ON-LINE DYNAMIC SECURITY ASSESSMENT OF POWER SYSTEMS IN LARGE ISLANDS WITH HIGH WIND POWER PENETRATION

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ABSTRACT

This paper describes the application of advanced inductive inference and statistical methods to on-line dynamic security assessment of the Crete island electric power system. A description of the problem and the data set generation procedure are included. Comparative results regarding performances of Decision Trees and Kernel Regression Trees are presented and discussed.

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, which is usual in many islands. 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 electric power system operation will not be adversely affected by an increased connection of this volatile form of energy in the system.

The main problems faced by isolated electrical power systems are related to system security, control of frequency and management of system generation reserve. 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. Thus, mismatches in generation and load and/or unstable system frequency control might lead to system failures. This type of instability is termed frequency instability and depends on the ability of the system to restore balance between generation and load following a severe system upset with minimum loss of load [1]. Generally, frequency instability problems are associated with inadequacies in equipment responses, poor coordination of control and protection equipment or insufficient generation reserve.

Additional difficulties are caused by the introduction of a high penetration from wind energy. Thus, 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 [2]. Moreover, frequency oscillations might easily trigger the under-frequency protection relays of the wind parks, thus causing further imbalance in the system generation/load.

In order to guard isolated power systems against these disturbances and retain acceptable security levels, on-line dynamic security assessment functions can prove very valuable for their operation. Such functions have been developed and are integrated within an advanced control system tailored to the needs of small isolated power systems with increased wind power penetration. A pilot control system has been installed on the Greek island of Lemnos [3], an isolated Diesel-wind system with a peak load of approximately 10 MW. In this system, dynamic security assessment (DSA) is taken care of by two modules based on Decision Trees and Neural Networks, respectively [4, 6, 7]. Decision Trees are used to check security for the operating schedules proposed by the economic dispatch module, with respect to characteristic wind power fluctuations. Neural Networks are used to give a real-time quantitative security evaluation of the current operating state system, by emulating the expected frequency deviation to the pre-define wind disturbance. In this way, the wind power penetration can be increased without jeopardising the system security.

The control system developed for small isolated power systems is currently extended within the frame of the European R&D JOULE (JOR3-CT96-0119) project to cover the needs of larger isolated systems with high wind power penetration. Larger systems are characterised by several conventional fossil-fuelled generation plants and meshed transmission networks. The dynamic behaviour performance of these systems depends not only on the total load and the size of the conventional units in operation, but also on their location and the response of the available spinning reserve [3].

The objective of this paper is to present the capabilities provided by advanced inductive inference and statistical methods to provide on-line dynamic security assessment and monitoring of these systems. It is shown that based on the artificial intelligence techniques proposed, efficient security rules can be provided. These rules are being integrated into CARE, the advanced control system aiming to achieve optimal utilisation of renewable energy sources, in a wide variety of medium and large size isolated systems with diverse structures and operating conditions. A pilot installation is foreseen on the energy management center of Crete, the largest Greek island, in 1999. The security evaluation structures that can be obtained provide a classification on dynamic security. Moreover, it is also interesting to obtain the degree of security, which in this case is evaluated by emulating the expected minimum value of system frequency and the maximal rate of frequency change for a selected disturbance. This complementary information can be provided by the kernel regression tree approach, as described in this paper. In the control center software, security evaluation functions can be activated “on call” by the operator, namely security monitoring.

2. THE STUDY CASE SYSTEM

The study case system is a realistic model of the power system of Crete, projected for the year 2000. It comprises several types of oil-fired units and a meshed 150 kV transmission network. The conventional generation system consists of two major power plants with twenty generating units installed. These are 6 Steam units of total capacity 103.5 MW, 4 Diesel units with 48 MW, 7 Gas turbines with 185 MW and three combined cycle plant with 132 MW. The plants are located near to the major load points. The system peak load is equal to 360 MW. The annual peak load demand occurs on a winter day and overnight loads can be assumed to be approximately equal to 25% of the corresponding daily peak loads. The base-load is mainly supplied by the steam and also by the Diesel units. The Gas turbine units normally supply the peak load at a high running cost, that increases significantly the average cost of the electricity being supplied.

