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APPLICATION OF MACHINE LEARNING TECHNIQUES ON THE DYNAMIC SECURITY OF ISOLATED POWER SYSTEMS WITH LARGE WIND POWER PENETRATION

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Abstract. In isolated power systems increased renewable power penetration with a high level of security can be achieved by the provision of advanced control tools to provide advice to the operators. The CARE system, an integrated control software that has been installed in the SCADA system of Crete includes on-line dynamic security assessment functions that supervise the security operating margins in case of pre-selected disturbances and are based on the application of Decision Trees and Neural Networks. In the paper the techniques applied for on-line dynamic security assessment are described and a preliminary evaluation of their application is provided.

1 Introduction

In isolated power systems, like the ones operating in large islands, electric power is usually produced by Diesel Units and Gas Turbines, resulting in high costs due to fuel imports and transportation. In these systems the production of electric energy from wind presents particular interest, especially when important wind energy potential exists. Significant displacement of conventional fuels can therefore be obtained by a high wind power penetration. In this case however, it is important to ensure that the power system operation will not be adversely affected by an increased connection of this volatile form of energy in the system.

In general, the main problems faced by isolated electrical power systems are related to system security, control of frequency and management of system generation reserve [1]. A common aspect to all these problems is the requirement to ensure that sufficient reserve capacity exists within the system to compensate for sudden loss of generation at adequate speed. Thus, mismatches in generation and load and/or unstable system frequency control might lead to system failures. The introduction of a high penetration from wind energy causes additional difficulties, i.e. fast wind power changes and very high wind speeds resulting in sudden loss of wind generator production can cause frequency excursions and dynamically unstable situations. Moreover, frequency oscillations might easily trigger the under-frequency protection relays of the wind parks, thus causing further imbalance in the system generation.

In order to guard isolated power systems against these disturbances and retain acceptable security levels, on-line dynamic security assessment functions need to be provided. Such functions have been developed within the European projects CARE and MORE CARE and have been integrated within an advanced control system installed on the island of Crete in Greece [2,6,8]. In this system, dynamic security assessment (DSA) is taken care of by a number of modules based on advanced inductive inference and statistical methods as well as artificial neural networks. More specifically, Decision Trees and Regression Trees are used for dynamic security classification, while Neural Networks emulate the degree of security, evaluated by predicting the expected minimum value of system frequency and the maximum rate of frequency change for each selected disturbance. In the control center software, the relevant security evaluation functions can be activated "on call" by the operator providing dynamic security monitoring. Initial valuation of these functions has shown that timely and quite accurate assessment of frequency deviations, during the dynamic disturbances recorded, is provided.

2 The Crete Power System

The power system of the island of Crete is the largest autonomous power system in Greece with the highest rate of increase in energy and power demand nationwide. Its conventional generation system consists of two major power plants with several types of oil-fired units. There are 20 thermal generating units with a total capacity of 518.9 MW installed, including 6 Steam Units of total capacity 112 MW, 4 Diesel Units with 50 MW, 7 Gas Turbines with 216,2 MW and one Combined Cycle plant with 133,4 MW. The peak load in summer 2001 was about 470MW. A total of 11 Wind Parks (WPs) with a nominal capacity of 68.3 MW are installed in Crete. These WPs, with the exception of one, are located at the eastern part of the island, which presents the most favorable wind conditions. As a result, in case of faults on some particular lines the majority of the wind parks might be disconnected. Furthermore, the protections of the WTs might be activated in case of frequency variations, decreasing additionally the dynamic stability of the system. Extensive simulations on the power system model using EUROSTAG software have shown that for the most common wind power variations, the system remains satisfactorily stable, if sufficient spinning reserve is provided [3]. On the other hand for various short-circuits and conventional unit outages, the system frequency might undergo fast changes and reach low values that can activate load shedding. In any case, the dynamic security of the system depends critically on the amount of spinning reserve provided by the conventional machines and the response of their speed governors. The model of the Crete system has been developed in Eurostag.

3 Creation Of Learning And Test Sets

The application of Automatic Learning techniques is based on previous knowledge about the behavior of the system, obtained from a large number of off-line dynamic simulations that define a data set. This data set is split into a Learning Set (LS), used to derive security evaluation structures, and a Test Set (TS) used for testing the developed structures. The data set consists of a large number of operating points (OPs) each characterized by a vector of pre-disturbance steady-state variables, called attributes. These can be directly measured (powers, voltages etc.) or indirectly calculated quantities (wind penetration, spinning reserve etc.).

