Neural Networks and Pseudo-Measurements for Real-Time Monitoring of Distribution Systems

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***Abstract*—A state estimation scheme for power distribution systems, based on Artificial Neural Networks (ANN's), is proposed. Despite the influence of measurement uncertainties, it allows quantities describing the distribution system operation to be identified on-line, thereby constituting neural "pseudo-instruments". Details of the design and optimization of such a neural scheme are discussed, underlining the importance of ANN tuning to achieve greater levels of accuracy. The performance obtained in a study case, for different types of operating conditions, was analyzed and confirmed the feasibility and the robustness of the proposed approach. This neural estimation scheme proves to be preferable to traditional mathematical approaches whenever there are on-line requirements, due, of course, to the typically high operating speed of ANN's.**

I. Introduction

THE monitoring of complex systems is usually performed by using a set of sensors which measure the quantities being controlled (mechanical stress in airplanes or buildings; voltage, current or power in electrical networks; flow in water distribution networks, etc.) [1], [2]. The choice of the number and type of sensors and their location is certainly the first task to be solved and probably one of the most troublesome. Additional problems may arise when some sensor locations prove to be either impossible or too expensive. To overcome these problems, mathematical models of the system under analysis can be used to optimize the number of sensors and to estimate the unmeasurable quantities (pseudo-measurements). Setting up and resolving these models is often a very complex matter due to the data corrupted by measurement uncertainties. When on-line performance has to be assured, this analytical approach can prove to be inapplicable.

On the basis of the work done in the development of instrument architecture for on-line measurement [3], [4] and in the application of Artificial Neural Networks (ANN's) [5]–[7], the authors propose an ANN-based solution to the problem. In particular, taking into account the capability of ANN's in on-line system modeling and simulation [8]–[10], the paper deals with the on-line state estimation of electric power distribution systems. In fact, the field of power systems was considered as a suitable subject for this kind of application, and this is confirmed by the noticeable number of ANN applications [11].

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After a brief outline of the state estimation problem in power distribution systems, this paper describes the different steps to be followed in designing and setting up an ANN for this application:

a) definition of the neural architecture in terms of input, output and "hidden" nodes;
b) building of "learning," "test" and "validation" sets, on the basis of simulation data from a model of the system under analysis;
c) setting up the ANN and tuning its architecture and parameters (learning phase);
d) verification of ANN performance (validation phase).

The paper finally reports the results obtained with the application of the proposed techniques to state estimation in a power distribution network.

II. State Estimation for Power Distribution Systems

State estimation is a major concern for every energy management system; its results are necessary for a secure and economic operation of the electrical power transmission system. The aim of state estimation is to obtain the best system state estimate starting from a set of redundant measurements; since every measurement is corrupted by errors, by measuring more quantities than are strictly necessary the state which minimizes overall measurement uncertainty (which then maximizes the likelihood of having observed the correct quantities) can be searched for.

Nowadays, the growing interest in the automation of power distribution systems also encourages state estimating in power distribution systems. In this case, the available measured quantities are often fewer than or different from the quantities necessary for correct system monitoring and control. Besides attempting to estimate as correctly as possible, state estimation, in these systems, is aimed at obtaining the values of unavailable quantities. A model for state estimation in distribution systems is proposed in [1]. This model uses the active and reactive powers flowing into the buses, and the bus voltage magnitudes squared, as the quantities which describe distribution system operation. The possible measurements are bus voltage magnitudes squared; active and reactive powers flowing into the buses; and active and reactive bus loads. The problem of state estimation can be formulated as

$$\min_{\mathbf{x}}[\mathbf{z}-\mathbf{h}(\mathbf{x})]^T\mathbf{W}[\mathbf{z}-\mathbf{h}(\mathbf{x})] \tag{1}$$

subject to $\quad \mathbf{c}(\mathbf{x}) = 0.$

In (1) vector $\mathbf{x}$ represents the state variables, while vector $\mathbf{z}$ represents the measurements; $\mathbf{h}$ is the measurement function vector, which describes the measurements as functions of the state variables; and $\mathbf{W}$ is a diagonal matrix representing the weights associated with the measurements. Finally, $\mathbf{c}$ is a vector function representing constraints in state-variable space; these constraints are needed here since the chosen state variables do not constitute a minimum set.

