ANN-Based LMP Forecasting in a Distribution Network with Large Penetration of DG

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***Abstract*— In recent years, power systems have experienced many changes in their paradigm. The introduction of new players in the management of distributed generation leads to the decentralization of control and decision-making, so that each player is able to play in the market environment. In the new context, it will be very relevant that aggregator players allow midsize, small and micro players to act in a competitive environment.**

In order to achieve their objectives, virtual power players and single players are required to optimize their energy resource management process. To achieve this, it is essential to have financial resources capable of providing access to appropriate decision support tools. As small players have difficulties in having access to such tools, it is necessary that these players can benefit from alternative methodologies to support their decisions.

This paper presents a methodology, based on Artificial Neural Networks (ANN), and intended to support smaller players. In this case the present methodology uses a training set that is created using energy resource scheduling solutions obtained using a mixed-integer linear programming (MIP) approach as the reference optimization methodology. The trained network is used to obtain locational marginal prices in a distribution network. The main goal of the paper is to verify the accuracy of the ANN based approach. Moreover, the use of a single ANN is compared with the use of two or more ANN to forecast the locational marginal price.

***Index Terms* — Artificial Neural Network (ANN), Distributed generation, Locational Marginal Price (LMP), Mixed Integer Linear Programming (MIP), Virtual Power Player (VPP)**

NOMENCLATURE

$c_{DG(g)}$	Distribution generation cost of unit g
$c_{SP(s)}$	Cost of supplier s
c_{EGP}	Excess generated power cost
$c_{StorageCharge}$	Storage charge cost
$c_{StorageDischarge}$	Storage discharge cost
c_{NSP}	Non-supplied power cost
g	Generator index
ng	Total number of generator
ns	Total number of supplier
$P_{DG(g)}$	Distributed generation power
$P_{DGMax(g)}$	Maximum generation power of generation type g
$P_{DGMin(g)}$	Minimum generation power of generation type g
P_{EGP}	Excess generated power
P_{Load}	Load power
P_{NSP}	Non-supplied power
$P_{StorageCharge}$	Storage charge power
$P_{StorageDischarge}$	Storage discharge power
$P_{SP(s)}$	Power of supplier s
$P_{SPMax(s)}$	Maximum power of supplier s
s	Supplier index
$X_{DG(g)}$	Binary variable for generation type

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I. INTRODUCTION

POWER systems have to deal with an increasing quantity of distributed energy resources, according to the smart grid paradigm. This requires new management and new operation methods because the currently used methodologies are not able to deal with the challenges that result from the new paradigms.

Virtual Power Players (VPP) that aggregate a set of resources in a given network zone, including distributed generation based on renewable sources, storage systems, demand response and electrical vehicles are very relevant players in the new context [1, 2]. One of the VPP main tasks is to determine the optimal resource scheduling able to minimize the costs or to maximize the profits. Achieving this optimal scheduling can require using forecasting tools for wind, insulation, load, and electricity prices. The VPP can, for example, use an Artificial Neural Network (ANN) [2] to forecast Locational Marginal Price (LMP) values. There are

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several techniques that can be required for the forecasting processes but artificial neural networks have shown their effectiveness for a diversity of forecasting needs in the scope of power systems.

This paper proposes an ANN based approach to forecast the LMP value in a distribution network. The forecast is based on the results of the optimal scheduling obtained using Mixed-Integer Linear Programming applied to data obtained by a resource scheduling optimization tool. The proposed method is able to provide the VPP with good quality information that can be used to support decision making concerning resource scheduling, aiming at the lowest possible operation costs. Moreover, this information is obtained in short times and requires modest computational means.

This paper is organized as follows: after the present section, Section II describes the general ANN concept. Section III presents the ANN based proposed methodology and addresses the optimization of energy resource scheduling. A case study is presented in Section IV. Finally, the main conclusions of the work are presented in Section V.

