Application of Neural-Network Modules to Electric Power System Fault Section Estimation

Ghendy Cardoso, Jr., Jacqueline Gisèle Rolim, and Hans Helmut Zürn

***Abstract*—This paper presents a neural system intended to aid the control center operator in the task of fault section estimation. Its analysis is based on information about the operation of protection devices and circuit breakers. In order to allow the diagnosis task, the protection system philosophy of busbars, transmission lines, and transformers are modeled with the use of two types of neural networks: the general regression neural network and the multilayer perceptron neural network. The tool described in this paper can be applied to real bulk power systems and is able to deal with topological changes without having to retrain the neural networks.**

***Index Terms*—Fault section estimation, neural networks, power system protection.**

I. Introduction

PROGRESS IN the areas of communication and digital technology has increased the amount of information available at supervisory control and data-acquisition (SCADA) systems. Although that information is very useful, during events that cause outages, the operator may be overwhelmed by the excessive number of simultaneously operated alarms, which increases the time necessary for identifying the main outage cause and to start the restoration process. Besides factors, such as stress and inexperience, can affect the operator's performance; thus, the availability of a tool to support the real-time decision-making process is welcome.

The protection devices are responsible for detecting the occurrence of a fault and, when necessary, they send trip signals to circuit breakers (CBs) in order to isolate the defective part of the system (selectivity). However, when relays or CBs do not work properly, larger parts of the system may be disconnected. After such occurrences, it is essential to restore the system as soon as possible, avoiding damages to energy distribution utilities and consumers.

Nevertheless, before starting the restoration, it is necessary to assess the event that produced the sequence of alarms, and problems, such as protection system failure, defects in communication channels, corrupted data acquisition, etc., may complicate this task [1].

The heuristic nature of the reasoning involved in the operator's analysis and the absence of an analytical formulation, induce the use of artificial intelligence techniques [2]. Expert systems, neural networks, fuzzy logic, genetic algorithms (GAs), and Petri nets constitute the principal techniques applied to the fault diagnosis problem.

Expert systems are one of the solution techniques more frequently adopted, since Wollenberg (1986) suggested its use for alarm treatment [3]. Its main drawbacks are the incapacity of generalization and the difficulty of validating and maintaining large rule bases. More recently, model-based systems including temporal characteristics of protection schemes have been proposed [4].

In the field of the neural networks (NNs), multilayer perceptron (MLP) nets with backpropagation as a learning algorithm are the most used. Hierarchical nets [5] have been proposed to reduce the dimension of the neural network, its computational effort, and training time. However, neural networks cannot theoretically guarantee that a correct result will always be provided, since it depends on the quality of the group of samples (training patterns) employed.

Fuzzy logic constitutes a means for modeling imprecision and presents flexibility as its main convenience. On the other hand, its greatest inconvenience lays in the choice of the membership functions, usually defined on a trial-and-error basis.

The application of GAs to the diagnosis problem [6] still needs to be studied further in order to improve their ability to deal with a certain degree of alarm corruption.

Petri nets [7] also lack in generalization capacity, and their graphic representation of the protection scheme, which facilitates the visualization of the protection operation, is less of an advantage when it is applied to real systems (great dimension).

Although the literature presents a great variety of works considering the problem in subject, few of them were totally developed and applied in real large-scale power systems [8].

The purpose of this research work is to overcome the main drawbacks of the majority of methods proposed in the literature: their difficulty in dealing with topological changes and real power systems dimension, besides excessive effort in training procedures in case of neural-network applications. To reach these purposes, instead of dividing the power system into smaller parts and training a neural network for each set of a few buses, neural networks are employed here to model the protection system philosophy of the main transmission system components (buses, lines, and transformers). The alarms corresponding to the operation of protection relays and CBs are the inputs to MLP neural networks trained with the backpropagation algorithm. The output of MLP neural networks feed general regression neural networks (GRNNs), which conclude whether the equipment is faulted, not faulted,

Manuscript received July 15, 2003. This work was supported in part by the Brazilian Agency for the Improvement of Higher Education (CAPES).

G. Cardoso, Jr. is with the Department of Electrical Engineering at the Federal University of Pará, Belém, Pará 66075-110, Brazil.

J. G. Rolim and H. H. Zürn are with the Department of Electrical Engineering at the Federal University of Santa Catarina, Florianópolis, Santa Catarina 88040-900, Brazil (e-mail: jackie@labspot.ufsc.br; hans@labspot.ufsc.br).