A very important issue in the construction of the knowledge base is the representativity of the knowledge base. In order to have good and accurate results the knowledge base should correspond as much as possible to real situations. In order to be as closer as possible to the real operation, the following method has been used. The production of the conventional machines has been taken from the database of the Crete Energy Management System, consisting of 6552 OPs. With this method we are accurate in the dispatch, with the exception of possible errors in the stored data. With the production of the conventional machines ready, the power of the wind parks is produced. For each park a random power between the maximum and the minimum capacity of the park is produced. The production of each park is independent. After by adding the total power of the conventional units and the wind parks we have the total load of the system. This load includes also the losses of the transmission system, which are estimated by a function obtained from interpolation of calculated losses for all range of load. After this estimation it is known which is the value of the load, which is distributed to the buses of the network according to participating factors. With all data specified, the appropriate input files for EUROSTAG are constructed. The load-flow and the dynamic simulation for each OP are executed next and the results are recorded in a file.

For each of the OPs, a number of disturbances have been simulated using EUROSTAG. Three major disturbances have been finally selected after studying extensively the behavior of the network. These are:

a) Loss of wind power
b) Trip of machine with the highest power production
c) Three-phase short-circuit at a critical bus near the Wind Parks in Eastern Crete.

In fact, a unit disconnection is a frequent event, while the other two disturbances are rare but severe event that can occur during extreme conditions.

For each OP, the minimum value of system frequency is recorded and checked against the values that activate the under-frequency relays that protect the WPs, and the OPs are then labeled as secure/insecure.

The list of attributes characterizing each OP, includes namely:

a) Active power and reserve of 7 grouped machines (14 attributes)
b) Wind power and wind power penetration, expressed as ratio of the total wind power to the load of the system (2 attributes).
c) Total load of the system (1 attribute).

The security criterion exploits the minimum frequency (fmin) of the system after the disturbance, according to the following rule:

If fmin <= 49 Hz **then** the OP is insecure
else it is secure

With the above procedure 6513,6552 and 6218 OPs acceptable OPs have been produced for the disturbances a, b and c respectively. The initial data set is randomly divided in two sub sets. The learning set, which consists of 70% of initial data set and used for the extraction of the decision trees and the test set, which consists of the 30% of the initial data set and is used for the evaluation of the decision trees.

4 Design Of Security Evaluation Structures

4.1 Decision Trees

The decision tree (DT) methodology is a non-parametric learning technique able to produce classifiers about a given problem in order to deduce information for new unobserved cases. The construction of a DT starts at the root node with the whole LS of pre-classified OPs. These OPs are analyzed in order to select the test T that splits them “optimally” into a number of most “purified” subsets. For the sake of simplicity, a two-class partition is considered. The test T is defined as:

$$T: Ai < t$$

where t is the optimal threshold value of the chosen attribute Ai.

The selection of the optimal test is based on maximizing the additional information gained through the test. The selected test is applied to the LS of the node splitting it into two subsets, corresponding to the two successor nodes. The optimal splitting rule is applied recursively to build the corresponding sub-trees. In order to detect if one node is terminal, i.e. “sufficiently” class pure, the stop splitting rule is used, which checks whether the entropy of the node is lower than a present minimum value. If it is, the node is declared a leaf, otherwise a test T is sought to further split the node. If the node cannot be further split in statistically significant way, it is termed a deadend, carrying the two class probabilities estimated on the basis of the corresponding OPs subset. A more detailed technical description of the approach followed is described in [4,5].

The most important evaluator of the DT reliability and performance is the rate of successful classifications, defined as the ratio of successfully classified OPs to the total number of OPs tested:

$$\text{Success Rate} = \frac{\text{OPs successfully classified by the DT}}{\text{Total number of OPs in the TS}}$$

For a two-class partition (Safe-Unsafe) there can be distinguished two types of error, depending on the actual class of the misclassified OP:

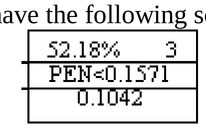
$$\text{False Alarm Rate} = \frac{\text{Safe OPs misclassified as Unsafe by the DT}}{\text{Total number of Safe OPs in the TS}}$$

$$\text{Missed Alarm Rate} = \frac{\text{Unsafe OPs misclassified as Safe by the DT}}{\text{Total number of Unsafe OPs in the TS}}$$

For the creation of the decision trees the following procedure is done:

The decision tree results and the number of nodes depend on the accuracy given from the user. Initially we give high-accuracy parameters to the decision tree in order to obtain the larger and more accurate tree. After the tree size is gradually reduced with respect to the accuracy indices in order to get a tree with more practical rules, because usually the initial tree is quite large with many non-important nodes, which have very small percent of OPs. This structure is not suitable for fast security assessment, taking into account that for corrective actions it is needed to cross the tree backwards. With this procedure finally it is obtained a decision tree, which in most cases has a little worst accuracy but has quite less nodes and gives more practical and clear rules for the security of the system.

