An Intelligent Adaptive Protection System in Complex Power Generating Units

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Abstract: - Practical successes have been achieved with neural network models in a variety of domains, including energy-related industry. The large, complex design space of electrical power systems (EPS) is only minimally explored in current practice. The satisfactory results that nevertheless have been obtained testify that neural networks are a robust modeling technology; at the same time, however, the lack of a systematic design approach implies that the best neural network models generally remain undiscovered for most applications. This paper presents an approach to an adaptive protective systems problem in complex power generating units. First, we demonstrate the complex interdependencies between various parameters of EPS protection systems. Then, we present an approach, based on protection and adaptation criteria, for designing a neural network based adaptive protection system.

Key-Words: - Electrical Power Systems, Power Generating Units, Power System Protection, Adaptive Systems, Neural Networks, Multi-Layer Perceptron, Supervised Learning

1 Introduction

Electrical Power Systems (EPS) comprise units characterized by a complex topology, both in respect of the quantity and the variety of electrical appliances, which constitute the unit, as well as the number of operating modes, which differ as to their configurations and functions.

From the point of view of the EPS protection systems, sweeping protection of such complex units necessitates the application of advanced adaptive protection systems.

The reliability of protection systems is determined mostly by the accuracy of decisions classifying the current operating mode of the protected unit as one of the two categories of events: normal or fault. This reliability is dependent on meeting several conditions, first of all on the possibility of acquirement and acquisition of a large number of data (binary and analog) concerning the protected unit, the speed at which data are processed and decisions are made, the ability to adapt their innate properties to the current operating mode of the unit, and the immunity to any disturbances and faults.

Digital technology makes it possible to adopt a new approach to the issue of identification of operating modes in a protected unit as well as the issue of correct adaptations of protection functions. The benefits of employing digital technology in complex protection systems are connected with the number and the variety of the acquired data, the possibility to process these data by using heuristic techniques, the speed at which the data are processed, as well as the digital pre-processing of the measurement signals, which, for example, eliminates disturbance factors.

Several basic protection functions, which are blocked in analog relays, are here activated, improving the overall quality and reliability with which the unit is protected from the consequences of disturbances. This happens because both measurement algorithms as well as the algorithms realizing particular protection functions are capable of adapting to the current frequency (in the operating

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modes of the unit which are characterized by the frequency of measurement signals, changing within a wide range, e.g. frequency start-up) and to the operating mode.

2 Protection Systems in Complex EPS Units

Taking advantage of the benefits offered by digital technology, one can create a concept of digital managing systems which are dedicated to complex EPS units and which are characterized by the following features:1. they are able to identify correctly the current operating mode of the unit, i.e. the realization of the *structure criterium; 2. t*hey provide a big accuracy and speed of the protection algorithms, both in all possible operating modes of the protected unit and in the frequency of the input measurement signals which changes within a wide range, i.e. the realization of the *protection criterium; 3.* the structure of protection system can be adapted quickly to the changing conditions and operating modes of the protected unit i.e. the realization of the *adaptation criterium; 4. t*hey are capable of a fast analysis of the in-flowing alarm signals and the data concerning responses of protection functions, which enables one to predict the place of disturbance, and to follow any necessary procedure aiming at the minimization of the consequences of such disturbances, i.e. realization of the *prevention-restitution criterium.*

Reversible hydrogenerators, which operate in conjunction with a unit transformer, have been here adopted as an example of a complex power unit. An adaptive managing system, that employs the above-mentioned criteria, has been proposed.

In an example of an adaptive managing system each of the modules realises the *protection* and the *adaptation criteria* and the digital protection systems with the open configuration, regularly equipped with nine input measurement channels, are used as the systems realising these criteria. The system is equipped with three basic modules (ID1, ID2, ID3) and one master system (GID), which realize the *structure criterium.* Four systems analysing alarm signals and predicting the place of disturbance (FID) have been employed to realize the *prevention-restitution criterium..*

Because of the complexity of the unit, the adaptive managing system has been split into modules dedicated to particular components of the unit. Decentralizing operation of the system into particular modules makes it possible to separate functions responsible for particular criteria, which increases the number of indispensable processors, but which also significantly decreases the load and the time in which the whole system responds to changes in the protected unit.

Placing the dedicated modules nearer the chosen components of the protected unit increases the accuracy and reliability of the data acquisition. Particular modules exchange information that has already been processed (for example, identification of the operating mode of the protected unit's component). That makes possible a prediction-based initial analysis of the protected unit's operating mode. The decrease in the number of operations realized by processors is also achieved through the division of the identified operating modes into groups and subgroups of active protection functions. Taking into consideration the level of complexity of a given operating mode, there is also a possibility of combining a particular group of protection functions into sets.

