nodes i and j, ohmic losses across line (i, j) are obtained as the difference between the power sent by node i and the power received by node j, giving the following well-known loss equation:

$$\ell_{i\to j} = 2g_{i\to j}(1 - \cos\theta_{i\to j}). \tag{8}$$

In DC models transmission losses are neglected, because they consider $\cos\theta_{ij} \approx 1$. However, in a large power system, transmission losses have to be considered. Non-linearity of Equation (8) introduces complexity. In fact, many techniques have been proposed in the literature to approximate losses: quadratic approximations in terms of phase angles [12], first-order Taylor expansion of loss expressions [13], quadratic loss approximation to distribute losses among the transactions in a multiple-transaction framework [14], [15], and static and dynamic piecewise approximations [16]. For the sake of simplicity, the model of the multi-objective power flow problem we use in this paper approximates transmission losses by means of a piecewise linearization.

C. Objectives

The MOED problem formalized in this paper considers four objectives: energy cost, distance of supply, environmental impact, and load balancing. Each objective is associated with an objective function that expresses a performance value of a power output configuration of scheduled and non-dispatchable generators. It is extremely important to point out that the focus of this paper is not the optimization itself, but the integration of the economic dispatch process with a system specifically designed to automatically prioritize the objectives, so as to profitably exploit an a priori scalarized method, like NWS, in the framework of a smart microgrid, without the need of decision makers. Hence, we do not need to choose a specific objective function for any given objective. Objective functions are symbolically indicated as f_i, where $i \in \mathcal{O}$.

D. MOED problem formulation with network constraints

Let us consider a smart microgrid modeled as explained in Section II. Let $\mathcal{N}$ and $\mathcal{A}$ be, respectively, the set of nodes and the set of arcs of the microgrid. Further, let $\mathcal{L} \subset \mathcal{N}$ be the set of the loads, i.e., loads and passive prosumers. Whenever there exists an arc connecting two nodes $i, j \in \mathcal{N}$, the two nodes are said to be directly connected. Given a node i, we indicate with $\mathcal{N}_i^{\leftarrow}$ and $\mathcal{N}_i^{\rightarrow}$ the sets of the nodes directly connected to node i, injecting/absorbing power in/from node i, respectively. Also, let $\mathcal{G}$ be the set of the generators, and let $\mathcal{P}$ be the set containing the active prosumers and the active generators exploiting renewable sources, e.g., wind farms, biomass power plants, solar parks and so on. Each node i of the microgrid has its own net power injection, denoted as n_i. A node $i \in \mathcal{G}$, representing a generator, has also a minimum and a maximum suppliable power, indicated with $\underline{P_i}$ and $\overline{P_i}$, respectively. The power flow on the line (i, j) is $p_{i\to j} \in \mathbb{R}$. A feasible configuration of flow over the power lines is indicated with $\mathbf{p} \in \mathbb{R}^{|\mathcal{A}|}$, where the symbol $|\cdot|$ denotes the cardinality. Given a power line (i, j), we indicate the power

loss with $\ell_{i\to j}$, the phase angle difference with $\theta_{i\to j}$, and reactance and conductance with $x_{i\to j}$ and $g_{i\to j}$, respectively. Further, the maximum and minimum flows on the power line (i,j) are indicated with $\underline{\varphi}_{i\to j}$ and $\overline{\varphi}_{i\to j}$, respectively. The MOED problem formulation we consider is the following:

$$\text{Minimize} \;\; z = \sum_{i\in\mathcal{O}} w_i N_{[0,1]}\left(f_i(\mathbf{p})\right) \tag{9a}$$

subject to:

$$\sum_{j\in\mathcal{N}_i^{\leftarrow}} (p_{j\to i} - \ell_{j\to i}) - \sum_{j\in\mathcal{N}_i^{\rightarrow}} (p_{i\to j} + \ell_{i\to j}) = n_i, \; \forall i \in \mathcal{L} \tag{9b}$$

$$p_{i\to j} = \frac{\theta_{i\to j}}{x_{i\to j}}, \; \forall (i,j) \in \mathcal{A} \tag{9c}$$

$$\ell_{i\to j} = 2g_{i\to j}\left(1 - \min_{k\in\{1,\ldots,NS\}} a_k\theta_{i\to j} + b_k\right), \; \forall (i,j) \in \mathcal{A} \tag{9d}$$

$$\underline{\varphi}_{i\to j} \le p_{i\to j} \le \overline{\varphi}_{i\to j}, \; \forall (i,j) \in \mathcal{A} \tag{9e}$$

$$\underline{P_i} \le \sum_{j\in\mathcal{N}_i^{\rightarrow}} p_{i\to j} \le \overline{P_i}, \; \forall i \in \mathcal{G}\cup\mathcal{P}. \tag{9f}$$