Digital Object Identifier 10.1109/TPWRD.2004.829911

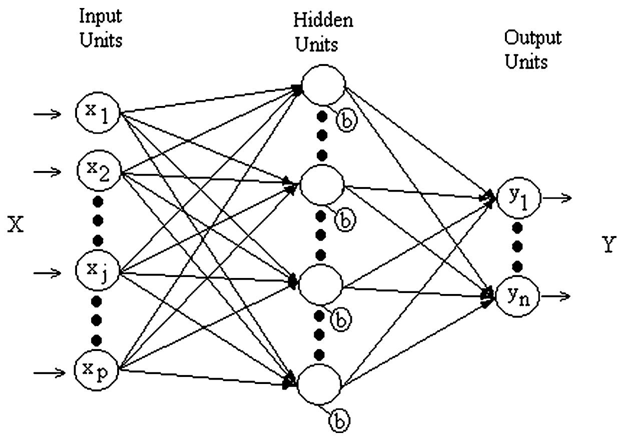

Fig. 1. MLP architecture.

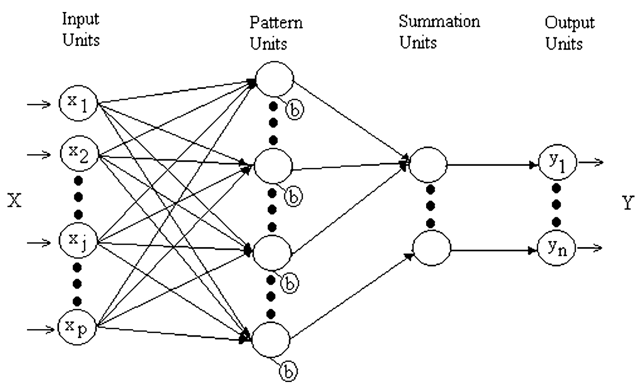

Fig. 2. GRNN architecture.

or there is a lack of information. The NN models developed for transformers and lines have additional information, which indicate the direction of external faults. This information can be combined and helps to conclude about which equipment started the occurrence.

With the NNs employed, the protection models and simulation results are described in the following sections.

II. MLP AND GRNN NNs

The MLP [9] nets with backpropagation learning algorithm (Fig. 1) constitute the NNs architecture most commonly used, since it is capable to approximate any nonlinear function. Its precision depends on the number of units that compose the net.

GRNNs [10] are feedforward networks that can be used to estimate an output vector Y from a measured vector X. An overview on GRNN architecture is shown in Fig. 2. Among the main advantages presented by GRNN, are the following.

- The learning process occurs in a single step (it is not iterative) and the net can generalize as soon as the examples are stored.
- They present satisfactory results even with few examples.
- They do not converge to a local minimum of the error criteria (as it sometimes happens with iterative training processes).

When GRNN is applied to classification problems, the connections between the pattern and summation units have fixed weights that can be 0 or 1. A weight of zero value is used when

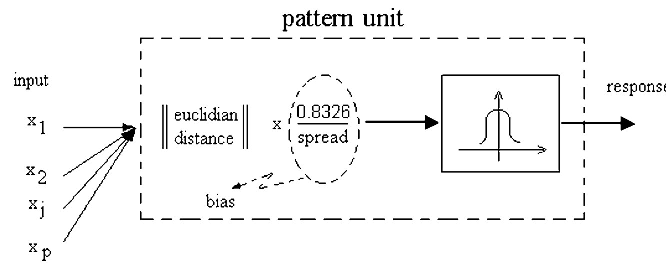

Fig. 3. Internal operation of the pattern unit.

there is no connection between these units, while a weight value of one represents a connection link between them. The value assigned to these weights is equal to the expected output vector, so there are as many summation units as there are outputs. To facilitate the understanding of the GRNN operation, the connections between the pattern and summation units with zero weights were omitted in Fig. 2.

The input units distribute the variables x_i (input variables) to all neurons in the pattern units. Each neuron belonging to the pattern layer corresponds to a sample or a cluster center. Therefore, the number of units that compose this layer are equal to the number of patterns used during the training process.

When a new vector X is presented to the network, the distance, usually Euclidian, between this vector and each cluster center previously defined and stored is computed.

The output values of pattern units decrease gradually as the distance between the input vector X and the vector that represents the stored pattern (cluster center) increases. Commonly, an exponential is used as an activation function [11]. The units belonging to the pattern layer are better shown in Fig. 3. The parameter *spread* is related to how much the neural network will generalize.

The outputs of the units belonging to the pattern layer are sent to the summation layer. The number of units that compose this layer corresponds to the number of observations (wanted outputs), in this case n. The summation units have the function of performing the sum of the outputs of the pattern units, according to the number of observations that each cluster center represents. The units that compose the output layer simply divide each result from the summation units by the total sum of all the summation unit outputs.

GRNNs are recommended for forecasting problems, modeling, mapping, interpolation, or control. The performance of the network depends on the bias adjustment (spread) and the stored patterns.