3 Digital System Responsible for Identification of Current Operating Mode

An accurate identification of operating modes in the protected unit on the basis of the data entering the system (the *structure criterium*) is the basic condition for correct functioning of the system. Three types of data acquirement are proposed [1] for identification purposes: 1. Using binary inputs representing the position of connectors in the protected unit (their quantity should be sufficient for an unequivocal identification of the current configuration of the protected unit); 2. Utilizing the output of measurement algorithms, for example the voltage measurement algorithm, frequency measurement algorithm (in the chosen places within the unit); and 3. Exchanging of binary data between the modules that constitute the protection system.

Each module identifies (by binary or binary-analog data concerning the position of the switches) the current configuration of the nearest component of the protected unit. That makes it possible to subdivide the identification of the operating mode of the whole of the unit into modules dedicated to a given function, which, in turn, depending on the situation exchange data among themselves.

Next, a sample module responsible for the identification of the operating mode of the protected unit will be presented. This module employs Artificial Neural Network (ANN) structures.

The reversible hydrogenerator with the configuration presented above is proposed as the protected unit. The protected unit has been divided into three parts for which ANN structures responsible for the initial identification of the global operating mode have been determined. This was done on the basis of the operating modes of its constituent parts. Input signals comprise of: binary and the binary-analog signals, exchange of data among given networks, as well as the information from the measurement algorithms.

The structure of the system responsible for the identification of the operating mode is based on ANNs. This is the structure of a feed-forward network of the multilayer perceptron (MLP) type, with three layers. The main advantage of such a solution is that in this case there is no explicit need to define relations between particular pieces of information (signals).

During the teaching process, the network optimizes its structure by choosing the number of neurons and appropriate weights and biases between them [2]. The process of adding neurons is explained in Section 6. This is done in such a way as to be able to identify and classify situations by which the network was taught, as well as situations that are their generalizations. They are different in respect of certain input signals, which, however, does not result in classifying them as a different category of events.

The main advantage of such a structure is the fact that it eliminates certain situations, such as incompatibility of binary signals or the case of missing signals, which are the primary source of the "error" signal generated by the identification system in binary logic. When we adopt the above mentioned structure of the identification system, the proper determination of the teaching base becomes the issue of paramount importance. The network must be taught by the greatest possible number of events that belong to all possible categories of events, i.e., operating modes of the unit.

In the case of the unit under consideration, any subsequent identification of the protected unit's operating mode is performed every second or every third period of the basic component of the current frequency. This occurs in the main identification unit in the case of all types, or stages, of start-up. It is necessitated by the need for the activation of the correct sets of protection functions, depending on the current frequency and the unit's operating mode. The protection system must be equipped with separate identification components that contain their own fast processors and memory buffers because of a high repeatability and complexity of the identification process.

In modes such as the generator mode, motor mode and stand-by (out-of-service) unit, identification can be repeated in much longer intervals, for example every five minutes. Identification is repeated in all components of the system, and it is synchronized both by the master identification output module and the communication system of the main machine protection.

The identification system is restarted immediately in the following situations: Activation or operation of the active protection function; Recognition of error by the main identification unit (GID).There is information about opening of the main circuit breaker of the system CB2, if the circuit breaker was previously switched on.

4 Adaptive Protection Systems

Adaptive protection systems that realize the *protection* and *adaptation criteria*, dedicated to complex EPS units, usually have a diffused structure. Such a structure is achieved through the subdivision of the unit into smaller protected fragments - similarly as in the case of the system responsible for the identification of operating modes in the protected unit. Making such an assumption makes it possible to establish protection systems that perform protection functions (with adaptive properties) and measurement functions. They also perform functions responsible for communication with adjacent systems, that is, with systems responsible for the identification of the operating mode (ID, GID), with systems responsible for the prediction of the place and type of disturbance (FID), or with the master system. In this system, a very important role is played by the module responsible for the adaptation of the digital protection system to the current operating mode of the protected unit. The protected mode is placed in the fragment of the protection unit dedicated to the synchronous machine. This module is the central managing system that controls protection systems dedicated to particular fragments of the unit. It also activates and oversees functioning of the measurement and protection algorithms established for the synchronous machine unit. The accuracy and reliability of the functioning of the module responsible for the adaptation of the digital protection system, that guarantees that protection functions are appropriately realized, are determined by the quality of the signals generated in the system responsible for the identification of the operating mode of the protected unit.

The adaptive criterium subdivides the set of active protective algorithms into four main groups: 1. A set of algorithms that are active in the generator-operating mode; 2. A set of algorithms that are active in the motor operating mode; 3. A set of algorithms that are active in the frequency start-up; 4. A set of algorithms that are active in the asynchronous start-up.