The techniques used to solve problems like (1) belong to the methods of mathematical programming. The efforts in choosing a well-suited method are mainly (and obviously) oriented toward obtaining the solution in the shortest possible time, while preserving adequate result accuracy; since state estimates are the input of other on-line monitoring and control functions, they are required as quickly as they can be obtained.

III. Design of an ANN-Based State Estimation Scheme

A. ANN Architecture Definition

Applications reported in the literature almost always make use of multilayer-perceptron ANN's [12], characterized by nodes (called *perceptrons*) organized in one input layer, one output layer and one or more internal layers (hidden).

In a state-estimation scheme, the number of output nodes is equal to the number of electrical quantities which are useful for describing system operation. For a power distribution system with n buses, with the choices stated in the previous section, the number of outputs equals $3n$. The inputs can be chosen among all the possible measurements on the basis of practical considerations of the specific quantity (availability and accuracy of the corresponding measuring instrumentation, range of the quantity under measure, required measurement uncertainty); the number of inputs depends on both the accuracy the output should have and on the system operation hypotheses that can be made. If no hypothesis can be made, the number of input nodes cannot be less than $2n + 1$ for the output values to be meaningful; this is the number of variables (among the ones we selected to describe system operation) that constitute the minimum set. The case is different when some hypotheses can be made, such as, for instance, on bus load similarity, or on their forecast value and/or their dependency on the bus voltage magnitude [2]. For a distribution network feeding homogeneous loads, bus loads can often be assumed to be similar. In the case of exact similarity, which would allow the value of all bus loads to be known starting from the value of just one of them, it could be thought that only 3 input nodes would be sufficient to obtain good output values. As a matter of fact, the ANN does not explicitly use any relationships between variables, and try to reconstruct links among them in the learning process; consequently such minimum numbers have to be considered as theoretical values to be verified in the particular application.

Hence, starting from the theoretical minimum number of input nodes, more input quantities can be considered, with a corresponding increase in the accuracy of the pseudo-measurements. Specific tests will enable the minimum number of input nodes required for a given accuracy to be obtained. As far as the number of hidden layers is concerned, the need to correctly build the decision regions of each class without excessive growth in ANN size [13] suggests a one-hidden-layer configuration. The number of nodes of this layer has to be fixed starting from heuristic rules [14] and then verified through suitable tests carried out on data specific to the application under analysis.

B. Building of "Learning," "Test," and "Validation" Sets

Learning, test, and validation sets are groups of examples chosen with reference to various operating conditions of the system within its nominal operating range. The learning and test sets are used during the learning phase for ANN training and for ANN generalization capability verification, respectively. The validation set is used to evaluate ANN performance. These sets are built up on the basis of experimental data, if available, or simulated data from a mathematical model of the system under analysis. The number of examples of any set is at first determined empirically [14], and then adjusted during the learning phase.

A two-step procedure is suggested for a state-estimation scheme. The learning set examples are at first considered with input quantities unaffected by measurement uncertainties; the analysis of this ideal situation gives preliminary suggestions on the ANN architecture with a lower computational effort. Then, the measurement uncertainties are considered. They are modeled as zero-mean random variables, with normal distribution of the given standard deviation. Values of these random variables are obtained by numerical simulation, and added to the input quantities. Each example of the learning set can thus be spread in, say, r examples, all with the same values of the output quantities. This is done in order to give the ANN the capability of filtering measurement uncertainties, which is one of the aims of state estimation. Also in this case, tests have to be performed in order to identify the value of r which assures an acceptable filtering capability without an undue increase in computational effort.

The ANN extrapolation capability could allow estimations to be made also in situations that were unforeseen in the learning phase (overloads, measurement uncertainties higher than foreseen). A fourth set of examples has to be collected for evaluating this capability (ANN-based state estimation robustness).

C. Setting up the ANN and Tuning Its Architecture and Parameters

The learning algorithm most often used for a multilayer perceptron ANN is certainly the back-propagation algorithm [12].