III. FAULT SECTION ESTIMATION PROCEDURE

After a contingency, only the NNs corresponding to de-energized equipment should be activated. Thus, first the fault scenario should be determined. An expert system has been designed for this task. The expert system is a topology tracker, which determines the active elements before and after the fault, using information about the breaker status. The fault scenario set $S = \{S_{1\ldots}S_n\}$ for $n = 1\ldots$ total number of elements involved in the fault is the difference between active elements before and after the fault.

Finally, for each element that composes the fault scenario set S, a neural-network module is activated according to its respective alarm inputs. Each net would try to classify the element S_i (ith element of S) into one of its outputs previously determined.

IV. Description of the Protection Scheme

This research work presently deals with three protection philosophies usually used in electric power systems. A scheme for 230/138-kV autotransformer protection; another for 230-kV transmission line protection, and still another for 230-kV bus protection.

The breaker failure protection is included in the 230-kV busbar protection systems, and has the objective of tripping all breakers connected to the bus if one of them fails to open after a protection request.

A. Autotransformer Protection Scheme

The autotransformer protection is composed of main and backup protection.

The main protection is performed by the following relays:

87-differential protective relay;
63 T-Buchholz relay;
63 VS-safety valve;
63 C-pressure relay of the onload tap changer;
86-blocking relay.

The backup protection is composed of the following.

94-auxiliary trip relay;
51 HV-time overcurrent relay, high-voltage side;
51 MV-time overcurrent relay, medium-voltage side;
51 N-ground time overcurrent relay.

Besides the operation of these relays, the information on dc source availability is also used.

B. Line Protection Scheme

The line main protection is based on a directional comparison carrier scheme, with directional phase distance (21P) and directional instantaneous overcurrent ground relays (67NP). On the other hand, the secondary protection is based on directional distance relays with three protection zones and instantaneous ground overcurrent (67NI) and time overcurrent (67NT) relays.

The first zone of the secondary protection is composed of a phase distance directional (21-1) and a ground (21N-1) relay both without time delay and set to 80% of the line length. The second zone is composed of distance relays (21-2) with time delay, adjusted to 120% of the line length. Finally, the third zone (21S) is reverse and its main function is to start the power line carrier (PLC) blocking the far end main protection operation for external faults, being therefore adjusted at a higher value than the reach of the distance relay used as main protection on the far end of the line. This zone is also equipped with a time delay (TU3) and may trip the breaker in case the main protection does not clear the fault after this time. The PLC can also be started by relay 67NP/G1 that also looks in reverse direction.

C. Bus Protection Scheme

Bus protection is accomplished through a differential relay (87), which would excite the auxiliary blocking unit (86) that sends a trip signal to all of the breakers connected to the bus. Besides these relays, the bus has overvoltage relays (59), which may also trip.

All breakers are equipped with breaker failure protection (86BF), which in case of a breaker failing to open sends a trip command to all of the breakers linked to the bus.

TABLE I
DC Source Logic

DC source	1	1	1	0	0	0	-1	-1	-1
Relay	1	0	-1	1	0	-1	1	0	-1
NN input	0	0	0	1	0	-1	1	0	-1

D. CB

The representative model of the CB takes into account the following information and alarms:

- direct current source of the opening circuit;
- manual command;
- breaker operated by protection (OPP);
- breaker status (closed or open);
- breaker protection—operation of internal breaker protection, for instance, low gas pressure, pole discordance, etc.

V. Input Logic

The inputs of neural networks have the following logic.

- For CB status:
  1-open;
  0-closed;
  -1-unknown.
- For alarm reception:
  1—indicates the reception of the alarm corresponding to the unit;
  0—means loss of signal due to failure in the data transmission system or remote devices (unknown);
  -1—the alarm has not been received.

Each neural model takes into account information on the dc source availability. If a dc source is lost (input 1), it is expected that the protection relays fed by it will not operate, despite the existence of a fault. For instance, suppose a loss of dc source at relay 86, but an alarm signaled relay 86 operation. In this case, the NN will be feed by a 0 (doubt, column 2 of Table I), since 1 (dc source) combined with 1 (86) is not possible. Therefore, these alarms are treated through the logic shown in Table I.

VI. Neural Models

Neural models have been designed for each protection scheme described in Section IV, using GRNN together with MLP.

A. Neural Model Proposed for the Autotransformer Protection

As shown in Fig. 4, five neural networks are used to model the autotransformer protection: four MLP—two to treat the messages related to protection (MAIN and NN_T) and the other two for breakers (NN_CB)—and a GRNN (NN_TR), whose input values are fed by the NN_T and NN_CB nets and are responsible for giving the diagnosis.

