Decision Trees Applied To Forecasting Switched Shunt Devices Within The Spanish Power System

*E. Lobato, F. M. Echavarren, L. Rouco and A. Ugedo

Abstract

Static security assessment within a power system requires: (a) building a scenario of the power system network that represents the state of the network for a particular time spot and (b) running a number of static security assessment tools that could be very time consuming. Short term forecasting of power system scenarios is required to foresee potential network problems and anticipate preventive or corrective measures to be taken under credible contingencies, thus increasing the reliability of the operation of the grid. The aim of this paper is to predict the values of switched shunt devices, i.e., reactors and capacitors in a short-term time scope (24 -36 hours ahead) in order to build a power system scenario. A methodology based on decision trees is proposed and its performance is validated by forecasting the reactive output of the shunt components of the Spanish power system.

Index Terms— power system operation, security assessment, artificial intelligence, decision trees.

I. INTRODUCTION

Static security assessment within a power system requires building a scenario of the power system network that represents the state of the network for a particular time spot. A power system scenario is determined by (a) the network topology, (b) the active and reactive power loads of each bus, (c) the generation of each unit and (d) the values of voltage control resources (generator voltages, transformer ratios, and shunt reactors or capacitors). Once the power system scenario has been built, a load flow is run to check if power system variables are within their limits in normal operating condition. Other static security tools such as contingency analysis [1-6], or detection of voltage collapse [7-13] are also essential useful tools to assess the security and reliability of the electricity supply under abnormal or emergency situations.

In real time operation, the system operator of a power system needs to check whether the power system variables are within their limits not only in normal operating conditions, but also when any credible contingency occurs. This verification includes running a number of static security assessment tools that could be very time consuming. In this context, the necessity of forecasting hourly power system scenarios emerges, with two main objectives: (a) to foresee potential network problems in normal operating conditions or under the occurrence of contingencies, and (b) to anticipate preventive or corrective measures for selected contingencies in order to comply with the N-1 or N-2 security criteria. A convenient time scope for forecasting future network scenarios may vary between several hours and few days, depending on different factors such as the complexity of the network (number of nodes, branches and generators), time consumption of the available security assessment tools, etc.

The topic of this paper is the forecasting of future hourly power system scenarios for the operation of Spanish electricity system, for a short-term time scope (24-36 hours ahead). In order to anticipate the future state of the power system the following data is required and must be forecast:

- The network topology is determined from the maintenance scheduling of the elements of the transmission system. Most of the network elements that are out of service for more than few instants are due to a planned maintenance working. Maintenance working is planned by the System Operator, and thus, it is known in advance.
- The active and reactive power loads of each bus are computed from the total demand and the active and reactive power distribution factors of each bus. The total demand can be easily predicted using the different geographical temperatures. Active and reactive power distribution factors are obtained from the historical values of real time scenarios of the power system provided by the state estimator of the energy management system.
- The generation of each thermal, hydro or nuclear unit is obtained from the clearing of the different markets (daily, intradaily and ancillary services) that comprise the sequence of the Spanish electricity market [14].

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- Due to the European community directives and the high incentive given by the Spanish government to renewable energy sources, wind power is growing at a very high rate in the Spanish system, and its forecasting is crucial for security assessment applications. Wind power prediction is provided in the Spanish market by a tool called SIPREOLICO [15].

- The setting of the voltage control resources, i.e. the generators, transformers, shunt reactors and capacitors are required for solving the load flow problem.

The setting of the voltage control resources is very difficult to anticipate. The different nature of the voltage control resources also suggests different forecasting methods for each. Generator voltages correspond to continuous variables. Transformer taps are discrete; however, the loss of accuracy by considering them as continuous (for optimization models for instance) might sometimes be neglected due to the fact that the difference between two successive transformer taps is usually small [16]. On the contrary, switched shunt elements (reactors and capacitors) are usually large, and their settings cannot be treated as continuous variables. Their discrete nature suggests that classification tools are appropriate to predict their value.