Due to the above setup, it is easy to choose a set of active algorithms dedicated to a given operating mode of the unit. It is achieved by using one control binary signal that activates an appropriately programmed unit of the protection system.

5 An Analysis of Alarm Signals and the Localization of the Place of Disturbance

The managing system's ability to undertake preventive actions (*prevention criterium*) is of paramount importance from the point of view of the correct functioning of the protected unit. It is especially useful in situations when alarm signals are received. This would indicate the occurrence of disturbances in the protected unit or in the systems co-operating with it, for example, a loss of synchronicity, a fluctuation of frequency, a current overloading, an asymmetrical load, or a damage of the cooling system of transformers. Procedures of this kind attempt to maintain functioning of the unit in disturbance conditions by influencing the control systems. Procedures of this kind comprise, among other: 1. the reduction of the generator’s load; 2. shifting from the automatic to manual voltage control in case when there are alarm signals about the loss of excitation (e.g., when the excitation circuit-breaker is closed). This would indicate a significant danger of a damage in the Automatic Voltage Regulation (AVR) unit; 3. shifting to manual voltage control when there are data indicating current overload of rotor, e.g., over-excitation. This could indicate a possible breakdown of the voltage limiters in the AVR unit.

In the situation when functioning of a given unit or one of its components cannot be maintained, and consequently, it must be switched off, it is possible to create an algorithm of a fast restitution of the unit after the disturbance has been dealt with (the *restitution criterium*). The following applies especially to generating sets such as plants with gas-driven turbines [3, 4] and pump-storage plants with reversible hydrogenerators, or to the plants where there is a high degree of redundancy of components (e.g., so it is possible to use start-up units from another machine, or having two hydrogenerators operating with only one unit transformer).

6 Teaching and Testing of the ANN-Based System

Artificial neural network models offer an attractive paradigm: they learn to solve problems from examples. These models achieve good performance via massively parallel nets composed of non-linear computational elements, sometimes referred to as units or neurons.

In this research one of the most popular and successful neural network architectures, a Multi-Layer Perceptron (MLP) was used. An MLP network comprises a number of identical units organized in layers, with those on one layer connected to those on the next layer so that the outputs of one layer are fed-forward as inputs to the next layer. MLP neural networks are typically trained using a supervised training algorithm known as "back propagation".

Typically, an MLP is used to classify patterns based on input vectors (a set of features taken from an example of the problem) presented to the network. An MLP network designed to discriminate between n classes would have n outputs. The network is trained with training cases such that a "one" on a particular output unit corresponds to a particular input class, while all other output units are "zeros". When used in recall mode, features are presented to the neural network and the output unit with the most significant output indicates the class of the input pattern.

The MLP architecture can be extended to produce a continuous-valued output that is a function of its inputs, resulting in a trainable function generator. If this configuration were used to model a process that is known to evolve with time, time would be one of the neural network inputs. However, a limitation of an MLP in recall mode is that it has no "memory" of previous inputs. Hence, to model a system that depends upon the time history of input variables, it is necessary to include the time history in the neural network input vector.

For example, an MLP network can be used as a predictor for time series data. For many time series, the value of the next sample in the series can be predicted as a function of a number of previous samples. To use an MLP to predict a value xt in a time series, the values xt-1, xt-2 ... xt-n form the input to the neural network. Existing time series data is used to train the neural network. In some cases, the network predictions are improved by including long-term running averages in the neural network input vector. An MLP neural network may be trained on data originating either from a real world system or from a sophisticated model of the process. In the latter case, the neural network learns to "model" the model. While a neural network is unlikely to provide a sophisticated model, it can often provide outputs of adequate accuracy over a limited range of input conditions, with the advantage of requiring far less computation than other modeling methods. It is also capable of modeling processes where the underlying principles are not fully understood.

It is generally accepted that the performance of a well-designed MLP neural network is comparable with, but generally no better than can be obtained using good classical statistical techniques. MLP networks score over classical techniques in their much reduced development time, their ability to adapt to changing situations, and their ability to make use of related information.

The process of teaching neural networks aims at finding a proper correlation between input signals and the target response of the network. The teaching process results in the correction of weights and biases of particular neurones of the network in relation to their initial values.

In our simulation tests, which have been carried out, the method of teaching with a teacher has been used. Systems responsible for the identification of the operating mode were made on the basis of the Multi Layer Perceptron (MLP) structures, and the algorithm of error back propagation was used as the algorithm responsible for updating weights.