The objective function $z : \mathbb{R}_+^{|\mathcal{A}|} \to \mathbb{R}^+$, in Equation (9a), is a normalized weighted sum of the objectives, where w_i is the weight of the i-th objective, and $\sum_i w_i = 1$. Further, $N_{[0,1]}$ is a normalization function to scale the values of all the objective functions in the same range, in this case, the interval $[0,1]$. Constraints in (9b) express the power balance; Equation (9c) is the DC power flow on each line (i,j); Equation (9d) is the piecewise linear approximation (using NS segments) for the power losses of each line, where a_k and b_k are, respectively, the slope and the y-intercept of the k-th segment; Equation (9e) constrains the active power flow on each line between its minimum and maximum sustainable flow; Equation (9f) shows the upper and lower active power limits for generators and active prosumers.

V. Artificial Neural Networks

A. Overview

An artificial neural network (ANN) is a mathematical model trying to emulate the learning-based strategy the human brain uses to solve complex problems [5]. The elementary component of an ANN is the artificial neuron. Hereafter, artificial neurons are simply referred to as neurons. A neuron can be viewed as a node having n inputs and one output. In an ANN, artificial neurons are connected to each other so that the output of a neuron is connected to the input of other neurons. Also, each connection is associated with a weight. There exists a wide variety of architectures of an ANN, i.e., ways to connect neurons to each other. Undoubtedly, one of the most popular architecture is the multi-layer perceptron (MLP). In MLP neural networks, neurons are organized in layers: one input layer, one or more hidden layers and one output layer. Each layer is composed of a number of neurons that is dependent on the problem.

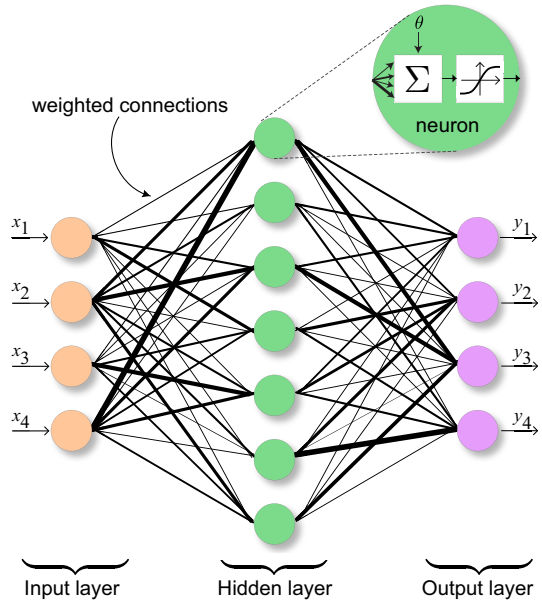

Fig. 2. A multi-layer perceptron neural network having four neurons in the input and in the output layers, and seven neurons in the unique hidden layer.

Further, the output y_j of the j-th hidden or output neuron is computed as

$$y_j = f\left(\theta_j + \sum_{i=1}^{k} \omega_{ij} x_i\right), \tag{10}$$

where k is the number of inputs to the neuron, θ_j is a threshold, ω_{ij} is the weight associated with the i-th input, and f is a linear/non-linear activation function (typically sigmoid, logistic or hyperbolic tangent). Fig. 2 shows an MLP neural network having four neurons in the input and output layers, and seven neurons in the hidden layer. The weight of each connection is represented by the thickness of the segment denoting the connection itself: the higher the thickness of the segment, the higher the weight of the connection.

ANNs wherein information exclusively propagates from the input layer to the output layer, without feedbacks, are called feed-forward. ANNs are able to solve complex problems through the learning process: one of the learning technique is the supervised learning.

B. Supervised learning

Supervised learning is based on a set of pairs (*input*, *desired_output*), called training set. During the learning process, the inputs of the training set are presented to the network, and the error, i.e., the difference between the actual output and the desired output, is measured. By means of a training algorithm (e.g., backpropagation) the weights of the network are progressively adjusted, in order to minimize the global error on the training set. The trained network is tested by comparing the actual output related to input data not contained in the training set with the desired output for such data.

If the learning process succeeds, the ANN has inferred the unknown relation between the inputs and the outputs, therefore, the trained ANN can be used to effectively predict the output related to new input data. One of the applications of ANNs is approximation of complex functions whose analytical expression is unknown.