A total of 11 Wind Parks (WPs) consisting of 160 Wind Turbines (WTs) with an installed capacity of more than 80 MW are or will be installed (have been approved) in Crete by the year 2000. These WPs will be connected at the MV (15 or 20 kV) network, which will be properly reinforced by new HV/MV substations. It is noted that with few exceptions, all WPs will be installed at the eastern part of the island, that presents the most favourable wind conditions. As a result, in case of faults on some particular lines the majority of the wind parks will be disconnected. Furthermore, the protections of the WTs might be activated in case of frequency variations, decreasing additionally the dynamic stability of the system. This might happen in case of frequency variations caused by wind fluctuations, conventional unit outages, faults or other disturbing conditions.

Extensive simulations on the power system model have been performed using EUROSTAG software. It is shown

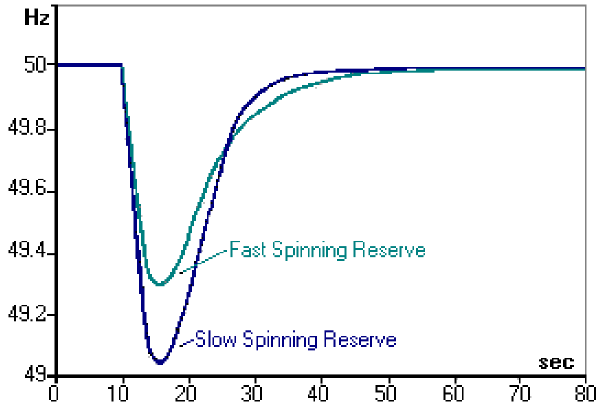

Figure 1. Frequency change.

that for the most common wind power variations, the system remains satisfactorily stable, if sufficient spinning reserve is provided. On the other hand for various short-circuits and conventional unit outages, the system frequency undergoes fast changes and might reach very low values. 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. As an example, Figure 1 shows the change of the system frequency in two different operating conditions, following the disconnection of three wind parks producing approximately 30 MW. First, the system is considered to operate with 28% of wind power, equal to 46 MW and with the fast thermal units, such as the Diesel machines and gas turbines to provide the spinning reserve (fast spinning reserve). The lower value of the frequency is 49.31Hz. Secondly, the system is again considered to operate with the same high penetration of wind power but with the slower machines, such as the steam turbines to cover mainly the spinning reserve plus some Diesel machines (slow spinning reserve). In this case, the lower frequency value, which is equal to 49.04Hz, will cause the operation of the protection devices of the rest of the wind parks. The total wind power disconnection may lead the system to collapse and certainly will trigger the load shedding mechanisms that will disconnect part of the system load.

3. CREATION OF THE LEARNING & TEST SETS

The application of “learning from examples” techniques, such as the Decision Trees (DTs) and the Kernel Regression Trees (KRTs), dealt within this paper, are based on previous knowledge about the behaviour of the system, obtained from a large number of off-line dynamic simulations that define a data set. This data set is afterwards split in two sub-sets: a learning set (LS) and a testing set (TS). The learning set is required to extract the knowledge needed to derive automatic security evaluation structures. It consists of a large number of operating points (OPs) covering all possible states of the power system under study in order to ensure its representativity. Each OP is characterised by a vector of pre-disturbance steady-state variables, called attributes, that can be either directly measured (powers, voltages etc.) or indirectly calculated quantities (wind penetration, spinning reserve etc.). The quality of the selected attributes and the representativity of the LS are very important for the successful implementation of the automatic structures.

For the creation of the global data set, a large number of initial operating points (OPs) are obtained by varying randomly the load for each load busbar, the wind power for each wind park and the wind margin. These variables are assumed to follow normal distributions around three operating profiles:

1. Low-load operating condition with a total load P_L =100MW.
2. Medium-load operating condition with P_L =180MW.
3. High-load operating condition with P_L =280MW.