Generator voltages are normally established by mutual interaction between the system operator and the unit owners. It should be expected that as the demand increases, generator voltages should also rise to support the grid with additional reactive generation. However, some units have historically shown low collaboration in sustaining the voltage profile. In addition, the recent creation of the voltage control ancillary service market [17] adds more complexity to the estimation of generator voltages. Concerning the prediction of transformer, only transformers with automatic load tap changing (ALTC) control must be targeted in the forecasting process. The tap of the generator transformers that connect the units to the high voltage grid are usually fixed; the taps are changed manually once or twice a year depending on the season. However, several transmission transformers are equipped with ALTC and their position needs to be estimated. The estimation of generator voltages and transformer taps is still under research, and will be presented in future papers (for generator voltages, ARIMA time series have proved to be the best option; for transformer taps, no completely satisfactory forecasting technique has been found yet).

This paper aims at forecasting the values of switched shunts (reactors and capacitors) for a short-term time scope. The value of bus voltages or system demand on their own are not enough to predict their status: sometimes the power system is operated with a high voltage profile in valley hours maintaining reactors in the system, and in some peak hours, the reactors remain connected even though the voltage profile is a little low. It should be noted, that the system operator tries to control the number of connections/disconnections of the reactors and capacitors in order to minimize the outwear and prolong their working life. In this way, artificial intelligence techniques that model human response (or grid operator response) are explored.

This paper proposes a method based on decision trees to estimate the switched shunt values for short term power system scenario forecasting. The methodology proposed has been implemented in a tool to forecast power system scenarios in the Spanish system, with a short-term time scope covering 24 and 36 hours ahead. The forecasting tool has been developed for Red Eléctrica de España, the Spanish SO.

The paper has been organized as follows. Section II. reviews the application of decision trees to different fields making an special emphasis on their use in power system security applications. Many different fields of real applications based on decision trees demonstrate the usefulness, robustness and interpretability of this particular forecasting tool. In section III. the identification of potential explanatory variables is discussed for the problem under consideration. It should be noted that an explanatory variable is useless if you cannot predict the input value to the selected forecasting method. Section IV is dedicated to a brief exposition of the main characteristics of decision trees. In section V the methodology proposed in this paper is illustrated building decision trees to predict the MVAR output of the shunt components of the Spanish power system. Finally, some conclusions are reached in section IV and the future research to be undertaken is outlined.

II. REVIEW OF APPLICATIONS BASED ON DECISION TREES

A decision tree is an automatic learning tool that can be used to solve both classification and regression problems, that can be situated within the artificial intelligence knowledge field. Decision trees are destined to face classification problems, dividing the output variable space by the evaluation of partition rules developed from explanatory variables. Different fields have been targeted with this powerful and robust technique: finance [18, 19], signals [20], word pattern recognition [21], market based applications [22, 23], transmission planning [24]. In the Spanish electricity market context, the authors have faced two different issues with encouraging results. On one hand, decision trees have been used to predict stochastic residual demand curves in the Spanish electricity market [25]. On the other hand, the authors have presented a methodology based on decision trees to estimate the daily load pattern of units, that have not been cleared in the daily energy market and can be connected to alleviate voltage constraints [26].

One of the main fields of applications of decision trees is the power system security assessment field. The main reference in this field can be found in [27]. The applications developed are related mainly with dynamic security assessment (transient stability and voltage stability), with multiple different applications environments and uses: generation –transmission planning, design of protection and control schemes, operation planning, on-line operation, real time monitoring and control or operator training [28-44].

The typical process of building a decision tree model for a power system security assessment problem comprises two steps:

- Building an extensive database by simulating a number of scenarios and running power flows and other security assessment tools. The state of each scenario is classified as secure or insecure according to the value of security parameters provided by the security assessment tool (for example, the load margin to voltage collapse). It should be noted that abnormal situation are not frequent in power systems, thus, for obtaining a sufficient number of examples of abnormal situations simulations are needed.