VI. Neural network-based prioritization of objectives

A. Overview

In this paper, neural networks are exploited to reproduce the preference function according to which the expert derives the weights to prioritize the objectives, in a given operating scenario of a microgrid. As it is well-known in the literature, preference relations are hard to deal with, and, in general, they can also be non-linear [4]. For this reason, in multi-objective optimization, whenever a priori methods are used, an expert is needed to assign reasonable weights to the objectives. With the neural network-based prioritization proposed in this paper, we try to emulate the expert in order to prioritize (with appropriate weights) the objectives described in Section IV-C, in a MOED problem. In particular, the power system we consider is a microgrid wherein four quantities describing the operational status are computed by using the data sensed by the information network, at regular time intervals. In the following, such quantities are formally defined and referred to as *operating condition indicators*. Also, operating condition indicators are all normalized in $[0, 1]$, by using a normalization function indicated with $N_{[0,1]}$. Finally, the values of the four operating condition indicators, and all their components, are strictly dependent on the instant T in which they are measured.

B. Operating condition indicators

The first operating condition indicator we consider is the mean-to-variance ratio (MVR) of the energy cost, that we define as the ratio of the average energy cost (considering scheduled generators, active prosumers, and active generators exploiting renewable sources at instant T) to the variance of the energy cost among all the considered generators and active prosumers. MVR can be mathematically expressed as

$$MVR = N_{[0,1]}\left(\frac{\alpha \sum_{i\in\mathcal{G}_{on}\cup\mathcal{P}_{on}} c_i}{\beta \sum_{i\in\mathcal{G}_{on}\cup\mathcal{P}_{on}} (c_i - \overline{c})^2}\right), \qquad (11)$$

where $\alpha, \beta > 0$ are postive coefficients, c_i is the energy cost of the i-th generator, $\overline{c} = \frac{\sum_{i\in\mathcal{G}_{on}\cup\mathcal{P}_{on}} c_i}{|\mathcal{G}_{on}|+|\mathcal{P}_{on}|}$, $\mathcal{G}_{on} \subseteq \mathcal{G}$ is the set of the scheduled generators, and $\mathcal{P}_{on} \subseteq \mathcal{P}$ is the set of the active prosumers and the active generators exploiting renewable sources. The second operating condition indicator, PRS, measures the percentage of the required power, at instant T, suppliable by renewable sources. We define PRS as:

$$PRS = N_{[0,1]}\left(\frac{\sum_{i\in\mathcal{P}_{on}} n_i}{\sum_{i\in\mathcal{L}_{on}} n_i}\right), \qquad (12)$$

where $\mathcal{L}_{on}$ is the set of the active loads at instant T, and n_i is the net power injection of node i. The third operating condition indicator, IND, expresses how much feeders are energy independent, i.e., how much of the power needed by each feeder at instant T can be supplied by scheduled generators, active prosumers, and active generators exploiting renewable sources, within the feeder itself. Rigorously, we define IND as:

$$IND = N_{[0,1]}\left(\frac{1}{|\mathcal{F}|}\sum_{j\in\mathcal{F}} \frac{\sum_{i\in\mathcal{G}^j_{on}\cup\mathcal{P}^j_{on}} n_i}{\sum_{i\in\mathcal{L}^j_{on}} n_i}\right), \qquad (13)$$

where $\mathcal{F}$ is the set of the feeders, $\mathcal{L}^j_{on}$ is the set of the loads within the j-th feeder, and $\mathcal{G}^j_{on}$ is the set of the scheduled generators belonging to the j-th feeder, and $\mathcal{P}^j_{on}$ is the set of the active prosumers and active generators based on renewable sources within the j-th feeder. Finally, we define the fourth indicator, UNB, to express the load unbalancing at instant T:

$$UNB = N_{[0,1]}\left(\frac{1}{|\mathcal{F}|}\sum_{j\in\mathcal{F}}\sum_{i\in\mathcal{L}^j_{on}} (n_i - \mu)^2\right), \qquad (14)$$

where $\mu = \frac{\sum_{i\in\mathcal{L}_{on}} n_i}{|\mathcal{L}_{on}|}$ is the average load among all the feeders. Of course, it is important to observe that the formulation we gave for each operating condition indicator is just one of the possible formulations to express the same information related to the current status of the microgrid. More accurate formulations can certainly be given, but they do not constitute the focus of this paper.

Each operating condition indicator represents an input of a multi-layer perceptron (MLP) neural network. The output of this network is a configuration of weights to be assigned to the objectives in the MOED problem described in Section IV-D. Therefore, the neural network we use for automatic prioritization has four neurons in the input layer (one for each operating condition indicator) and four neurons in the output layer (one for each objective weight). The number of neurons in the single hidden layer was tuned during the simulations.