For each one of the 11 load busbars and each one of the 4 aggregate wind parks in operation, a perturbation of approximately ±10% is applied around each one of the above operating profiles. A dispatch algorithm approximating actual operating practices followed in the control system of Crete is applied next in order to complete the pre-disturbance OPs. For a given load demand P_L and wind power P_W, the total conventional generation P_C is given by

$$P_C = P_L - P_W \tag{1}$$

and is after dispatched to the units in operation, depending on their type and their nominal power.

For each one of the produced OPs a number of possible disturbances has been simulated, where EUROSTAG was used to obtain the system dynamic behaviour. Two major disturbances have been finally selected. These are:

a) outage of a major gas turbine
b) three phase short-circuit at a critical bus near the Wind Parks.

These disturbances were selected according to utility criterion. In fact, a unit disconnection is a frequent event and a tree-phase fault, although rare, is a severe event that can occur during stormy conditions.

For each OP the minimum value of system frequency and the maximal rate of frequency change are recorded. Both of these parameters are checked against the values that activate the under-frequency relays that protect the WPs, and the OPs are labelled accordingly.

The list of activated attributes, that characterise each OP, is described in Table 1 and includes namely:

- Active and reactive power of all power sources.
- Spinning reserve of the conventional units.
- Wind power penetration, expressed as the ration of the total wind power to the load of the system.
- Wind margin, expressed as the ratio of the conventional units spinning reserve to the total wind power.
- Active and reactive loads.

In this part of our research the variable used to verify security is the minimum frequency the system experiments after the disturbance. The security criteria used was

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

Table 1 - List of activated Attributes

AT ID	Description	units	symbol
AT23	Wind Park 1	MW	-
AT24	Wind Park 2	MW	-
AT25	Wind Park 3	MW	-
AT26	Wind Park 4	MW	-
AT27	Wind Power$_{TOTAL}$	MW	ΣP_W
AT28	Wind Q$_{-TOTAL}$	MVAr	-
AT37	Power Gen.1	MW	Pg1
AT38	Spinning Res.1	MW	SR1
AT39	Power Gen.2	MW	-
AT40	Spinning Res.2	MW	-
AT41	Power Gen.3	MW	Pg3
AT42	Spinning Res.3	MW	-
AT43	Power Gen.4	MW	-
AT44	Spinning Res.4	MW	-
AT45	Wind Penetration	%	WP
AT46	Wind Margin	-	-
AT47	Active Power	MW	-
AT49	Reactive Power	MVAr	-
AT51	Conv. Gen. $_{TOTAL}$	MW	ΣP_C
AT52	Total Active Load	MW	ΣP_L
AT55	Total React. Load	MVAr	-
AT57	Capacitors	MVAr	-

Using the approach described in this section, 2765 acceptable operating points have been obtained, which are divided in the two sets mentioned before, (by sending 2 OPs to the LS and 1 OP to the TS). The LS comprises 1844 OPs and the TS used for testing the developed classifiers comprises 921 OPs. In this way, the capability of the security evaluation structures to evaluate correctly the security of unforeseen states can be estimated on a more objective basis.

4. APPLICATION OF MACHINE LEARNING TECHNIQUES

4.1 Decision Trees

The decision tree methodology is a non-parametric learning technique able to produce classifiers about a given problem in order to deduce information for new unobserved cases. This approach has been successfully applied in security assessment as reported in [5]. The DT has the hierarchical form of a tree structured upside down. The construction of a DT starts at the root node with the whole LS of pre-classified OPs. These OPs are analysed 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:

$$T: A_i \leq t \quad (2)$$

where t is the optimal threshold value of the chosen attribute A_i. 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 subtrees. 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 can be found in [4].

4.2 Kernel Regression Trees

As the KRT approach is being applied for the first time in this field, a short description of the main stages of the method are included in the next paragraphs.