- Developing a decision tree that classifies the power system as *"stable" vs "unstable"* or *"secure" vs "insecure"*, as a function of separation rules based on the explanatory variables saved in the database. It should be noted that the security assessment application proposed in this paper has a different philosophy focusing only on forecasting the power system scenario. The main advantages with respect to the traditional approach outlined are:

- Running security assessment tools to each scenario of the database is not needed. Instead, once the power system scenario is built, the security assessment tools are only run over the predicted scenario. Since only one scenario is to be assessed, more complex or time consuming security assessment tools can be chosen to evaluate the state of the power system.

- Since it is a short-term application, it is easier to account for unexpected events that can be included in the forecast scenario. In the traditional approach, if a very rare event occurs that was not taken into account in the simulations to build the database, the tree will not be able to assess this situation.

- Operator immediate decisions are easily introduced.

- In the approach presented in this paper, forecasting inaccuracies can be handled by augmenting the accepted ranges of the power system variables or incrementing the accepted security criteria (for example N-2 or even N-3 instead the usual N-1).

III. IDENTIFICATION OF POTENTIAL EXPLANATORY VARIABLES

Shunt reactors and capacitors are used within a power system to control the voltage profile within the electrical area where they are connected. Thus, it should be expected that its operating value should be the active and reactive loading of the power system, which translates into a specific voltage profile.

In this way, the voltage magnitude of selected important buses of the network is the main explanatory variable one may think at first to use. However, to obtain the voltage magnitude of this chosen pilot buses an available power flow solution would be required; without having the power system scenario, it is not possible to know in advance the voltage of these buses. Thus voltage related magnitudes are not available and cannot be used as explanatory variables. Taking into account that the voltage profile of a power network is a dependent variable of the active and reactive loading outline, the unavailability of voltages of the scenario under consideration is not a drawback for the methodology proposed in this paper.

Another point of view that must be considered is that value of bus voltages or system demand on their own are not enough to predict the shunt devices value, since the system operator tries to minimize the number of switching actions to avoid a big outwearing. Thus, other types of variables (type of day, retards of variables) should be considered to account for this fact. Therefore, in this research the following potential explanatory variables have been initially considered to explain the value a reactor/capacitor in a short-term time scope (between 24 and 36 hours ahead):

a) Spanish active system demand [MW].
b) Spanish reactive system demand [MVAR].
c) Active demand of the electrical area of the reactor/capacitor under consideration [MW]
d) Reactive demand of the electrical area of the reactor/capacitor under consideration [MVAR]
e) Increase of active power system demand from the preceding hour [MW]
f) Increase of reactive power system demand from the preceding hour [MVAR]
g) Increase of active power system demand from the preceding hour, in the electrical area of the reactor/capacitor under consideration [MW]
h) Increase of reactive power system demand from the preceding hour, in the electrical area of the reactor/capacitor under consideration [MVAR]
i) Power factor of the Spanish electrical system.
j) Power factor of the electric area of the reactor/capacitor.
k) Type of day: it can take the value "Week day", "Saturday" or "Sunday")
l) Hour: takes the value "H1" to "H24"
m) Reactor/capacitor value for the preceding hour.
n) Reactor/capacitor value for the same hour in the previous day.
o) Reactor/capacitor value for the same hour in the

previous week.

p) Bus voltages of pilot buses in the power system scenario of the preceding hour.

IV. BRIEF DESCRIPTION OF DECISION TREES

A. Definition

A decision tree is a classification data-mining tool aimed to extract useful information contained in large data sets [26]. The decision tree proposed in this paper is used to estimate the value of a shunt element of the power system. It should be noted that reactors and capacitors are discrete in nature, they are usually large, and cannot be treated as continuous variables maintaining high accuracy. Typically they comprise two or three possible values, and thus classification tools seem adequate to predict their behavior. As an example, the reactance ALDEADAV1 of the Spanish power system can take two possible patterns: 0 MVAR or –89 MVAR.