II. ANN Concepts and Applications

Artificial neural networks are a computational model inspired by the human brain with some specific characteristics such as the capacity to learn [3-5]. The basic concept of ANNs consists in the use of neurons that have memory and the capacity to process different types of information [3]. An ANN consists in several layers of three different types, the input layer, one or more hidden layers and the output layer. Moreover, the organized neurons can be modified according to the desired organization and thus can approximate the results of sample functions. The general structure of a neural network is illustrated in Fig. 1.

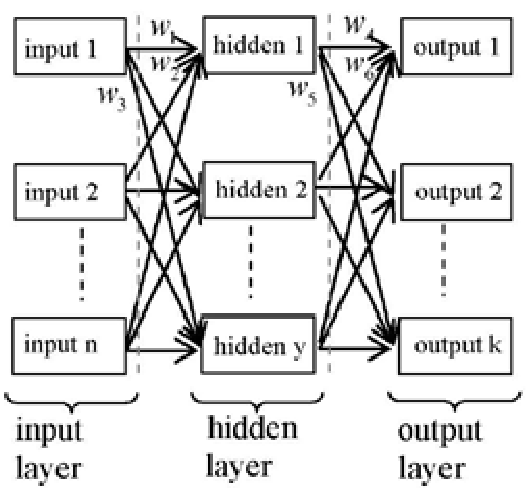

Fig. 1. General structure of artificial neural network [3]

According to Fig. 1, the hidden layers are connected with input and output layers by weighted synapses. ANNs do not require an explicit mathematical model of the addressed physical elements and/or systems to obtain results; these results depend on the ANN internal constitution which is obtained after a training phase [3, 6]. The learning process can be time expensive but, after that, ANN requires lower execution time than other techniques [4, 6-9]. In the training phase ANNs are able to learn the relationships between input and output for known cases [10], using for instance logistic regression [11].

ANN is a functional, robust and interesting structure to the engineering of electrical systems [7]. ANNs have been used with success in a wide range of power system applications with emphasis to forecasting problems.

In the context of smart grids it is necessary to use optimization, monitoring, forecasting, decision-making and control methods that should be increasingly fast and dynamic. Computational intelligence has the capacity to provide solutions for algorithms that are able to learn and adapt themselves to different cases with specific features [9]. In many situations, the limitations of traditional techniques have been successfully overcome with the use of neural networks.

An application example of a neural network for scheduling problems is described in [12] where it is proposed a network based on the Hopfield network yet with some important differences. The main difference lies in the existence of an additional external processor that can monitor and control the evolution of the network.

III. Proposed Methodology

This paper proposes an ANN based methodology to provide VPPs with LMP forecasting, which can support decision-making for energy resource scheduling. The method involves two steps. The first step corresponds to the ANN training, using the results of energy resource scheduling optimization. The second step is dedicated to forecast the LMP for situations envisaged in the study.

A. Problem Formulation

The energy resource scheduling optimization uses a mathematical formulation based on Mixed Integer Linear Programming (MIP) which is implemented in General Algebraic Modeling System (GAMS) optimization software [13]. The objective function presented in (1) is formulated with the aim of finding the optimal energy resource scheduling that leads to the minimal operation cost of supplying the demand [14].

Minimize

$$f = \begin{pmatrix} \sum_{s=1}^{ns} (P_{SP(s)} \times c_{SP(s)}) \\ + \sum_{g=1}^{ng} (P_{DG(g)} \times c_{DG(g)}) \\ - P_{StorageCharge} \times c_{StorageCharge} \\ + P_{StorageDischarge} \times c_{StorageDischarge} \\ + P_{NSP} \times c_{NSP} \\ + P_{EGP} \times c_{EGP} \end{pmatrix} \qquad (1)$$

Equations (2) to (5) refer to the constraints that are considered. Equation (2) refers to the first Kirchhoff Law or power balance constraint.

$$\sum_{s=1}^{ns} P_{SP(s)} + \sum_{g=1}^{ng} P_{DG(g)} + P_{StorageDischarge} + P_{NSP} = P_{Load} + P_{StorageCharge} + P_{EGP} \tag{2}$$

Equations (3) to (5) represent the constraints concerning the maximum capacity considering the available resources, for generators (3, 4), for all the suppliers (5); for storage units the constraints applied are presented in [15].