The Kernel Regression Tree (KRT) is an hybrid algorithm that integrates recursive partitioning (regression trees – RT) with kernel regression (KR), dealing with continuous goal variables (i.e. regression problems). The first application of RTs in dynamic security assessment is due to Wehenkel [8], in 1995, and recently an application of the KRT approach in the voltage stability assessment problem was presented in [9].

Like in decision trees, the design of a RT consists in the extraction of interpretable security rules. Kernel regression models provide quite opaque models of the data, but, on the other hand, are able to approximate highly non-linear functions. By integrating this regression procedure in the tree leafs, we can obtain a model that keeps the efficiency and interpretability of a RT, but with a better accuracy, by increasing the non-linearity of the functions used at the leaf nodes.

The regression problem consists in obtaining a functional model that relates the *output y* with the *inputs* $a_1, a_2, ..., a_n$ (OP attributes), where the output *y* (denominate as goal variable) is, in this case, a numerical value of any electrical security index of the power system. For the problem under analysis the security index adopted is the minimum frequency - fmin (Hz). The design of a KRT involves two stages:

- Determination of the regression tree;
- Definition of the regression models in the leafs.

Building the RT

The learning of a RT consists in the decomposition of the attribute hyperspace into a hierarchy of regions. In our application, it consists in the decomposition of the LS into regions where the severity/security of a disturbance (*y* value) is as constant as possible. The main practical difference between decision and regression trees, is that the latter determines automatically the appropriate numerical value of the severity into subintervals, whereas the former merely reproduce a predefined classification.

Starting with the root node (and exploiting the learning set data), the growing of the RT is made by successive splitting their nodes. The splitting rule of a node is defined by a dichotomic test as described in (2).

The split of each node, i.e. the optimal splitting test, is determined so as to reduce as much as possible the MSE (Mean Square Error) of *y*. In other words, the best split is the one that provides a maximum amount of information on the security index (*y*). Thus, the optimal split *s* at each node *n* is the one that maximizes:

$$\Delta MSE(y)_{sn} = MSE(y)_n - P_L MSE(y)_{nL} - P_R MSE(y)_{nR} \quad (3)$$

where:

– P_L and P_R is the proportional number of OPs at the left and right subsets resulting from the split;
– $MSE(y)_n$ is the mean square error at node n;
– $MSE(y)_{nL}$ and $MSE(y)_{nR}$ are the mean square error at the left and right subsets.

This splitting rule is the one described by Breiman et al. (1984) and employed in CART[11]. Once the optimal test is found, the next step consists in creating two successor nodes, corresponding to the two possible instances of the test

$$\{a_k() > u_k\} \text{ and } \{a_k() \leq u_k\}.$$

The procedure continues splitting the created successor nodes, until a stop splitting criterion is met. This decides whether a node should indeed be further developed or not. There are the two possible stop splitting rules:

- Rule 1: It is not possible to reduce the MSE further in a statistically significant way;
- Rule 2: The variance has been sufficiently reduced;

When, in a node, one of these rules is verified it becomes a terminal node, i.e. a leaf node. Stop splitting at leaf nodes prevents the tree from overfitting the learning set, and hence allows the method to reach a better compromise between accuracy and simplicity.

Deriving Kernel regressors

Kernel regression is a non-parametric statistical methodology. Given a **new operating point Q**, a prediction for its security index is obtained using the LS OPs that are "most similar" to Q. Kernel methods obtain the prediction by a weighted average of the response of these OPs. The weight of each neighbour (X_i) is provided by a kernel function. This function gives more weight to neighbours that are nearest to Q. The notion of neighbourhood is defined in terms of distance from Q measured in the attribute hyperspace. This algorithm sets the bandwidth as the distance to the kth nearest neighbour of Q. The prediction for Q is obtained by

$$f\min'(Q) = \frac{1}{SK}\sum_{i=1}^{OPs} K[D(X_i;Q)/h] f\min(X_i) \tag{4}$$

where D is the distance function between two instances (using an Euclidean norm), $K(d) = e^{-d^2}$ is the kernel function, h is the bandwidth value, X_i are OPs of the LS and $SK = \Sigma K[D(X_i;Q)/h]$.