A decision tree is made up of a set of nodes that classify the past realizations of the objective variable. Each classification is achieved by separation rules according to the numerical or categorical values of the explanatory variables. The classification rules of each node are derived from a mathematical process that minimizes the impurity of the resulting nodes, using the total available data set. In this way, by evaluating the separation rules using the numerical or categorical values of the explanatory variables a final node is reached. In a final node no more separation rules are applied. This final node contains the proportion (or probability) of each type of pattern according to the explanatory variables estimates.

B. Graphical representation of a node

A convenient graphical representation of the nodes of a decision tree was proposed in [27] and represented in Fig. 1. Each node represents the total number of examples traversing the node (referred as L in Fig. 1) and the total number of examples of each pattern (referred as a for the third pattern in Fig. 1). Thus, the probability of pattern three ρ_{P3} is given by the ratio a/L. The classification rule at each node is derived from a mathematical process that minimizes the impurity of the resulting nodes with respect to the purest node that contains a single pattern.

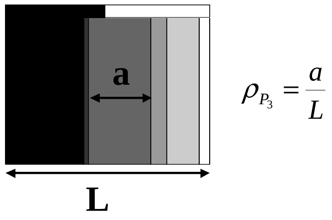

Fig. 1: Structure of a node of a decision tree and computation of the probabilities of each pattern.

The final node reached in the decision tree forecasting process can be used to predict the probability of each classified pattern. This way of estimating probabilities does not requires the assumption of specific probability distributions for the variables, which represents an important advantage for the methodology based on decision trees to classify patterns.

The application developed in this research assumes a deterministic approach, i.e., the probability of each possible value of a reactance/capacitor is not used. Instead, the MVAR value of the most probable pattern in the final node is assumed as the forecast of the switched shunt device to build the future power system scenario.

C. Training data set and test data set

The process of building the classification rules at each node of a decision tree is referred in the technical literature as the training process of the decision tree. For this purpose, the total available historic data set of the objective variable and explanatory variables is divided appropriately in the training data set and the test data set. The training set corresponds to the data that will be used to train the tree, in other words, the tree computes the best separation rules learning from the information hidden in the training set. The test data set is formed by a portion of the total available data that must be saved to assess the capability of generalization of the decision tree. A reasonable amount between 20% and 30% of the data must compose the test data set, while the rest form the training data set.

A similar value of the efficiency index of the tree applied to the training data set (used to build the tree) and the efficiency index of the tree applied to the test data set (used to assess the capability of generalization of the tree) represents a valuable measure to guarantee that the tree is neither over-fitted nor over-smoothed. These efficiency indexes reveal a good forecasting ability of the decision tree, at least in the short term where the separation rules do not change. Once the tree has been built, if a significant reduction of the initial tree efficiency is observed when supplied with new data, new explanatory variables may need to be considered and a new analysis must be done to update the decision tree.

V. RESULTS

This section presents the performance of the reactor/capacitor forecasting tool applied to the Spanish power system. In subsection A the shunt devices of the Spanish power system are presented. Subsection B is dedicated to the description of the overall data set and its division in training set and test set. Subsection C is devoted to evaluate the performance of the decision trees to forecast individual shunt reactors and capacitors, while subsection D analyses the performance of the overall set of switched shunt devices of the Spanish power system. Finally, subsection E defines two efficiency indexes to measure the quality of forecasted power system scenarios.

A. Enumeration of the reactors/capacitors of the Spanish power system

Five electric areas compose the Spanish power system. Fig. 2 shows approximately the situation of each area (area 1- Northwest, area 2 – North, area 3 – East, area 4 – Center, area 5 – South). Areas 6, 7 and 8 correspond respectively to the foreign Portuguese, Moroccan and French systems.