$$P_{DG(g)} \leq P_{DGMax(g)} \times X_{DG(g)};\ X_{DG(g)} \in \{0,1\} \tag{3}$$

$$P_{DG(g)} \geq P_{DGMin(g)} \times X_{DG(g)};\ X_{DG(g)} \in \{0,1\} \tag{4}$$

$$P_{SP(s)} \leq P_{SPMax(s)} \tag{5}$$

B. Proposed Method

Fig. 2 presents the diagram of the proposed methodology to obtain the LMP forecasted values. In the first phase the methodology uses Mixed-Integer Linear Programming (MIP) to optimize the energy resource scheduling for the considered scenario set. The ANN is trained with these scenarios.

Fig. 3 contemplates the data treatment in each scenario. The variables considered in each scenario are the capacity limits, costs from DG, storage, load, suppliers and DR contracts, among other variables. For each variable, considering the amplitude of its values and its importance for the final solution, the number of discrete values (and, consequently, the increment to be used) to be considered is determined. These values should be representative of the variable. With the determined values, it is possible to define the number of simulations to be undertaken.

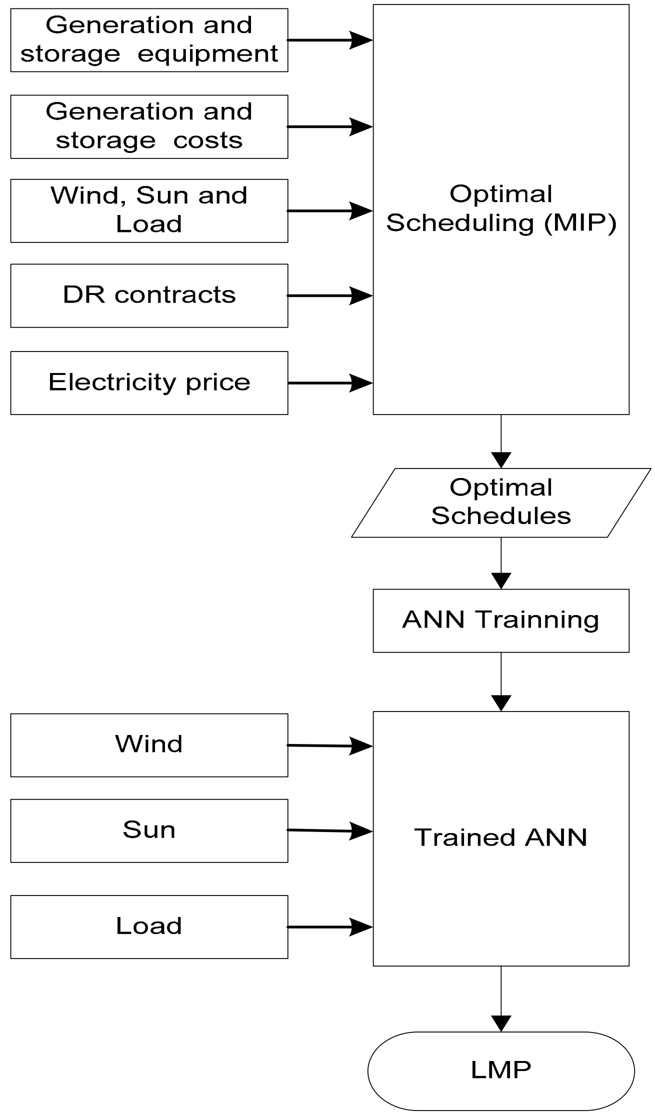

Fig. 2. Diagram of the proposed methodology.