The choice of the cycle number at which learning has to be stopped is usually based on the evaluation of suitable error indexes (differences between ANN outputs and expected ones, or elaboration of them) associated to this phase. It is important to underline that the minimization of these indexes in the learning set does not always give an error reduction in the validation set; the ANN could become too accurate in recognizing learning examples, thereby limiting its general-

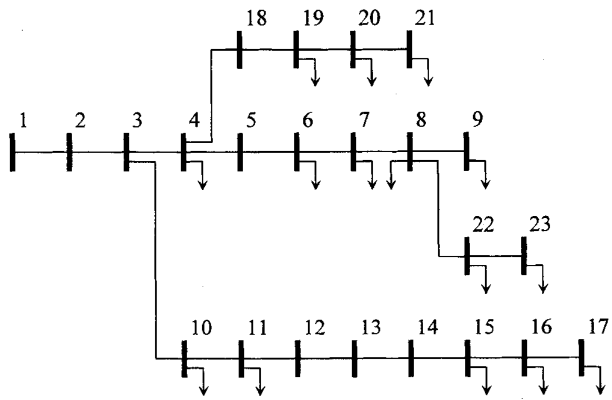

Fig. 1. Power distribution network under study.

ization capability. This effect, known as "overtraining," can be reduced by analyzing errors in both learning and test sets versus the number of learning cycles [14].

The optimum number of learning set examples is determined by the following iterative procedure. First, a test set with a fixed number of examples and a suitable error index are predetermined. Then, the number of learning set examples is optimized starting from a minimum number, which is increased until the error that the ANN makes dealing with the predetermined test set becomes lower than a fixed value. This value represents the ANN's generalization capability.

In order to improve learning efficiency, it is necessary to normalize ANN input data; furthermore, in order to avoid polarization problems, the learning set examples are put in a random order [14].

D. Verification of ANN Performance

ANN scheme performance is evaluated with reference to the validation set. The outputs given by the ANN can be considered as the output of a neural "pseudo-instrument," that can, thus, be characterized in terms of maximum error and average error with its own standard deviation. Finally the robustness of the pseudo-instruments is evaluated by analyzing the measurements in the case of overloads or increased measurement uncertainties.

IV. Study Case

In order to clarify the design aspects of a neural state estimation scheme, the previously described methodology was applied to the power distribution network shown in Fig. 1. Table I reports the data of the network, taken from [15]; the rated voltage is 12.66 kV. The load data represent the maximum daily load value.

The ANN was simulated by using the Neural Network toolbox of Matlab, which allows the ANN architecture and its working parameters to be easily modified.

A. ANN Architecture Definition

According to the previously described procedure, and neglecting the load-free buses (2, 5, 12, 13, 14, 18), the number of output nodes of the ANN was fixed at 51 (17 bus voltage magnitudes, 17 active and 17 reactive powers flowing into the buses). As far as the input nodes are concerned, the following ANN architectures were analyzed:

a1) 3 input nodes (1 bus voltage, 1 active bus load and 1 reactive bus load);
a2) 5 input nodes (1 bus voltage, 2 active bus loads and 2 reactive bus loads);
a3) 11 input nodes (1 bus voltage, 5 active bus loads and 5 reactive bus loads);
a4) 21 input nodes (1 bus voltage, 10 active bus loads and 10 reactive bus loads);
a5) 31 input nodes (1 bus voltage, 15 active bus loads and 15 reactive bus loads).

One hidden layer with 150 nodes was adopted after some tests on ANN's with different hidden-layer structures.

As far as the perceptron transfer function is concerned, the ANN hidden layer had a hyperbolic tangent-sigmoid transfer function, and the output layer had a linear transfer function. With these two transfer functions, the ANN operated as a general function approximator, with the capability of approximating any function with a finite number of discontinuities, given sufficient perceptrons in the hidden layer [16].