The nodes of the decision trees have the following scheme:



There are 4 attributes. In the upper right side is the number of the node. In the upper left side is the percentage of the OPs that go in the node. In the middle is either the separation criteria of the node or if the node is deadend or leaf. In case there is a separation criteria, if it is true we go on the left node, otherwise we go on the right. Finally in the bottom is the safety index, which is the safe OPs of the node divided to the total OPs of the node. A small number shows that most of the OPs are insecure, while a large one indicates that most of the OPs are secure.

4.2 Artificial Neural Networks

Three multi-layer ANNs were trained (one for each disturbance) using an adaptive back propagation algorithm [7]. The structure selected is presented in Figure 1. One input layer with 17 input attributes, two hidden layers with 12 and 8 units and one output layer with the minimum frequency. This structure has been proved to be very appropriate for the case studied in this paper. More complicated structure does not provide any improvement in the results.

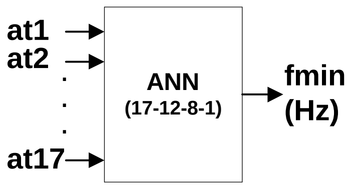


Fig. 1. Structure selected for training the ANNs.

5 Numerical Results

In figures 2-4 are presented the decision trees extracted for the three disturbances. These are the most appropriate trees obtained for the dynamic security assessment. Also the performance of the decision trees is analyzed in tables 1-3. The results of the ANNs are presented in figures 5-7 and tables 4-6.

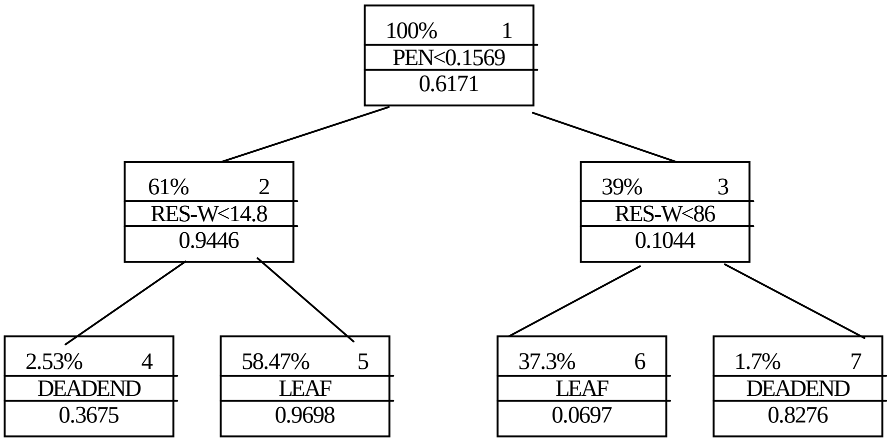


Fig. 2. Decision tree structure for wind loss disturbance

Wind Loss Disturbance	
Classification Performance Evaluation	
Success	94.4%
False Alarm	5.72%
Missed Alarm	5.41%