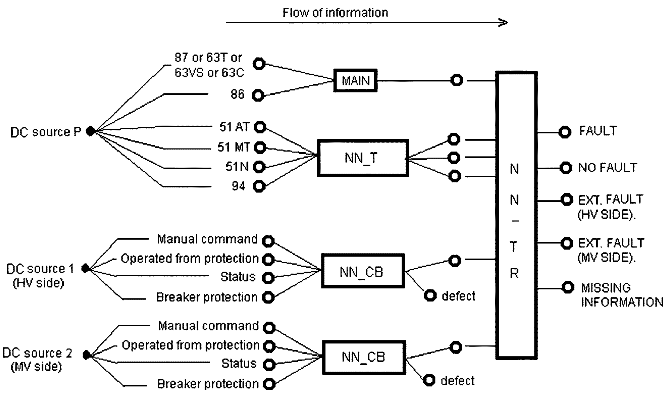

Fig. 4. Neural model proposed to represent the autotransformer protection.

The main reason for using MLP together with GRNN is the reduction in the dimension of the neural network, without oversimplifying the protection system. The division in several subnetworks, with fewer connections, but specialized at the execution of certain tasks made the training phase simpler and faster.

The MAIN neural network module was trained through all of the nine (3^2) possible examples. This module determines the operation or not of the main protection devices.

The NN_T neural network was trained through 61 examples, and the efficiency of the network (generalization capacity) was tested with 20 new examples. The first hidden layer has seven neurons and tangent hyperbolic activation function; the second hidden layer has four neurons and tangent hyperbolic activation function. The success rate was 100%. This module verifies whether the fault is external at high or medium voltage side or at both sides.

The NN_CB neural network was trained through 65 examples, and the efficiency of the network (generalization capacity) was tested through 16 new examples. The hidden layer has ten neurons and tangent hyperbolic activation function, and the output layer has two neurons. The success rate was 100%. This module determines whether the breaker was opened and/or defective (pole discordance, low SF6, or oil pressure).

The NN_TR was trained through 49 examples. It uses the output values of the MLP networks and determines whether the component is faulty or not, whether the fault is external toward the high-voltage or medium-voltage side, or even whether the information provided to the network is insufficient for the diagnosis. The choice among the first four options is made if its output presents a value higher than 0.7; otherwise, the "missing information" output is chosen, except when the net is in doubt with respect to the external fault direction, then the two choices are pointed out. To evaluate this neural-network performance, it was tested with 639 examples randomly generated. The results are presented in Table II. The diagnosis is correct in all cases and the percentage of missing information classification should be considerably smaller in real cases.

B. Neural Model Proposed for Line Protection

The neural network proposed for modeling the transmission line protection is shown in Fig. 5. As the tool is expected to be used in control centers, the transmission line model uses information on events on both sides (S and R) of the line.

TABLE II
CLASSIFICATIONS OF NEURAL NETWORK NN_TR

Outputs	Number of Cases	Percentage
Fault	176	27.54
No Fault	7	1.10
External Fault at HV direction	77	12.05
External Fault at MV direction	77	12.05
Missing Information	302	47.26
Number of tested patterns	639	100

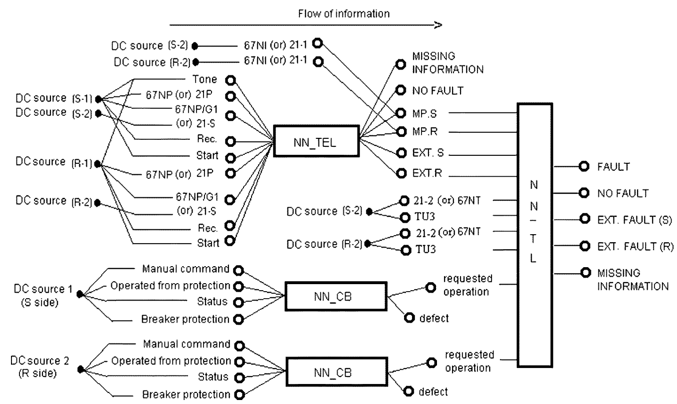

Fig. 5. Neural model proposed to represent the 230-kV line protection.

TABLE III
CLASSIFICATIONS OF NEURAL NETWORK NN_TEL

Outputs	Number of Cases	Percentage
Main Protection – Sending End (MP.S)	101	6.45
Main Protection – Receiving End(MP.R)	101	6.45
External Fault at Sending End Direction	57	1.73
External Fault at Receiving End Direction	57	1.73
No Fault	248	15.83
Missing Information	1062	67.81
Number of tested patterns	1566	100

In Fig. 5, some of the alarms presented have not been commented so far.

DC Source (x-y)-dc source on the x side (S-sending; R, receiving), circuit number y (1 or 2);
Rec.-auxiliary relay for carrier signal reception;
Start-auxiliary relay for carrier start;
Tone-tone equipment supervision.

The automatic line reclosure scheme is not considered in the model, since this system will only be applied after the occurrence of permanent faults in the equipment.

The NN_TEL module is a GRNN specialized in representing the operation of the pilot relaying outline described in Section IV-B.