VII. Experiments and discussion

A. Dataset

With reference to a simulated prototype microgrid, the dataset we used consists of 150 input-output samples, i.e., 150 combinations of the values of the operating condition indicators, each one associated with its own vector of weights, representing the priorities of the objectives. The 150 available samples have been obtained by sampling the input space in a uniform way so as to highlight all the meaningful operating conditions of the microgrid.

For each input an expert has been required to define the weights to be associated with the objectives in the MOED problem formalized in Section IV-D.

B. Neural network architecture

Diverse simulations were carried out, in the MATLAB® environment, to find out the best MLP neural network architecture. As already stated, the network has four input neurons and four output neurons. We chose one hidden

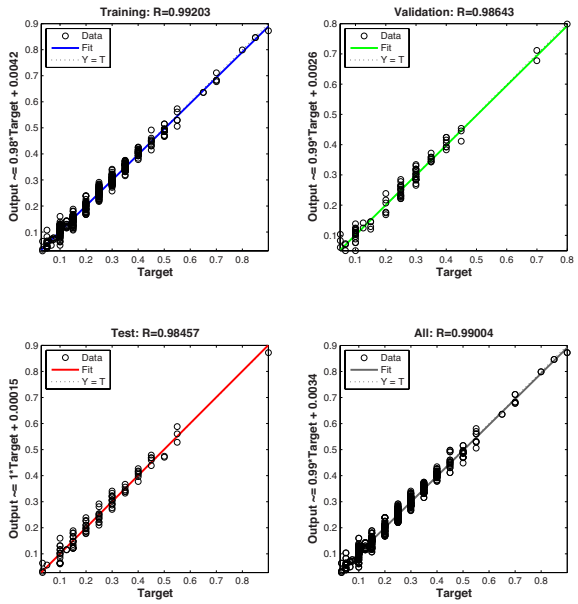

Fig. 3. Regression.

layer whose neurons have the hyperbolic tangent sigmoid activation function, and a linear activation function for the four output neurons. To find out the best number of neurons for the hidden layer, we performed different simulations by varying the number of neurons from 10 to 20, with step one, based on heuristic considerations. For each tested number of neurons, we performed 30 trainings and we computed the average *MSE* (mean squared error) on the test set over all the trials. We achieved 17 as the number of hidden neurons characterized by the minimum *MSE*. Consequently, considering all the trained networks with such number of hidden neurons, we selected the one having the best performance, i.e., the minimum *MSE* on the test set. The 70%, 15% and 15% of the dataset described in Section VII-A were randomly extracted to form, respectively, the training, test and validation sets.

C. Performance results

We obtained regression coefficients for the training set and the test set of 99.203% and 98.457%, respectively. Regression is shown in detail in Fig. 3. Also, the mean squared errors on the training set and on the test set, respectively, are $3.2379 \cdot 10^{-4}$ and $6.1592 \cdot 10^{-4}$. The error histogram is shown in Fig. 4. As it can be seen, the error is bounded in the interval $[-0.05964, 0.05048]$, meaning a high accuracy of the proposed neural network-based prioritization tool in reproducing the preference function of the expert.

D. Advantages of the proposed method

By integrating the proposed neural approach into MOED, weights are automatically assigned to the objectives, according to the current status of the microgrid, with negligible deviation if compared to the weights expressed by the expert. In fact, such a little deviation does not substantially influence the outcome of the optimization process. Actually, as previously stated, a priori methods are computationally more efficient than a posteriori methods, but they require an expert with deep understanding of the context to properly prioritize the objectives in any operating status of the microgrid. Thanks to our approach, it is possible to profitably use a priori methods to solve the MOED problem, taking advantage of their simplicity and computational efficiency, without requiring an expert.

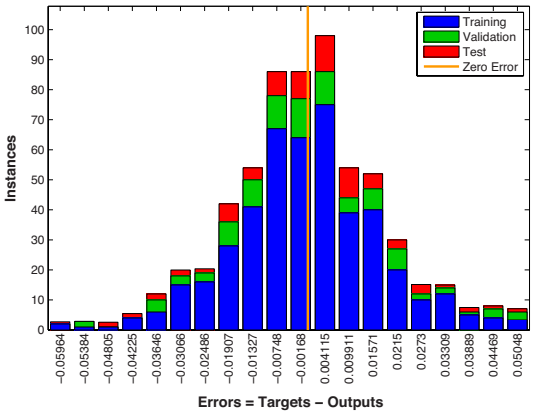

Fig. 4. Error histogram.