Table 1. Performance evaluation of decision tree for wind loss disturbance

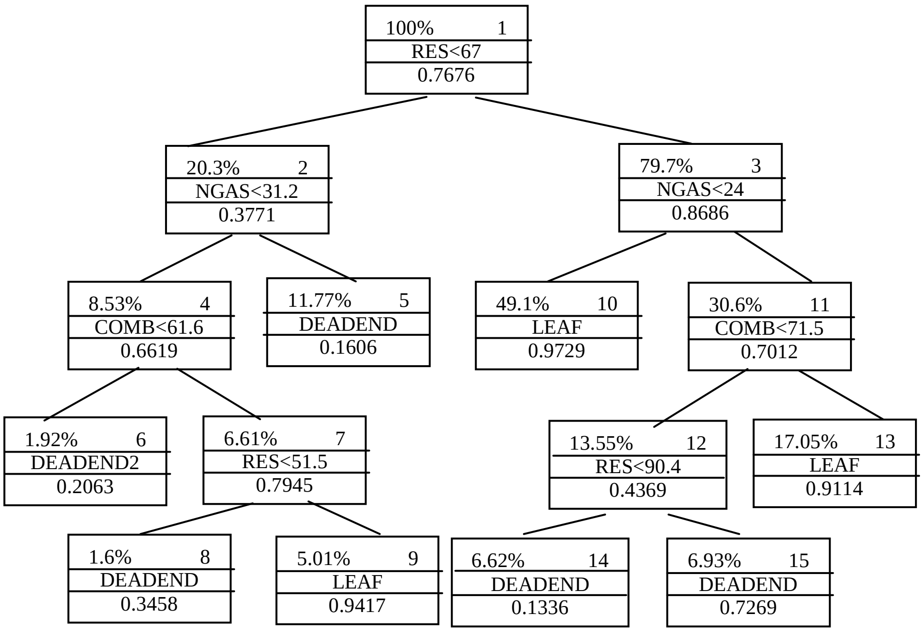


Fig. 3. Decision tree structure for machine trip disturbance

Machine Trip Disturbance	
Classification Performance Evaluation	
Success	90.7%
False Alarm	4.1%
Missed Alarm	10.41%

Table 2. Performance evaluation of decision tree for machine trip disturbance

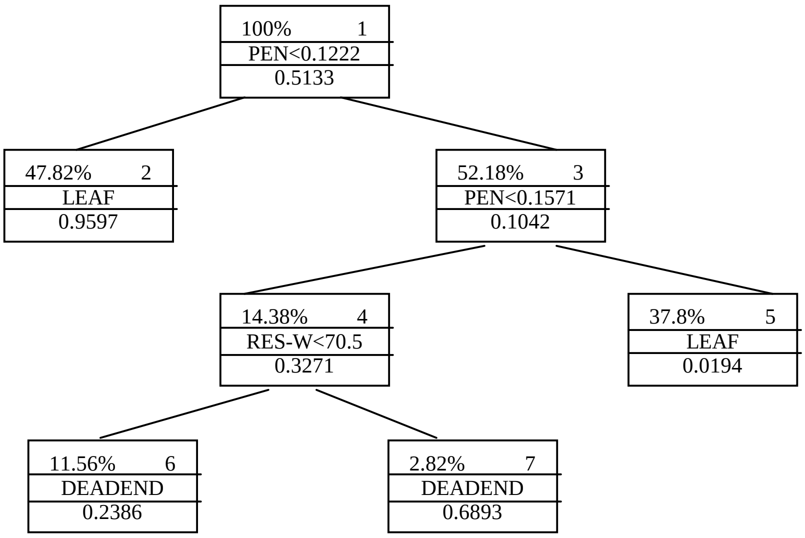


Fig. 4. Decision tree structure for short-circuit disturbance

Short-Circuit Disturbance	
Classification Performance Evaluation	
Success	93.7%
False Alarm	6.8%
Missed Alarm	5.76%

Table 3. Performance evaluation of decision tree for short-circuit disturbance

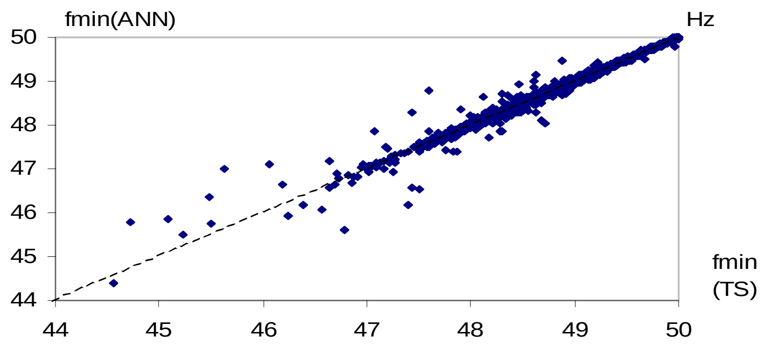


Fig. 5. Comparison of predicted and actual values for ANN for wind loss disturbance

Wind Loss Disturbance	
Classification Performance Evaluation	
Success	98.3%
False Alarm	0.99%
Missed Alarm	1.72%

Table 4. Performance evaluation of ANN for wind-loss disturbance

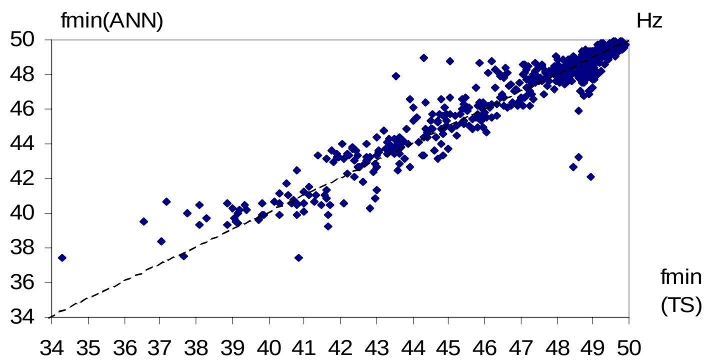


Fig. 6. Comparison of predicted and actual values for ANN for machine-trip disturbance