The most important questions in determining a feedforward neural network architecture are how to calculate the number of nodes in hidden layers, and how to calculate the number of hidden layers. Lippmann [5] argued that a network with two hidden layers could solve arbitrary classification problem. Irie and Miyake [6] showed that a one hidden layer back propagation network with an infinite number of nodes in the hidden layer could also solve arbitrary mapping problems. However, these results have little practical value. Lippmann [5] also argued that the nodes in a hidden layer corresponded to separate decision regions into which training examples were mapped. Kung and Hwang [7] used the algebraic projection approach to specify how each node should be created. In those approaches, however, we have to know the properties of the training data, such as decision regions or pattern properties, thus their applications are limited. The determination of feedforward neural network architectures has been an important area in neuroengineering research.

Practical approaches for dynamic neural network architecture generation have been sought by Sirat and Nadal [8], and Bichsel and Seitz [9]. In those architectures, at the end of a training process, all training examples are recognized and a neural network architecture is generated. In particular, the “tiling” algorithm of Sirat and Nadal [8] generates a feedforward network architecture by adding nodes and layers in a sequential manner. However, the algorithm does not give us the exact sequence in which a node is added to achieve the optimal classification of training examples. A similar algorithm of Bichsel and Seitz [9] uses information entropy to determine generation of nodes and hidden layers. Other algorithm of a special interest, the ID3 algorithm of Quinlan [10] dynamically generates a decision tree using information entropy functions. Studies by Dietterich et. al. [11] and Fisher and Mckusick [12] revealed strong evidence that information entropy could be used as a criterion for determining the number of hidden layers in feedforward neural network architectures. Sztandera and Cios [13] also addressed the problem of a dynamic generation of neural network architectures. The results presented here are based on outcomes obtained by Sztandera [2], Sirat and Nadal [8], Bichsel and Seitz [9] and Sztandera and Cios [13]. The algorithm used generates nodes and hidden layers until a learning task is accomplished. The algorithm operates on continuous data and equates a decision tree with a hidden layer of a neural network. A learning strategy used in this approach is based on minimization of the entropy function. This minimization of entropy translates into adding new nodes to the network until the entropy is reduced to zero. When the entropy is zero then all training examples are regarded as correctly recognized.

After applying the above described approach it was established that the first layer would contain 15 neurones, the second one 10, and the number of neurones in the third layer would be equal to the number of outputs of a given module in the identification system. Hyperbolic tangent was used as the function activating the first and the second layer. The linear function, on the other hand, is the activating function for the third layer.

In the process of teaching neural networks, the order in which teaching patterns are presented is the issue of great importance. Situations wherein all patterns belonging to one class, and then patterns belonging to the next class, etc. are presented, are to be avoided because the network forgets the patterns it has previously learnt.

Generally, patterns belonging to the teaching base have been divided into two groups: the group that contains signals carrying information about the operating mode of the unit; and the group that carries erroneous signals.

In the teaching process, the principle of turn-taking teaching was adopted (first the pattern carrying information about a given operating mode, then the pattern carrying error information). A variety of operating modes have been taken into consideration, i.e. generator, motor, and asynchronous start-up. However, it was assumed that some of the patterns would not be provided at the input of the neural network in order to check the neural network's ability to generalize events.

Establishing initial weights is also a very important issue in the teaching process. In the case of MATLAB program with the Neural Network toolbox, the *initff* command is responsible for establishing initial weights. This command generates initial weights and biases of the network, making use of the first pattern in the teaching base. Taking into consideration the fact that the algorithm of back propagation does not guarantee that a global minimum of a function will be found, it was necessary to provide random input signals, belonging, however, to the range, which they really assume. The user of the program introduces the initial input vector. In the situation when we suspect that the local minimum was achieved, the teaching process must be repeated.

7. Conclusions

The managing system presented in this paper performs protection, measurement, adaptation and identifying functions, using the network of relations among the constituent modules. Establishing the four basic criteria for such systems, that is *the protection criterium, the adaptation criterium, the structure criterium, and the prevention-restitution criterium,* significantly increases the range of their possibilities. The systems of this kind, based on the intelligent identification systems, are capable of an automatic adaptation of their measurement and protective functions to the variable working conditions of the protected unit. Those conditions include changes of the connections among particular components of the unit, as well as the changes of the parameters that characterize the input measurements (frequency, voltage, current, etc.). Such systems are dedicated first of all to the generating sets with a high-degree redundancy of components, for example the combined plants with steam- and gas-driven turbines [3, 4], where it is easy to replace one component with another. Systems of this kind are characterized by a complex structure, a short start-up time, thus, becoming a fast source of power control. Due to these properties, it is possible to work out autonomous algorithms of the adaptive prevention-restitution automation.

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