VIII. Conclusion

In this paper we presented a neural-network based approach for automatic prioritization of objectives applied to the MOED problem in a smart microgrid. We defined four operating condition indicators, regularly sensed by the information network, i.e., the mean-to-variance ratio of the energy cost, the percentage of the required power suppliable by renewable sources, the energy independency of the feeders, and the load unbalancing. We used a multi-layer perceptron neural network having 4 input neurons, representing the operating conditions of the microgrid, at a given time instant, 4 output neurons, representing the weights associated with the four objectives taken into account, and 17 hidden neurons, as experimentally determined. With reference to a simulated prototype microgrid, we collected, at given time intervals, a set of pairs consisting of the operating conditions of the microgrid and the related weights of the objectives, explicitly expressed by an expert. After appropriately training the neural network, we achieved accuracies of 99.203% and 98.547% on the training and test sets, respectively, with MSEs of $3.24 \cdot 10^{-4}$ and $6.59 \cdot 10^{-4}$ on the training and test sets, respectively.

References

[1] B. Lasseter, "Microgrids (distributed power generation)," in *Proc. IEEE Power Engineering Society Winter Meeting*, vol. 1, Ohio, USA, February 2001, pp. 146–149.

[2] B. Bahrani, M. Saeedifard, A. Karimi, and A. Rufer, "A multivariable design methodology for voltage control of a single-dg-unit microgrid," *IEEE Trans. Ind. Inf.*, vol. 9, no. 2, pp. 589–599, 2013.

[3] I. J. Balaguer, S. Y. Qin Lei, U. Supatti, and F. Z. Peng, "Control for grid-connected and intentional islanding operations of distributed power generation," *IEEE Trans. Ind. Electron.*, vol. 58, no. 1, pp. 147–157, 2011.

[4] R. T. Marler and J. S. Arora, "Survey of multi-objective optimization methods for engineering," *Struct. Multidisc. Optim.*, vol. 26, no. 6, pp. 369–395, 2004.

[5] S. Haykin, *Neural Networks: A Comprehensive Foundation (3rd Edition)*. Upper Saddle River, NJ, USA: Prentice Hall PTR, 2007.

[6] B. Lazzerini and F. Pistolesi, "Efficient energy dispatching in smart microgrids using an integration of fuzzy AHP and TOPSIS assisted by linear programming," in *Proc. 8th Conf. of European Society for Fuzzy Logic and Technology*, 2013, pp. 310–317.

[7] I. G. Damousis, B. A. G., and D. P. S., "Network-constrained economic dispatch using real-coded genetic algorithm," *IEEE Trans. Power. Syst.*, vol. 18, no. 1, pp. 198–205, 2003.

[8] A. M. Jubril, O. A. Komolafe, and K. O. Alawode, "Solving multi-objective economic dispatch problem via semidefinite programming," *IEEE Trans. Power. Syst.*, vol. 28, no. 3, pp. 2056–2064, 2013.

[9] A. Man-Im, W. Ongsakul, J. Singh, and C. Boonchuay, "Multi-objective economic dispatch considering wind generation uncertainty using non-dominated sorting particle swarm optimization," in *Int. Conf. and Utility Exhibition on Green Energy for Sustainable Development*, 2014, pp. 1–6.

[10] M. Avinaash, G. Kumar, K. Bhargav, T. Prabhu, and D. Reddy, "Simulated annealing approach to solution of multi-objective optimal economic dispatch," in *Int. Conf. on Intelligent Systems and Control*, 2013, pp. 127–132.

[11] S. Keshmiri and W. Gao, "Multi-objective stochastic economic dispatch," in *North American Power Symposium*, 2010, pp. 1–8.

[12] R. A. Jabr, "Modelling network losses using quadratic cones," *IEEE Trans. Power. Syst.*, vol. 20, no. 1, pp. 505–506, 2005.

[13] S. de la Torre and F. D. Galiana, "On the convexity of the system loss function," *IEEE Trans. Power. Syst.*, vol. 20, no. 4, pp. 2061–2069, 2005.

[14] G. Gross and S. Tao, "A physical-flow-based approach to allocating transmission losses in a transaction framework," *IEEE Trans. Power. Syst.*, vol. 15, no. 2, pp. 631–637, 2000.

[15] Q. Ding and A. Abur, "Transmission loss allocation based on a new quadratic loss expression," *IEEE Trans. Power. Syst.*, vol. 21, no. 3, pp. 1227–1233, 2006.

[16] T. N. dos Santos and A. L. Diniz, "A dynamic piecewise linear model for dc transmission losses in optimal scheduling problems," *IEEE Trans. Power Syst.*, vol. 26, no. 2, pp. 508–519, 2011.