Fig. 2. Area division of the Spanish power system

TABLE I
SWITCHED SHUNT DEVICES OF EACH AREA OF THE SPANISH POWER SYSTEM

	REACTORS		CAPACITORS	
AREA	nº	Mvar	nº	Mvar
1	3	362	0	0
2	11	1801	0	0
3	9	1031	0	0
4	11	1314	10	835
5	7	930	0	0
TOT	41	5438	10	835

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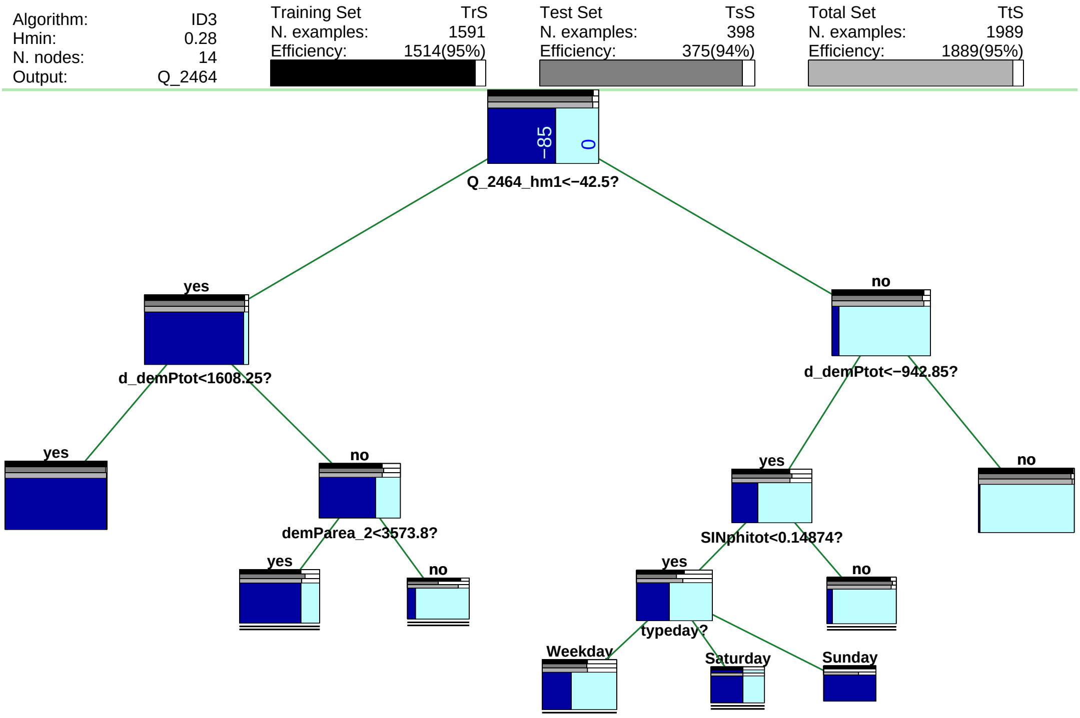

Fig. 3. Decision tree used to forecast the value of reactor ALDEADAV1

The Spanish power system has a total of 51 shunt devices (41 reactors and 10 capacitors) with a total generation capacity of 835 MVAR and a total consumption capacity of 5438 MVAR. TABLE I specifies the distribution of the switched shunt devices between the different electrical areas.

B. Description of the data set

In the methodology presented in this paper, one forecasting tree has been trained for each shunt device. In order to build the trees, historical values of the shunt devices and explanatory variables have been gathered for three months. The data has been extracted from real time scenarios of the power system provided by the state estimator of the energy management system. The real time scenarios correspond to dates between hour 23 of February 19th 2004 and hour 22 of May 13th 2004. An overall data set of 1989 cases has been used in the study. The overall data set (set TtS) has been divided in training set and test set in the following manner:

- The training data set used for training (set TrS) contains 80% of the data, which represent 1592 examples corresponding to dates between hour 23 of February 19th 2004 to hour 20 of April 26th 2004.

- The test data set saved to assess the generalization capability of the trees (set TsS) contains 20% of the data, which represents 397 examples corresponding to dates between hour 21 of April 26th 2004 to hour 22 of May 13th 2004.