Machine Trip Disturbance	
Classification Performance Evaluation	
Success	93.2%
False Alarm	6.66%
Missed Alarm	7.42%

Table 5. Performance evaluation of ANN for machine-trip disturbance

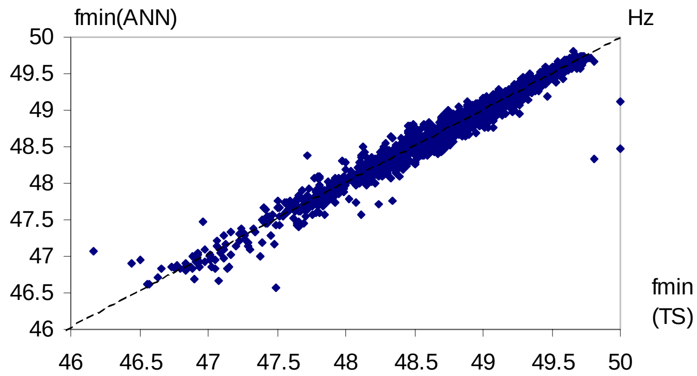


Fig. 7. Comparison of predicted and actual values for ANN for short-circuit disturbance

Short-Circuit Disturbance	
Classification Performance Evaluation	
Success	95.4%
False Alarm	5.24%
Missed Alarm	3.88%

Table 6. Performance evaluation of ANN for short-circuit disturbance

As it can be seen the results are very good in the cases of wind loss and short-circuit, while for the machine-trip disturbance the results are a little worse. This happens because the machine that is tripped in this disturbance is not the same in all cases, but depends on which machines are in operation in each OPs. As a result the learning set consists of very different OPs. This leads to a more complicated decision tree compared to the others. The most important attribute appeared in the above DTs is the wind power penetration (PEN) which shows the high influence of wind power in the dynamic behavior of a system. In the machine-trip disturbance the most significant attribute is the total reserve of the system (RES), which is very important as we have loss of produced power and the remaining units must take the extra power. These attributes were expected to be present before the construction of the DTs. This proves that the DTs are efficient to describe the dynamic behavior of the system. Concerning the ANNs it can be seen that the performance is a little higher than the DTs. Of course we have to take into account the procedure for the DTs building described above, which gives us smaller DTs with lower accuracy. The performance of the initial DTs was similar to the ANNs ones. In all cases the decision trees give simple rules for security assessment. The great advantage of the decision trees is that simple "if-then-else" rules can be obtained for security assessment. For example for the wind loss disturbance the rules are presented in table 4. On the other hand the ANNs can provide as and the expected value of the minimum frequency for each disturbance. This is very useful for economical reasons in case the system is labeled unsafe, in order to know how large is the dangerous for the system. This information can also be provided from decision trees with more than two classes for the classification, but the accuracy of this method may be lower than ANNs.

Insecure	If {(PEN<0.1569) AND (RES-W<14.8MW)} OR {(PEN>0.1569) AND (RES-W<86MW)}
Secure	IN OTHER CASES

Table 7. Security rules for wind loss disturbance in Crete

Similar security rules are also obtained for the other two disturbances. These rules can be integrated very easily in a Dynamic Security Assessment tool, which show to the operator of the electrical system if the dispatch is secure or not. Also a corrective dispatch algorithm can be used in order to make a re-dispatch based to safety indices.

These two security tools will be integrated in the More Care program in Crete as modules. The dynamic security module is used, upon operator request, for evaluating the dynamic robustness of economic dispatch module and the present system operating state. It will also provide corrective control measures, i.e. the produced generator set points and voltages will be modified in case an insecure state is detected. When insecurity is detected, active power re-dispatch can be performed exploiting rules derived from the DTs and ANNs. In addition these control measures will not concern only frequency, but also voltage deviations of the system. For this scope, additional DTs are going to be developed, with the voltages being additional input attributes.

6 Conclusions

The paper describes the application of machine learning techniques to the evaluation of the dynamic security of isolated power systems with increased wind power penetration. The main conclusion is that the decision tree and neural network methods that were used are capable to evaluate the dynamic performance of an isolated power system with quite large accuracy. These techniques will be integrated in the dynamic security module of the advanced control system of Crete “MORE CARE”, helping to security assessment of the system and corrective dispatch actions in case of insecurity.

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