TABLE I
Study Network Characteristics

Send. bus	Recv. bus	Branch parameters R [Ω]	X [Ω]	Recv. bus load P [kW]	Q [kVAR]
1	2	0.0005	0.0012	0.0	0.0
2	3	0.0005	0.0012	0.0	0.0
3	4	0.0015	0.0036	537.0	378.2
4	5	0.0251	0.0294	0.0	0.0
5	6	0.3660	0.1864	2.2	1.9
6	7	0.3811	0.1941	35.1	26.1
7	8	0.0922	0.0470	65.2	46.9
8	9	0.0493	0.0251	1810.8	1279.5
3	10	0.0044	0.0108	22.6	16.2
10	11	0.0640	0.1565	22.6	16.2
11	12	0.3978	0.1315	0.0	0.0
12	13	0.0702	0.0232	0.0	0.0
13	14	0.3510	0.1160	0.0	0.0
14	15	0.8390	0.2816	12.2	8.7
15	16	1.7080	0.5646	17.0	12.2
16	17	1.4740	0.4873	5.2	3.5
4	18	0.0034	0.0084	0.0	0.0
18	19	0.0851	0.2083	68.7	49.0
19	20	0.2898	0.7091	334.5	238.6
20	21	0.0822	0.2011	334.5	238.6
8	22	0.0928	0.0473	35.2	24.6
22	23	0.3319	0.1114	3.1	2.3

B. Building of "Learning," "Test," and "Validation" Sets

The learning and test sets were built up with reference to the previously described ANN architectures and assuming two working hypotheses of (1) completely correlated loads or (2) completely uncorrelated loads. Both sets were built up in both the absence and presence of measurement uncertainties.

1) The number of examples of the learning set was equal to 48; they were chosen homogeneously within a typical daily period. A test set of 48 different examples was then built to verify the ANN generalization capabilities.
2) The number of examples of the learning set was varied from 48 to 480 in order to search for the optimum value. The same test set of case (1) was considered to verify the ANN generalization capabilities.

In the presence of measurement uncertainties, for every example of the learning set, 10 new examples were built up ($r = 11$). The standard deviations of the random variables which simulate the measurement uncertainties were varied from 0.3% to 5%, thus simulating instruments with maximum relative errors ranging from 1% to 15% (assuming the maximum error equal to three times the given standard deviation).

C. Setting up the ANN and Tuning Its Architecture and Parameters

The ANN input data were randomized and normalized in the range $[-0.7, 0.7]$.

Correlated Loads: A comparison of ANN architectures from a1 to a5 was carried out in the absence of input data measurement uncertainties. The analysis of the errors obtained with the different architectures and for each pseudo-measurement allows the following conclusions to be reached: (i) the voltage pseudo-measurements are all characterized by relative error lower than 0.1%; (ii) the unacceptable results of architecture a1 confirm that the theoretical minimum number of input nodes is not practically usable; (iii) the best results are obtained with architectures a3 and a4, indicating that an increase in the number of input nodes can be useless and even dangerous.

On the basis of these results, the subsequent analysis was carried out only on architectures a3, a4, and a5. This latter architecture was still considered in order to investigate whether the presence of measurement uncertainties should require more input quantities. The results obtained with input data affected by maximum relative uncertainties equal to 5% (typical value of instruments used in power distribution systems) are shown in Fig. 2 (the voltage pseudo-measurements are not reported since they assure relative errors always contained within 0.4%). These results favor architecture a3, which assures pseudo-measurements with maximum relative error of about 5%.

Uncorrelated Loads: For completely uncorrelated loads, a5 is the architecture characterized by the theoretical minimum number of input nodes; simpler architectures were therefore not investigated. More complex architectures were not considered in order to not increase the difficulty in setting up the ANN. Tests were carried out on the input data with measurement uncertainties being absent and the number of learning-set examples ranging from 48 to 480; they highlighted that the best ANN performance was obtained with 480 examples, with maximum relative error contained within 10%.