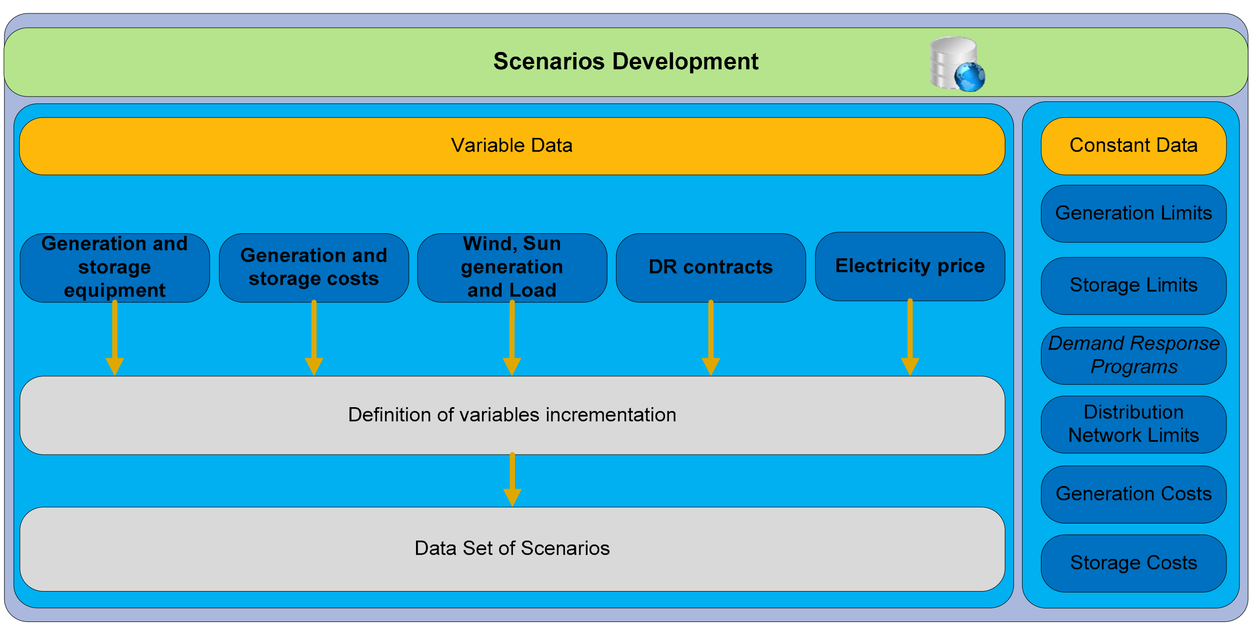

Fig. 3. Methodology for scenarios development

The proposed ANN approach uses the solutions obtained by the optimization method presented in sub-Section A as input to the ANN training process. Fig. 4 illustrates the used ANN architecture.

The considered input variables are:

- Total wind resources by network zone;
- Total photovoltaic resources by network zone;
- Total forecasted load by network zone.

The output layer has a single neuron that returns the LMP value.

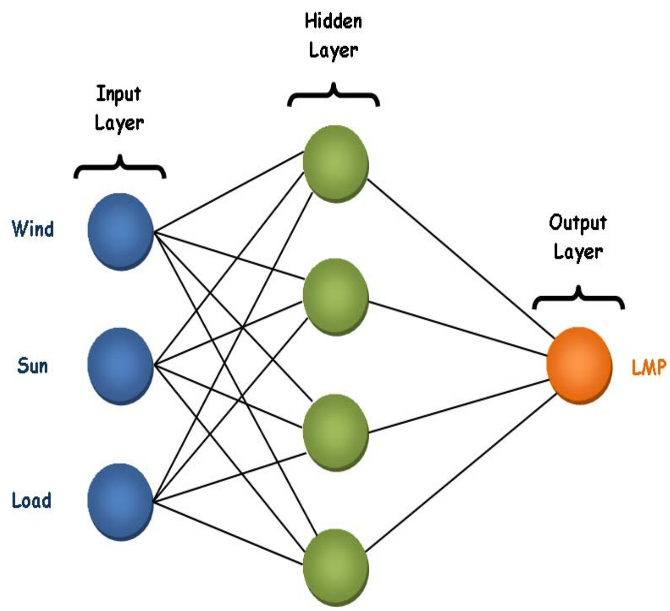

Fig. 4. Used ANN architecture

The authors have experimented multiple ANN structures and data sets. In what concerns the input layer, other variables were tested, such as electricity market price, interconnection acquired power, and other distributed resources related variables. In the case of hidden layers, as well as the number of neurons in each layer, after testing several quantities of hidden layers, a single hidden layer with four neurons was adopted.