Through the integration of both methods (RT and KR) the efficiency and interpretability of regression trees are maintained while their accuracy is improved by the non-linearity of the regression functions used in the leafs.

The model used in this research to obtain the KRT is the one described by Luís Torgo, 1997 [10].

5. NUMERICAL RESULTS

In any machine learning approach the quality of the results needs to be evaluated through classification errors (global classification error, false alarm and missed alarm errors) relatively to *a priori* classes or by quantifying mismatches relatively to the target output values *y*, in this case the minimum frequency - *fmin*. These indicators are namely the mean relative error, the mean absolute error and the mean square error. The performance evaluation for both disturbances are shown in the next tables for the DT and KRT approaches.

5.2 Decision Trees performance

Table 2 - Performance evaluation with DT

Decision Tree – Disturbance (Machine-Loss)	
Classification Performance Evaluation	
Global Error	1.84%
False Alarm	1.31%
Missed Alarm	4.4%

Table 3 - Performance evaluation with DT

Decision Tree – Disturbance (Short-Circuit)	
Classification Performance Evaluation	
Global Error	2.17%
False Alarm	1.87%
Missed Alarm	2.58%

The DT designed to deal with this short-circuit disturbance can be observed in figure 3.

5.2 Kernel Regression Trees performance

For the application of the KRT approach the following parameters were adopted relatively to the stopping criteria:

- Minimum number of operating points - 10 (STOP=1);
- Minimum variance - 0,001 (STOP =3).

After several experiences the number of neighbours used to design the KRTs were set to 3.

The results obtained with the KRT approach are presented in tables 4 and 5 and correspond, for the two disturbances addressed, to regression trees with 57 and 43 nodes, which can be considered as a complex decision model, when compared namely with the DT obtained by inductive inference with only 23 nodes for the short circuit case.

Table 4 - Performance evaluation with KRT

Kernel Regress. Tree – Dist. (Machine-Loss)	
Classification Performance Evaluation	
Global Error	0,33%
False Alarm	0,00%
Missed Alarm	15,00%
Numerical Performance Evaluation	
Mean Relative Error	0,000357
Mean Absolute Error	0,017489
Root Mean Square Error	0,041144

Table 5 - Performance evaluation with KRT

Kernel Regress. Tree – Dist. (Short-Circuit)	
Classification Performance Evaluation	
Global Error	2,39%
False Alarm	1,83%
Missed Alarm	3,22%
Numerical Performance Evaluation	
Mean Relative Error	0,000542
Mean Absolute Error	0,026163
Root Mean Square Error	0,10537

5.3 Classification trees obtained

Next two figures (figure 2 and 3) present respectively the RT and the DT designed for the short-circuit disturbance.

Nodes in the RT are of two types: non-terminal and terminal nodes (leafs). In the root node (node number 1) we included information related with the number of OPs (1844 - total learning set), the total mean square error in the learning set and the splitting test. In figure 2 non terminal nodes present the node number and also contain information related to the splitting test, for instance in node 2 the decision rule is WP>17,6%. In the leaf nodes we can get information related with the node number, the number of OPs that belong there, the mean and the mean square error (MSE) of the security index (minimum frequency in Hz) of those OPs and the stopping criteria used. In this classification structure one can assigned a given degree of security to each leaf accordingly to the mean value of the OPs that belong to the node.

For the DT described in figure 3, the contents of the box representing each node are the following: - node number; number of OPs that belong to it, safety ratio (given by the ratio of the number of LS secure operating points over the total number of LS OPs belonging to the node) and the splitting test for non terminal nodes. Leaf nodes with a safety ratio larger than 0,5 correspond to secure nodes.