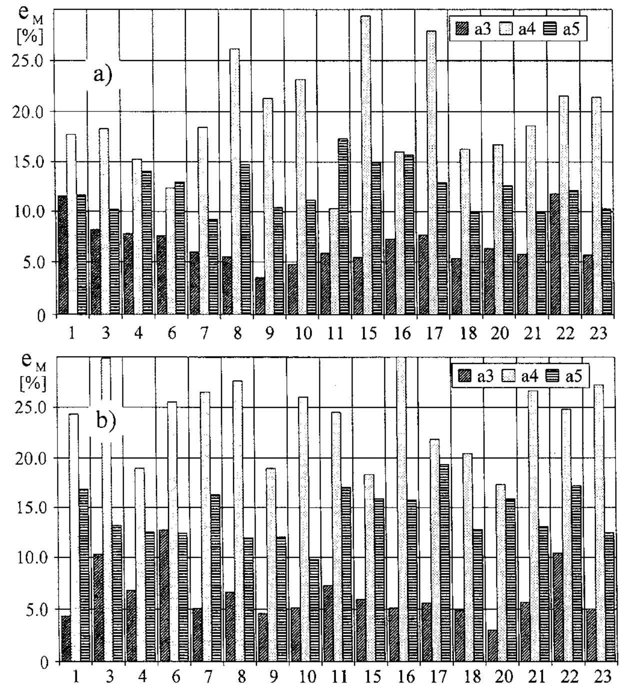

Fig. 2. Correlated loads. Maximum pseudo-measurement relative errors with different ANN architectures and with a 5% maximum relative uncertainty on the input data: a) Active bus load, b) Reactive bus load.

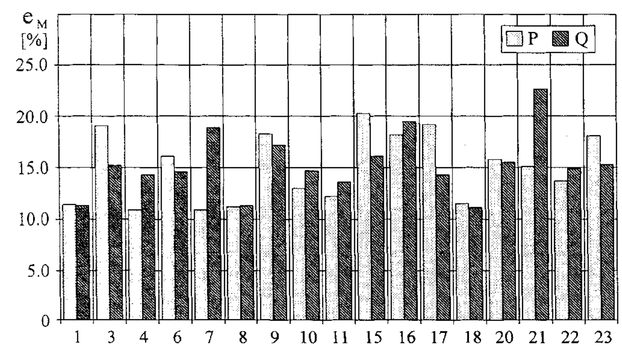

Fig. 3. Uncorrelated loads. Maximum pseudo-measurement relative errors on active (P) and reactive (Q) bus loads with 31 input nodes and with a 5% maximum relative uncertainty on the input data.

The results obtained with input data affected by maximum relative uncertainties equal to 5% are shown in Fig. 3 (the voltage pseudo-measurements are not reported since they assure relative error always contained within 0.3%).

D. Verification of ANN Performance

With reference to architectures a3 for correlated loads and a5 for uncorrelated loads, trained on input data corrupted by 5% maximum relative uncertainty, tests were performed on two validation sets each composed of 48 examples, and with input data corrupted by, respectively, 5% and 1% maximum relative uncertainty.

The metrological characteristics of the pseudo-instruments thus set up are reported in Tables II and III, in terms of maximum relative error e_M, average relative uncertainty $\underline{e}$,

TABLE II
PSEUDO-INSTRUMENT PERFORMANCE FOR CORRELATED LOADS

N	$V \cdot 10^2$ [%]			P [%]			Q [%]		
	e_M	$\underline{e}$	σ	e_M	$\underline{e}$	σ	e_M	$\underline{e}$	σ
1	0.4	0.0	0.1	11.5	-0.5	3.1	4.4	-0.3	1.5
3	0.5	0.0	0.1	8.2	0.3	2.2	10.3	-0.7	3.3
4	0.4	0.0	0.1	7.8	-0.9	2.6	6.8	0.4	2.5
6	2.5	-0.1	1.0	7.6	0.5	2.1	12.8	0.2	4.0
7	5.5	-0.1	2.1	6.0	-0.2	2.5	5.1	-0.2	2.1
8	5.9	0.6	2.5	5.5	0.2	2.1	6.6	0.5	2.4
9	9.7	-0.1	2.3	3.5	-0.5	1.4	4.6	-0.4	1.4
10	0.5	0.0	0.1	4.8	0.0	2.0	5.2	-0.2	1.6
11	0.4	0.0	0.1	5.8	-0.1	1.9	7.3	-0.6	2.4
15	0.7	0.0	0.3	5.4	-0.4	2.0	6.0	0.4	2.2
16	0.7	0.1	0.3	7.2	-0.2	2.7	5.1	0.1	1.9
17	0.7	0.1	0.3	7.7	-0.3	2.6	5.6	0.6	1.9
19	1.1	-0.1	0.4	5.3	0.1	1.8	4.9	0.0	1.7
20	2.9	0.3	1.0	6.3	0.0	1.7	3.0	-0.2	1.3
21	1.9	-0.4	0.8	5.7	0.4	2.5	5.7	0.1	2.0
22	8.5	-0.4	2.9	11.8	-0.5	2.6	10.4	-0.4	2.9
23	9.4	0.3	2.7	5.6	0.0	2.0	5.0	0.2	1.6