In both input and hidden layers structure studies, the results shown that the increase in the ANN dimension and complexity is not benefic for the aimed target.

The forecasting error evaluation is performed using the Mean Absolute Percentage Error (MAPE) presented in equation (6).

$$MAPE = \frac{1}{nr}\sum_{r=1}^{nr}\left(\frac{\left|R_r^{reference} - R_r^{proposed}\right|}{R_r^{reference}}\right)\times 100 \qquad (6)$$

IV. Case Study

This section presents a case study that illustrates the application of the proposed methodology to the distribution network presented in [16]. The case study includes three scenarios of data organization to be used by the used ANN.

A. *Characterization of Distribution Network*

The used distribution network was initially presented in reference [17]. Reference [16] presents the used distribution network after applying several studies concerning the evolution of both load and DG to a 2040 scenario regarding an intensive use of DG. Fig. 5 shows the 2040 updated scenario.

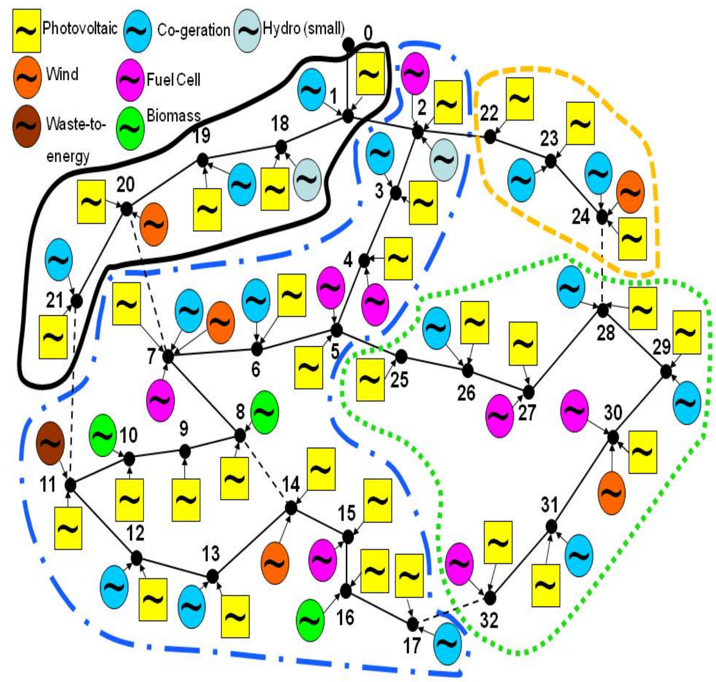

Fig. 5. Distribution network with the considered zones

As seen in Fig. 5, the network has been divided in four zones. Table I shows some details about these zones. The color and patterns signalizing each zone according to Fig. 5, as well as the buses in each zone, are presented in this table.

TABLE I
NETWORK DIVISION BY ZONES

Zone	Color/Line	Buses
1	Black/Solid	1, 18, 19, 20, 21
2	Blue/Long Dash Dot	2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17
3	Orange/Dashed	22, 23, 24
4	Green/Dotted	25, 26, 27, 28, 29, 30, 31, 32

The way that these zones were defined concerns the existing network breakers in the network nodes. Although a feeder can have a large extension, a reduced dimension branch beginning in one of the referred breakers can eventually connect to other substation.

After distribution network division in the four indicated zones, it is important to consider the characteristics of each zone. The most important data for each zone are: the buses in the zone, the wind and photovoltaic generators, the demand in each bus. The considered values of demand are presented in Table II. These demand values regard a base scenario presented in [16]. In the present paper, the values of load demand result from variations in a daily load diagram.