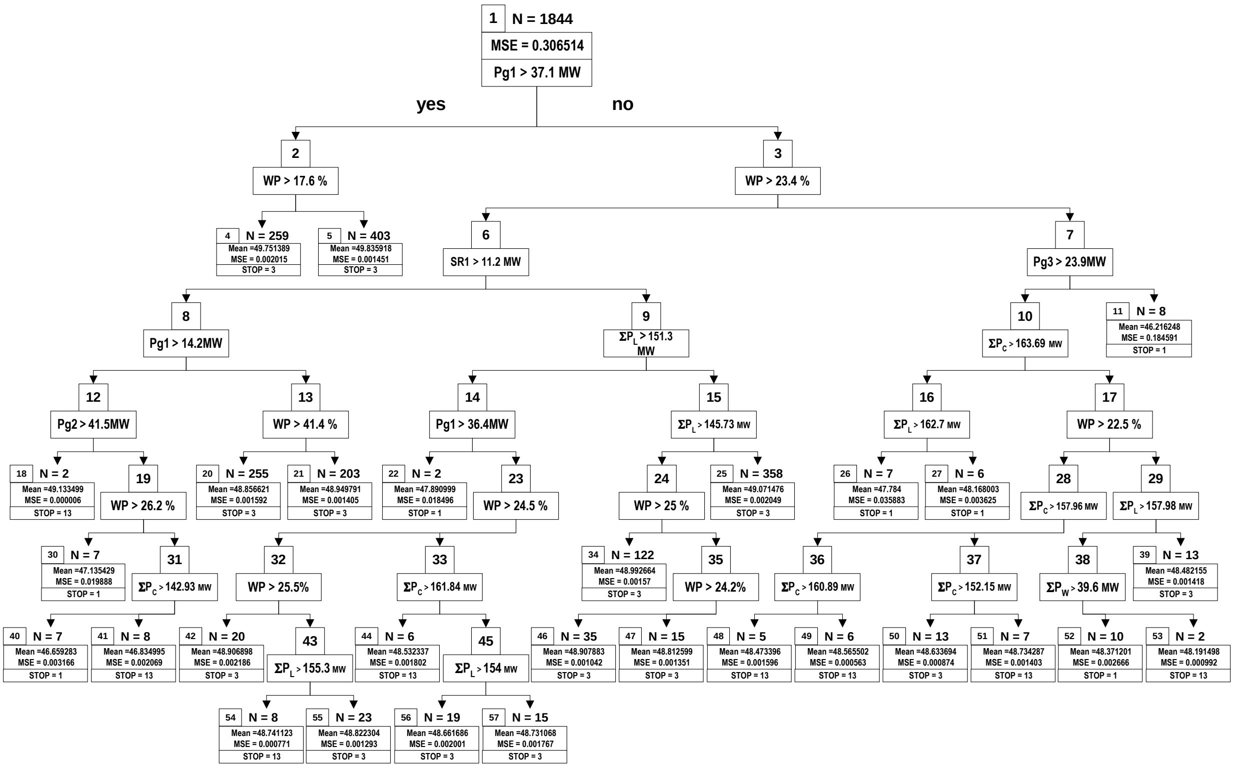

Figure 2 – Regression tree obtained for the short-circuit disturbance

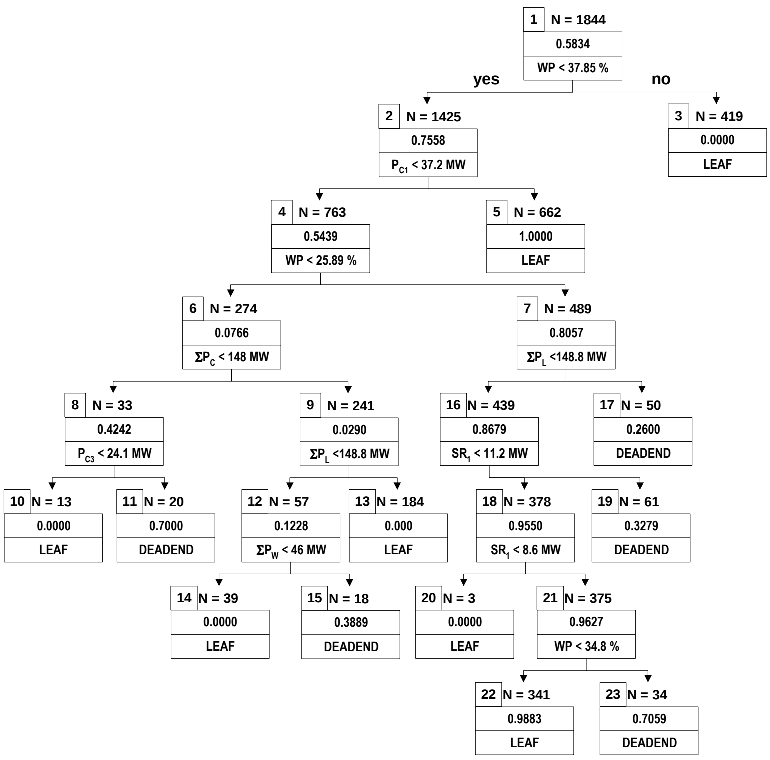

Figure 3 - Decision Tree obtained for the short-circuit disturbance.

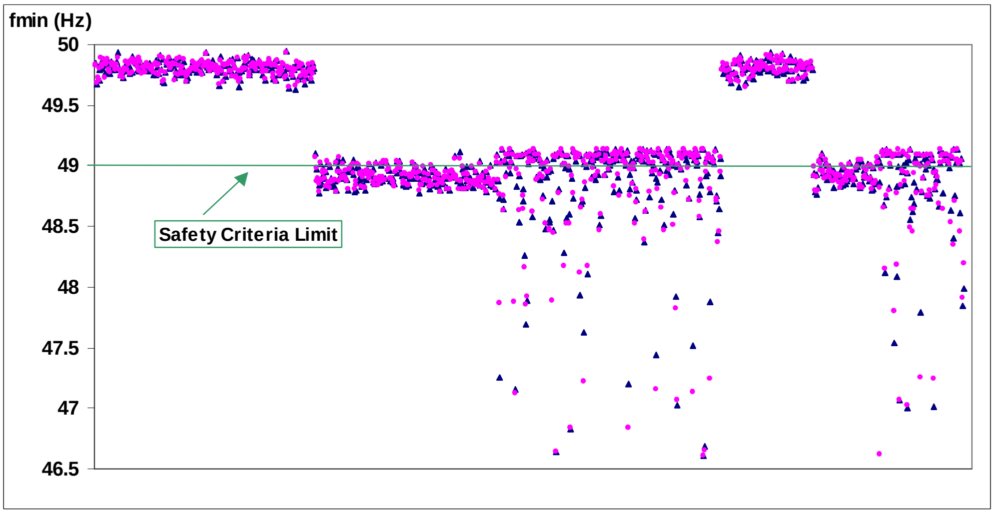

Figure 4 - Real and predicted values for *fmin* OP of the testing set

For the prediction of the minimum frequency value associated to each OP, it was observed that kernel regressor are able to predict these values with good accuracy. Figure 4 presents the real (black triangles) and the predicted values (grey circles), obtained with the KRT, for the minimum frequency value presented by the system in the short circuit disturbance. All the OPs presented in figure 4 belong to the testing set.

5.4 Comparative Assessment

From the results obtained with the two approaches one can derive the following main conclusions:

- Both techniques were capable of selecting the same attributes as the most important ones (although sometimes in a different order);
- When used for security classification both approaches lead to decision structures with comparable performance.
- KRTs have the advantage of producing simultaneously a classification structure and giving the degree of robustness of the system through the predicted value of *fmin*;
- The DTs obtained presented simpler classification structures, which makes easier any interpretation of the phenomena and of the influence of the relevant parameters.

6. CONCLUSIONS

This paper described an application of two machine learning approaches oriented to deal with the evaluation of the dynamic security of a medium size power system.

These structures will be integrated in the dynamic security assessment module of the advanced control system of the island of Crete, helping to identify the operating conditions and parameters, namely wind power penetration, that lead to a less robust operation of the system.

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