The output of this network determines whether the main protection of the line on the sending or receiving side (MP.S/MP.R) operated, or if the protection indicates the possibility of an external fault to the S (send) side or R (receive). The training was accomplished through 25 examples. The threshold employed for choosing the output of NN_TEL is 0.8. With this value, the diagnosis is always correct or, at worse, missing information. Table III presents the results obtained when NN_TEL was evaluated with 1566 randomly generated examples.

TABLE IV
CLASSIFICATIONS OF NEURAL NETWORK NN_TL

Outputs	Number of Cases	Percentage
Fault	494	16.83
No Fault	12	0.41
External fault at sending end direction	180	6.13
External Fault at receiving end direction	180	6.13
Missing Information	2069	70.50
Number of tested patterns	2935	100

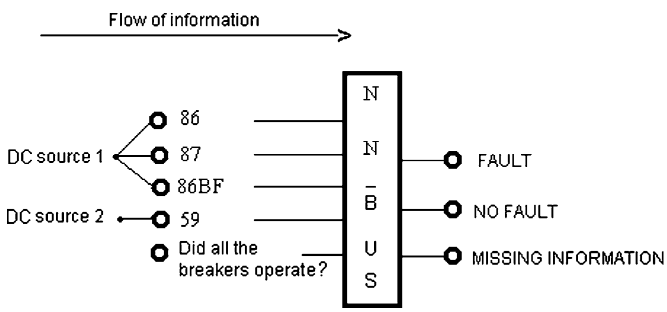

Fig. 6. Neural model proposed to represent the 230-kV bus protections.

TABLE V
CLASSIFICATIONS OF NEURAL NETWORK NN_BUS

Outputs	Number of Cases	Percentage
Fault	86	35.39
No Fault	42	17.28
Missing Information	115	47.33
Number of tested patterns	243	100

The NN_CB module is the same used in the autotransformer model.

The NN_TL is a GRNN and was trained through 52 examples. It is fed by the previous modules and determines whether the component is faulty or not, if the fault is external toward the S or R side, or if the information is not sufficient to produce a diagnosis. The threshold used in this network was 0.67 because, with this value, the diagnosis is always correct or missing information. NN_TL performance was evaluated with 2935 randomly generated examples and the results are shown in Table IV.

C. Neural Model Proposed for Buses

The neural model used to represent the bus protection scheme is only composed of the GRNN, as shown in Fig. 6.

The NN_BUS module was trained though 13 examples. The output of the network indicates whether the component is faulty or not, or whether there is not enough information for the diagnosis. The threshold used for choosing one of the outputs is 0.7. When evaluated through 243 randomly generated examples, the neural network provides the results outlined in Table V.

One of the efforts of this work is to simplify the neural net training process, because it would be sometimes necessary to train various neural models in a real application, when the protection philosophy adopted varies. Only simple cases were used as training patterns. The criterion adopted was to supply the neural modules with information about the protection system operation in cases of an internal or external fault, considering the possibility of correct breaker operation or failure. The examples used in the NN training follow the reasoning about the functionality of each protection scheme, in agreement with the interpretation of dc schematic diagram of the protection system. For the cases where the breaker failed to operate, the net was supplied with information about the performance of the local backup protection, considering its operation time.

TABLE VI
ARRIVED ALARMS FOR A FAULT AT BL230P1

Electric Component / Breaker	*Alarms*
L_JB-BL	21P(S), 21-S(R), Start(R)
L2_JV-BL	Start(S), 21P(R), Rec.(R)
BL230P1	87
BLD06	OPP, status
BLD05	OPP, status
BLD04	OPP
BLD03	Status
BLD02	OPP, status
Unknown alarms	
L2_JV-BL	21-S(S)
BL230P1	86
BLD03	OPP
BLD04	Status

(S) – side S; (R) – side R. The side S and R of the transmission lines are shown in Fig. 7.

VII. SIMULATIONS

In order to verify the efficiency of the developed tool, some occurrences were simulated on a real 230-kV test system, which is composed of five substations, 11 autotransformers, 19 main and transfer buses, and 14 transmission lines. The single line diagram of this system is shown in Fig. 7 (Appendix A).

The neural modules always provide the correct diagnosis in simple cases, when there is no failure in the protection and communication systems. The two cases presented in this section have some alarm discrepancies or represent severe faults with backup relay tripping.

The NN module outputs for line and autotransformer are $\mathrm{R}1, \ldots, \mathrm{R}5$, which means fault, no fault, external fault to S (line), or HV (autotransformer) side, external fault to R (line) or MV (autotransformer) side, and missing information, respectively. For busbar $\mathrm{R}1, \ldots, \mathrm{R}3$ means fault, no fault, and missing information, respectively.

A. Case 1

This case presents a fault at bus BL230P1. The bus differential protection operates sending trip signals to all CBs connected to BL230P1. Table VI shows the alarms arrived at the control center in addition to a list of lost information (unknown alarms).