TABLE II
BASE ACTIVE POWER DEMAND

Bus	Demand (kW)	Bus	Demand (kW)	Bus	Demand (kW)
1	169.1	12	91.3	23	674.8
2	148.9	13	181.3	24	669.3
3	147.1	14	91.1	25	93.8
4	145.5	15	91.1	26	93.2
5	94.2	16	91.9	27	92.2
6	311.1	17	135.5	28	183.0
7	308.7	18	152.4	29	295.3
8	89.3	19	151.7	30	225.4
9	90.6	20	151.6	31	315.1
10	97.0	21	151.5	32	89.8
11	91.1	22	147.3	Total	5831.3

B. *Data characterization*

In the present case study, the network is connected to an upstream main network in bus number 0. The Suppliers 1, 2 and 3 are connected in bus number 0, allowing electrical energy to be bought from the upstream main network. The production capacity and the price of each type of energy resource are presented in Table III.

TABLE III
GENERATION RESOURCES AVAILABILITY AND COSTS

Generation resource	Capacity (kW)	Price (m.u./kWh)
Co-generation	1240	0.00015
Waste-to-energy	800	0.03000
Hydro (small)	70	0.03200
Supplier 1	1500	0.04000
Supplier 2	1500	0.05000
Biomass	350	0.06000
Wind	800	0.06200
Fuel cell	210	0.10200
Photovoltaic	1800	0.11000
Supplier 3	2000	0.13000

The input data of the neural network correspond to load values, wind and photovoltaic power generation of the considered distribution network. The training of the ANN used the data shown in Table IV which correspond to the above mentioned variables. The neural network was configured with one hidden layer and four nodes in hidden layer.

TABLE IV
ANN TRAINING SET CHARACTERIZATION

	Load range (MW)	PW range (MW)	PV range (MW)	LMP range (m.u./MWh)
Zone 1	0.11-1.05	0-0.1	0-0.06	0.02-0.13
Zone 2	0.34-3.18	0-0.4	0-0.29	0.02-0.13
Zone 3	0.19-1.95	0-0.1	0-0.03	0.02-0.13
Zone 4	0.19-1.85	0-0.1	0-0.18	0.02-0.13
Global	1.24-6.61	0-0.7	0-0.56	0.02-0.13

This case study considers three different scenarios. In each scenario, the value of the average LMP is estimated by the ANN model presented in Fig. 4 of subsection III.B. The difference between the three scenarios regards the organization of the input data and the number of independent ANNs that are used for the LMP forecast.

Fig. 6 presents the overall scenarios organization indicating the way that is used to divide the input data for each scenario. Scen1 uses one ANN that receives as input the values of wind and photovoltaic based generation and of the load for the whole considered network (i.e. the global values for the four zones shown in Fig. 5). The output is the estimated average value of the 32 LMPs in each one of the network buses.

The Global input training matrix dimension corresponds to 4 columns by 845 rows. The second scenario (Scen2) uses two ANNs with the structure shown in fig. 3. In this scenario, the data concerning zones 1 and 2 are fed to one ANN and the data concerning zones 3 and 4 are fed to the other ANN. The result of each ANN is the forecasted value of the average value of the 32 LMPs in each one of the network buses. The maximum of the two obtained values is used as the result for this scenario. The second scenario input training matrix dimension corresponds to 7 columns by 845 rows.

Finally, Scen3 considers four ANNs, whose input data correspond to the input data of each zone. Similarly to Scen 2, the final result is determined as the maximum value of the four forecasted LMP values. This scenario input training matrix dimension corresponds to 13 columns by 845 rows.

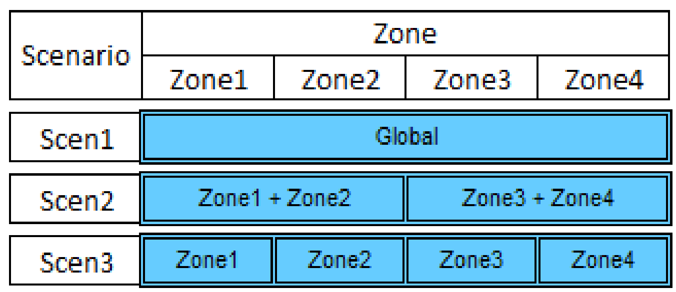

Fig. 6. Diagram of proposed methodology

Table V summarizes the main characteristics of the test data set used for this case study. The wind and photovoltaic power are fixed and load is variable. The test case corresponds to a situation for which the wind based generation will be negligible, the photovoltaic generation is accurately forecasted (0.28 MW) and for which there is incertitude in the forecasted load (from 4.42 to 6.03 MW). For this case study, the total number of considered simulations is 86.