TABLE III
PSEUDO-INSTRUMENT PERFORMANCE FOR UNCORRELATED LOADS

N	$V \cdot 10^2$ [%]			P [%]			Q [%]		
	e_M	$\underline{e}$	σ	e_M	$\underline{e}$	σ	e_M	$\underline{e}$	σ
1	0.6	-0.1	0.2	11.4	-1.2	3.8	11.3	-0.5	3.7
3	10.6	0.4	3.2	19.1	-0.8	5.1	15.2	-0.9	5.0
4	19.1	1.7	6.0	10.9	-2.2	4.9	14.3	-1.1	5.2
6	29.5	2.3	6.7	16.1	-1.7	5.6	14.6	-2.1	4.8
7	20.6	1.8	6.5	10.9	-2.2	5.2	18.9	-2.1	5.7
8	0.0	0.0	0.0	11.2	0.5	3.1	11.3	0.4	3.0
9	1.3	-0.1	0.4	18.3	0.7	5.1	17.2	-0.7	4.3
10	0.8	0.0	0.2	13.0	-0.8	3.8	14.7	0.6	3.8
11	0.9	0.1	0.3	12.2	-0.3	4.2	13.6	-0.4	4.6
15	1.3	-0.1	0.4	20.3	0.4	4.7	16.1	-0.6	5.1
16	1.2	0.0	0.3	18.2	0.1	5.5	19.5	0.9	5.9
17	2.1	-0.4	0.6	19.2	0.6	5.1	14.3	-0.8	4.6
19	1.1	0.0	0.4	11.5	0.0	3.8	11.1	0.3	4.2
20	5.7	-0.2	1.7	15.8	0.8	4.2	15.5	-0.2	4.7
21	7.7	0.4	1.7	15.1	-0.3	5.9	22.7	-0.6	5.6
22	23.7	3.1	6.0	13.7	-1.4	5.4	14.9	-0.2	4.9
23	19.3	1.3	6.7	18.1	0.2	5.2	15.3	-0.3	5.2

and standard deviation σ. It is possible to note that "pseudo-voltmeters" with maximum relative error of 0.1% (correlated loads) and 0.3% (uncorrelated loads), "pseudo-wattmeters" and "pseudo-varmeters" with maximum relative errors of 10% (correlated loads) and 20% (uncorrelated loads) were obtained. It is important to stress that in real applications the presence of some degree of correlation between loads will permit intermediate performances compared to the ones obtained for completely correlated and uncorrelated loads.

Computation times strongly depended on the hardware used. In any case, the chosen ANN architectures required about 10^4 sums, 10^4 products and 200 perceptron transfer function activations in order to give the 51 outputs. To improve ANN speed for on-line applications, the perceptron output can be computed by means of two suitable look-up tables instead of by prefixed mathematical functions. In any case, the specific on-line requirements will help in the choice of the most appropriate hardware.

Finally, pseudo-instrument robustness was evaluated by means of tests in conditions of (i) overloads and (ii) increased measurement uncertainties.

i) Tests performed with a 15% overload indicate pseudo-measurement error two to three times greater than nominal.
ii) Tests carried out with maximum relative uncertainties on the input data greater than nominal, showed errors two to three times greater than nominal.

V. CONCLUSIONS

The paper proposes a state estimation scheme for power distribution systems based on Artificial Neural Networks. A suitably designed ANN, starting from measurement data affected by uncertainties, was able to produce a number of pseudo-measurements capable of describing system operation. The different phases to be followed in the design of this neural state estimation scheme and the results obtained in a case study are described in detail. In order to highlight the usefulness of the neural approach in state estimation problems, a comparison with traditional mathematical programming techniques can be performed.

i) *Setup phase:* The neural approach requires a noticeable number of parameters to be tuned in order to attain the best estimation performance (e.g., number of input and hidden nodes, number of learning-set examples). This phase is certainly more onerous on computing resources than is the case for mathematical programming.
ii) *Estimation accuracy:* The maximum accuracy obtainable by means of the neural approach (relative uncertainties of about 10% in pseudo-measurements of voltage, and active and reactive power) proves to be comparable with the accuracy typical of mathematical programming [2].
iii) *Estimation time:* Once the ANN was trained, it was characterized by a very low computational complexity compared to the requirements of recursive estimation algorithms and by an elaboration time that is always constant. Consequently, on-line estimation can easily be carried out.