Notice that the entire list of unknown alarms in Table II should have operated, that is, instead of 0 (unknown); a 1 (operation) would be expected. The auxiliary relay for carrier signal reception alarm (Rec.) on the S side of the transmission line L_JB-BL is not observed.

After an event occurrence, the NN modules are fed by the alarms in order to produce a diagnosis. The neural-network outputs per equipment are shown in Table VII. The outputs with the largest numeric value are in bold. In the same way, the estimated faulted component is highlighted.

TABLE VII
NN MODULES OUTPUTS FOR A FAULT AT BL230P1

FAULT SCENARIO	*NN MODULES OUTPUTS*				
	R1	**R2**	**R3**	**R4**	**R5**
L_JB-BL	0,00	**0,94**	0,03	0,01	0,00
L2_JV-BL	0,00	**0,96**	0,01	0,03	0,00
BLTF02	0,00	**1,00**	0,00	0,00	0,00
BLTF01	0,00	**1,00**	0,00	0,00	0,00
BL230P1	**1,00**	0,00	0,00	---	---

TABLE VIII
ARRIVED ALARMS FOR A FAULT AT L2_JV-CT

Electric Component / Breaker	*Alarms*
L_SM-CT	21-S(S), Start(S), 21P(R), Rec.(R)
L2_UMBARA	21-S(S), Start(S), 21P(R), Rec.(R)
L1_JV-CT	DC source (S-1), DC source (S-2), Tone
L2_JV-CT	DC source (S-1), DC source (S-2), 21-1(R), Tone, 21P(R), 21-S(R)
L1_JV-BL	DC source(R-1), DC source(R-2), Tone, 21-2(S)
L2_JV-BL	DC source(R-1), DC source(R-2), Tone, 21-2(S)
JVTF05	DC source P
JVTF04	DC source P
JVTF03	DC source P
JVTF02	DC source P
JVTF01	DC source P
JVA138	DC source 1, DC source 2
JVA69	DC source 1, DC source 2
JV230P	DC source 1, DC source 2
CT230P2	86BF
CTD10	OPP, status
CTD08	OPP, status
CTD02	OPP, status
BLD11	OPP, status
BLD06	OPP, status
JVD13	DC source
JVD12	DC source
:	:
:	:
JVD03	DC source
JVD02	DC source

B. Case 2

This case represents a fault at line L2_JV-CT near to the substation CT (receiving end).

In this case, a fault condition in the line L2_JV-CT is presented, during a complete loss of dc source at JV substation. Besides, the breaker CTD03 at substation CT did not open (stuck), leading to a more severe condition, with the breaker failure protection operation at CT230P2. The alarms arrived at the control center can be shown in Table VIII.

Notice that in this case, the line neural network classifies the line L2_JV-CT as 0,65 and 0,32 for the fault and no fault possibility, respectively (see Table IX). This means that the net recognizes the alarms as being more similar to the patterns used to represent the fault condition than those used to represent the no-fault condition.

The operation of the remote backup protection is also discriminated by the net in the outputs R3 and R4 for autotransformers and lines. The operation of the second zone distance relay at terminal BL on both lines L1_JV-BL e L2_JV-BL, together with the trip of breakers BLD11 and BLD06, respectively, was sufficient for the neural network to classify each line as an external fault in the R direction (R4).

TABLE IX
NN MODULES OUTPUTS FOR A FAULT AT BL230P1

FAULT SCENARIO	*NN MODULES OUTPUTS*				
	R1	**R2**	**R3**	**R4**	**R5**
L_SM-CT	0,00	**0,96**	0,01	0,03	0,00
L2_UMBARA	0,00	**0,96**	0,01	0,03	0,00
L1_JV-CT	0,00	**0,96**	0,03	0,01	0,00
L2_JV-CT	**0,65**	0,32	0,01	0,01	0,00
L1_JV-BL	0,01	0,01	0,00	**0,97**	0,00
L2_JV-BL	0,01	0,01	0,00	**0,97**	0,00
JVTF05	0,00	**1,00**	0,00	0,00	0,00
JVTF04	0,00	**1,00**	0,00	0,00	0,00
JVTF03	0,00	**1,00**	0,00	0,00	0,00
JVTF02	0,00	**1,00**	0,00	0,00	0,00
JVTF01	0,00	**1,00**	0,00	0,00	0,00
JVA138	0,00	**1,00**	0,00	---	---
JVA69	0,00	**1,00**	0,00	---	---
JV230P	0,00	**1,00**	0,00	---	---
CTAUMBARA	0,00	**1,00**	0,00	---	---
CT230P2	0,00	**1,00**	0,00	---	---

This information is essential in cases of protection relays or breaker failure, where the net was sometimes not able to identify the defective component. This situation needs an additional treatment of the backup protection so that the faulty component can be found. An expert system considering the overlap and reach of this protection could be used for this purpose. The expert system designed for this purpose can be found in [12].