The LMP limits of variation presented in table V are the same for all scenarios. The LMP value depends on the price of the DG resources used for each scheduling solution.

TABLE V
TEST DATA SET CHARACTERIZATION

	Load range (MW)	PW (MW)	PV (MW)	LMP range (m.u./MWh)
Global	4.41-6.03	0	0.28	0.03-0.13

C. *Results*

The results of the case study for each scenario are presented in Fig. 7.

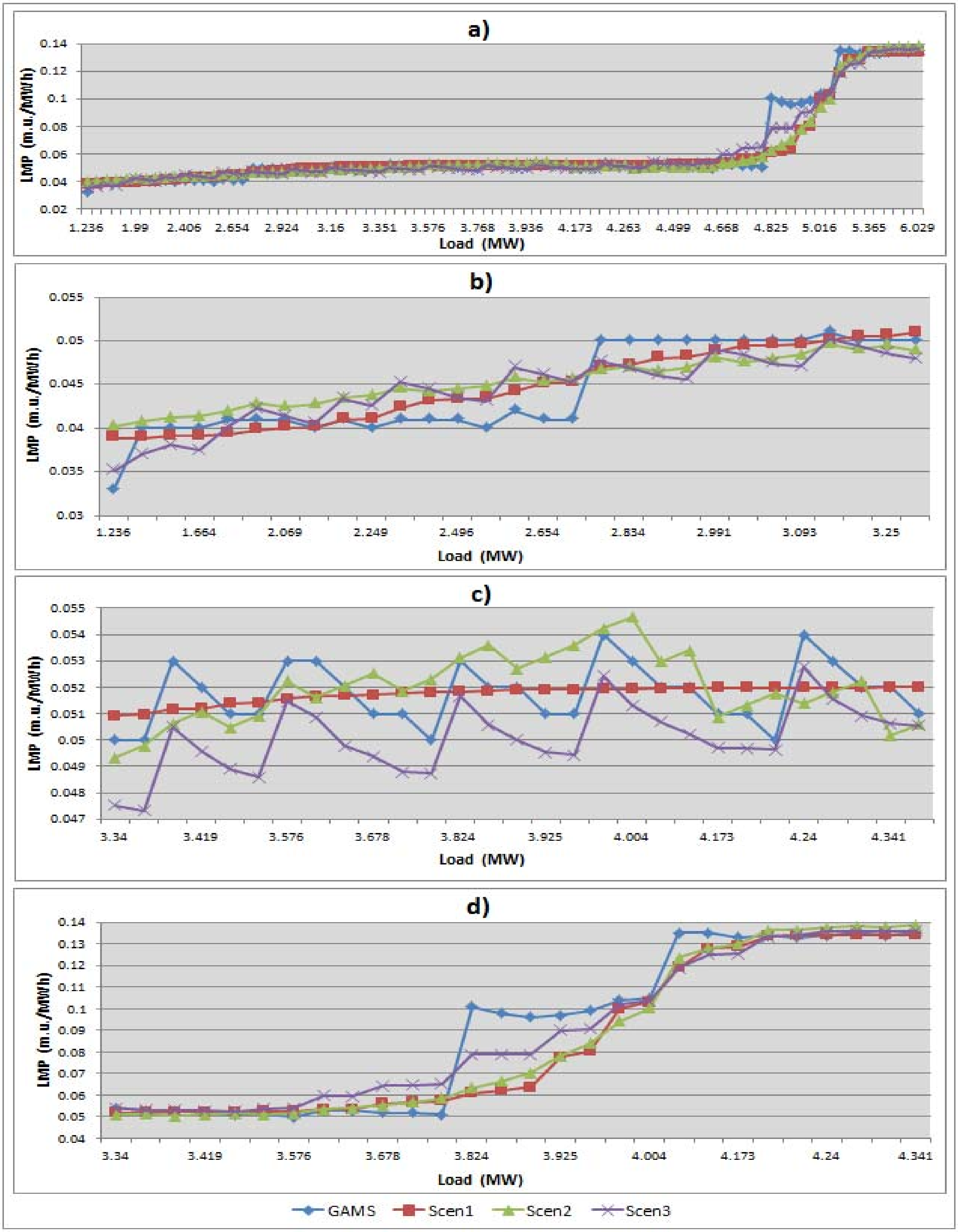

Fig. 7. Results of the LMP forecast in each scenario, for the analyzed load range (a), the lowest (b), medium (c), and highest (d) load values.

The results presented in Fig. 7 were obtained by using the MIP approach (obtained using GAMS) and the ANN approach. The ANN results in Fig. 7a) were obtained by training the network with the data set corresponding to each scenario of Table IV and by testing the network with the data set presented in Table V. This figure shows the variation of LMP with the variation of the load. Figures 7b), 7c) and 7d) show more detailed views of these results for the lowest, medium and highest load ranges, respectively.

The ANN approach had an excellent performance for low variations of LMP. However, when the change of LMP is significant, the ANN has difficulty to follow the results of the MIP approach, as shown in Fig. 7. As expected, this difference is even more significant for the first scenario, since its training is considered for the data set of all zones.

An evaluation of the results has been made by comparing the execution time (Table VI) and the Mean Absolute Percentage Error (MAPE) between the MIP and the three used scenarios for the ANN approach. The error results are presented in Table VII. MIP is therefore used as the reference method to validate the ANN approach results.

By analyzing the values presented in Table VI, it can be easily concluded that the ANN approach achieves results much faster than the MIP approach.

TABLE VI
EXECUTATION TIME IN SECONDS

	MIP	Scen1	Scen2	Scen3
TIME	1.6	0.034	0.032	0.036

Using the results of the MIP approach as reference values, MAPE (Mean Absolute Percentage Error) has been calculated using (6). MAPE values are presented in Table VII.

TABLE VII
ERROR RESULTS (%)

		Minimum	Average (MAPE)	Maximum
Scen1	b)	0.050	3.983	17.756