To conclude, the proposed neural approach can be usefully applied whenever on-line estimations are required. Work is in progress to optimize the setup phase by applying more advanced ANN learning techniques (such as genetic algorithms).

REFERENCES

[1] F. F. Wu and A. F. Neyer, "Asynchronous distributed state estimation for power distribution systems," in *Proc. of X Power System Computation Conf.*, 1990, pp. 439–446.

[2] I. Roytelman and S. M. Shahidehpour, "State estimation for electric power distribution systems in quasi real-time conditions," *IEEE Trans. Power Delivery*, vol. 8, pp. 2009–2015, 1993.

[3] A. Bernieri, G. Betta, and M. D'Apuzzo, "Measurement problems arising from the use of a recursive algorithm for model identification of electrical systems," *IEEE Trans. Instrum. Meas.*, vol. 41, pp. 240–245, 1992.

[4] A. Bernieri, C. De Capua, and A. Pietrosanto, "A measurement apparatus for on-line diagnosis of electrical systems," in *Proc. of 6th IMEKO-TC4 Int. Symp. on Intelligent Instrumentation for Remote and On-Site Measurements*, Brussels, 1993, pp. 95–101.

[5] A. Bernieri, M. D'Apuzzo, L. Sansone, and M. Savastano, "A neural network approach for identification and diagnosis on dynamic systems," *IEEE Trans. Instrum. Meas.*, vol. 43, no. 6, pp. 867–873, 1994.

[6] A. Bernieri, G. Betta, A. Pietrosanto, and C. Sansone, "A neural network approach to instrument fault detection and isolation," *IEEE Trans. Instrum. Meas.*, vol. 44, no. 3, pp. 747–750, 1995.

[7] A. Bernieri, G. Betta, and M. D'Apuzzo, "A DSP-based measurement apparatus for fault detection and diagnosis using neural algorithms," in *Proc. of XIII IMEKO World Congress*, Torino (I), 1994, vol. 2, pp. 1294–1299.

[8] R. K. Hartana and G. G. Richards, "Harmonic source monitoring and identification using neural networks," *IEEE Trans. Power Appar. Syst.*, vol. 5, pp. 1098–1104, 1990.

[9] K. S. Narendra and K. Parthasarathy, "Identification and control of dynamical systems using neural networks," *IEEE Trans. Neural Networks*, vol. 1, pp. 4–27, 1990.

[10] M. Savastano, L. Lecce, F. Marulo, and C. Sansone, "Use of artificial neural networks for optimal sensing in complex structures analysis," in *Proc. of IEEE Instrumentation/Measurement Technology Conf. IMTC/94*, Hamamatsu, Japan, 1994, vol. 1, pp. 127–130.

[11] D. Niebur and members of CIGRE TF 38-06-06, "Artificial neural network for electrical systems: A literature survey," *Int. J. Eng. Intell. Syst.*, vol. 1, no. 3, pp. 133–158, 1993.

[12] D. E. Rumelhart, G. E. Hinton, and R. J. Williams, "Learning internal representation by error propagation," in *Parallel Distributed Processing*, D. Rumelhart and J. L. McClelland, Eds. Cambridge, MA: MIT Press, 1986, ch. 8, pp. 318–362.

[13] R. P. Lippman, "An introduction to computing with neural nets," *IEEE ASSP Mag.*, vol. 4, pp. 4–22, 1987.

[14] J. A. Freeman and D. M. Skapura, *Neural Networks: Algorithms, Applications and Programming Techniques*. Reading, MA: Addison-Wesley, 1992.

[15] M. E. Baran and F. F. Wu, "Optimal capacitor placement on radial distribution systems," *IEEE Trans. Power Delivery*, vol. 4, pp. 725–734, 1980.

[16] H. Demuth and M. Beale, *Neural Network Toolbox—User's Guide*, The MathWorks, Inc., 1994.

Andrea Bernieri, for a photograph and biography, see this issue, p. 633.

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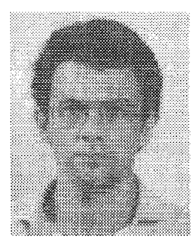

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