As can be seen in Tables VII and IX, the system was able to find the faulty component in all cases, that is: case 1, BL230P1 at substation BL; case 2, L2_JV-CT between substations JV and CT.

VIII. CONCLUSION

The purpose of using neural models to represent each equipment protection is to determine the initial faulty component after contingencies with permanent outages. This approach reduces neural-network dimension and makes the system independent of the electric network configuration. Therefore, the proposed methodology may be applied in large-scale systems, because it does not depend on the size of the electric network. Besides, usually electric companies follow a standard protection philosophy, so the design and maintenance of neural models are easier.

The GRNN provides a numerical result, a value that can be used as a degree of how close an input vector is from the stored examples used during the learning phase. These indexes can be further explored. For instance, when a result is not satisfactory, the answer with the next largest result may be used.

The cases in which the input data are too corrupted may result in dubious output or an answer of *missing information*. Those cases would demand a user interpretation on all of the components that have tripped. This analysis can be accomplished with the aid of an expert system, which would use all neural-network outputs to try to infer the faulty components.

APPENDIX A

The 230-kV test system topology is shown in Fig. 7.

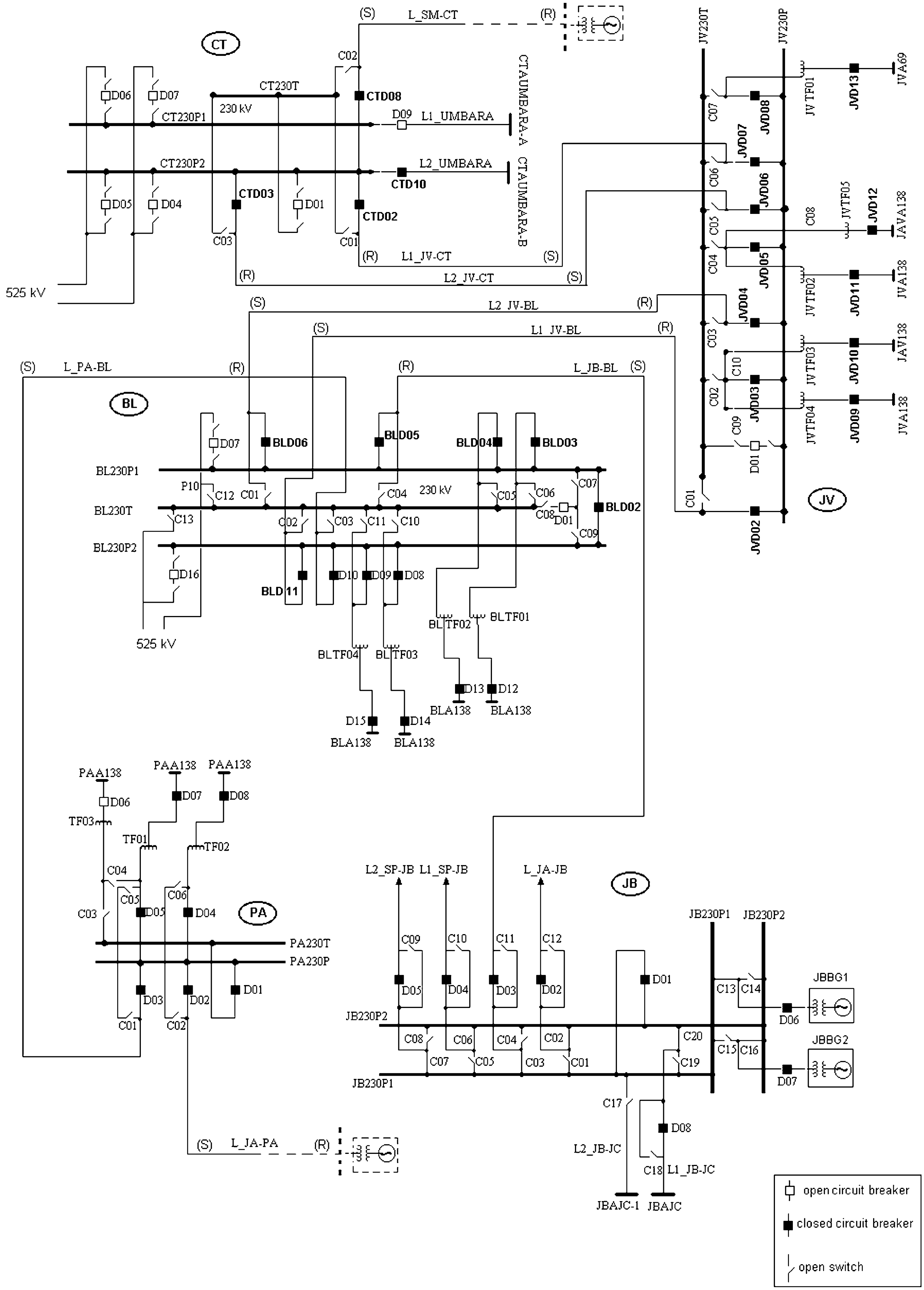

Fig. 7. 230-kV test system.