	c)	0.012	1.740	3.963
	d)	0.173	8.108	39.445
Scen2	b)	1.042	6.210	21.821
	c)	0.125	2.103	5.089
	d)	0.124	8.102	37.214
Scen3	b)	0.910	5.717	12.570
	c)	0.766	3.224	5.344
	d)	0.119	8.134	28.015

In all scenarios the best result was in the first scenario, as seen in Fig. 7 c), because that scenario has a better individual MAPE value. For the lowest values of load demand, seen in Fig. 7 b), the best scenario is Scen1. In what concerns the minimum and maximum error values, the best results are obtained for the medium values of load, for Scen1. The worst results are the ones obtained for the highest values of load, for Scen1.

V. CONCLUSIONS

Distributed generation impact on distribution networks has been increasing and will reach much higher values in the future. This requires an optimized management of distributed resources putting players in face of new technical and economic challenges. For smaller players it is difficult to obtain decision support tools and computational resources capable of solving the problem due to low financial resources. Therefore it is necessary that these players can have access to alternative methods to support their decisions.

This paper presents a methodology based on ANN to forecast the value of locational marginal price for a distribution network with intensive use of distributed resources. This methodology allows obtaining the desired results with limited computational resources.

The proposed method has been computationally implemented and its application is illustrated with a case study that considers a 32 bus network with intensive use of distributed generation.

The results of the reference optimization methodology (mixed-integer linear programming) have been used to train the ANN used by the ANN approach. The ANN approach results have been compared with the results obtained with the reference method. The ANN approach has been used for three scenarios allowing comparing the accuracy of the results when using a single ANN or several ANNs to forecast the LMP value.

The results show that the ANN approach can provide good results for calculating the LMP. In addition, the runtime of this approach is much lower when compared with the reference method.

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