REFERENCES

[1] J. C. S. de Souza, M. A. P. Rodrigues, M. T. Schilling, and M. B. do C. Filho, "Fault location in electrical power systems using intelligent systems techniques," *IEEE Trans. Power Delivery*, vol. 16, pp. 59–67, Jan. 2001.

[2] Z. A. Vale and C. Ramos, "Temporal reasoning in AI applications for power system control centers," in *Proc. IFAC Control of Power Plants and Power Systems*, Cancun, Mexico, 1995, pp. 297–302.

[3] B. Wollenberg, "Feasibility study for an energy management system intelligent alarm processor," *IEEE Trans. Power Syst.*, vol. PWRS-1, pp. 241–247, May 1986.

[4] S. C. Bell, S. D. J. McDonald, G. M. Burt, R. Mather, and T. Cumming, "Model-based analysis of protection system performance," *Proc. Inst. Elect. Eng., Gen. Transm. Dist.*, vol. 145, no. 5, pp. 547–552, Sept. 1998.

[5] H. T. Yang, W. Y. Chang, and C. L. Huang, "A new neural network approach to on-line fault section estimation using information of protective relays and circuit breakers," *IEEE Trans. Power Delivery*, vol. 9, pp. 220–229, Jan. 1994.

[6] F. S. Wen and C. S. Chang, "Probabilistic approach for fault-section estimation in power systems based on a refined genetic algorithm," *Proc. Inst. Elect. Eng., Gen. Transm. Dist.*, vol. 144, no. 2, pp. 160–168, Mar. 1997.

[7] J. Tang and F. Wang, "Modeling of a transmission network protection system using Petri nets," *Elect. Power Syst. Res.*, vol. 44, pp. 175–181, 1998.

[8] C. Rodríguez, S. Rementería, J. I. Martín, A. Lafuente, J. Muguerza, and J. Perez, "Fault analysis with modular neural networks," *Elect. Power Energy Syst.*, vol. 18, no. 2, pp. 99–110.

[9] L. V. Fausett, *Fundamentals of Neural Networks Architectures, Algorithms, and Applications*. Englewood Cliffs, NJ: Prentice-Hall, 1994, p. 461.

[10] D. F. Specht, "A general regression neural network," *IEEE Trans. Neural Networks*, vol. 2, pp. 568–576, Nov. 1991.

[11] M. J. Sinclair, M. T. Musavi, and M. Qiao, "Radial basis function neural network as predictive process control model," in *Proc. IEEE Int. Symp. Circuits Syst.*, vol. 3, 1995, pp. 1948–1951.

[12] G. Cardoso, Jr., J. G. Rolim, and H. H. Zürn. Interpretation of remote backup protection operation for fault section estimation by a fuzzy expert system. presented at Proc. IEEE Bologna Power Tech Conference

Ghendy Cardoso, Jr. received the B.Sc. degree in electrical engineering from the Federal University of Santa Maria, Santa Maria, Brazil, in 1995, the M.Sc. degree in power systems from the Federal University of Pará, Pará, Brazil, in 1997, and the Ph.D. degree from the Federal University of Santa Catarina, Santa Catarina, Florianópolis, Brazil, in 2003.

Currently, he is a Lecturer with the Federal University of Pará, where he has been since 1997. His research interests are short circuit, protection systems, and artificial intelligence techniques applications to power systems.

Jacqueline Gisèle Rolim received the B.S.E.E. and M.Sc. degrees in power systems from the Federal University of Santa Catarina (UFSC), Santa Catarina, Brazil, in 1982 and 1988, respectively. She was in a split Ph.D. program at UFSC and Brunel University, Uxbridge, U.K. and received the Ph.D. degree from UFSC in 1995.

Currently, she is an Associate Professor at UFSC and works with artificial intelligence applications to power system operation. From 1985 to 1991, she worked in high-voltage (HV) and extra high voltage (EHV) substation projects in Southern Brazil.

Hans Helmut Zürn received the engineering degree from the Federal University of Rio Grande do Sul, Porto Alegre, Brazil, in 1966. He received the M.Sc. degree from the University of Houston, Houston, TX, in 1969, and the Ph.D. degree from the University of Waterloo, Waterloo, ON, Canada, in 1976.

Currently, he is a Lecturer on power systems, dispersed/renewable generation, and stochastic methods with the Federal University of Santa Catarina (UFSC), Santa Catarina, Brazil, where he has been since 1967.