C. *Individual forecasting results*

The shunt reactor of ALDEADAV1 in area north, connected at node 2464 of voltage level 24 kV, has been selected to show the forecasting capabilities of decision tree. The reactor of ALDEADAV1 has two possible MVAR values corresponding to –85 MVAR (connected) and 0 MVAR (disconnected).

Fig. 3 depicts the decision tree built by the tool to predict the MVAR output of reactor ALDEADAV1, containing a total of 14 nodes. It should be noted that for the application described in this paper, in practice the resulting trees rarely exceed 20 nodes. For other more complex different applications developed by the authors using decision trees [25-26], optimal trees contained up to 50 nodes. An adequate number of nodes should be such that the resulting tree is nor over-fitted nor over-smoothed, which means that efficiency index of the tree applied to the training data set (used to build the tree) and the efficiency index of the tree applied to the test data set (used to assess the capability of generalization of the tree) present similar values.

Fig. 3 shows that efficiency indexes of the decision tree present similar values for the training set TrS (95% of right guesses) and for the test set TsS (94% of correct forecasts) and thus, a good generalization capability should be expected from the decision tree.

The first explanatory variable selected by the tree to explain the pattern of reactor ALDEADAV1 corresponds to its status in the preceding hour (Q_2464_hm1 in Fig. 3). The subsequent nodes are divided using the explanatory variables:
increase of active power compared with the preceding (d_demPtot), the active power demand of the electric north area (demParea_2), the power factor of the system (SINphitot) and the type of day (typeday). It should be noted that in the majority of the trees developed, the first explanatory used for classification corresponds to the shunt device position of the preceding hour, clearly stating that the system operator tries to minimize the number of control actions to prolong the device working life.

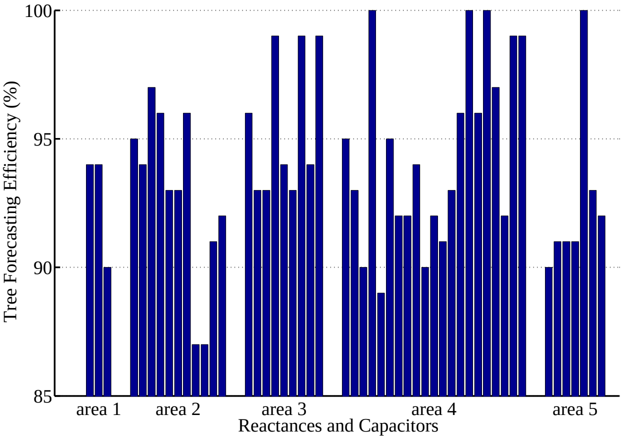

Fig. 4. Tree forecasting efficiency for the total set of 51 shunt devices of the Spanish power system, classified by electric area.

Fig. 4 displays the forecasting efficiency of the individual decision trees built to forecast each shunt device of the Spanish power system, classified by electric area. It should be noted that the worst tree has an efficiency index of 87% applied to the test set TsS. Some shunt devices present an efficiency index of 100%, which means that they present always the same pattern, i.e., the are not used as voltage control devices for normal situations. TABLE II summarizes the results of the forecasting decision trees efficiency (applied to the test set TsS) built for the whole set of shunt devices of the Spanish power system. As can be seen, the mean efficiency of right predictions is 94%.

TABLE II

SUMMARY OF THE EFFICIENCY RESULTS

AREA	Mean efficiency in TsS
1	93%
2	93%
3	96%
4	95%
5	93%
TOTAL	94%

D. *Overall forecasting results*

Since the main objective of the forecasting tool is the forecasting of power system scenarios, we are not interested in individual shunt device right predictions, but rather in the overall prediction in the whole power system. Fig. 5 depicts the cumulative distribution function of the number of simultaneous wrong predictions for the whole Spanish system. Fig. 5 for example indicates that the probability of failing less or equal than twice in predicting the 51 shunt devices of the Spanish power system is about 40%, and failing more that 6 shunt values is very unlikely.

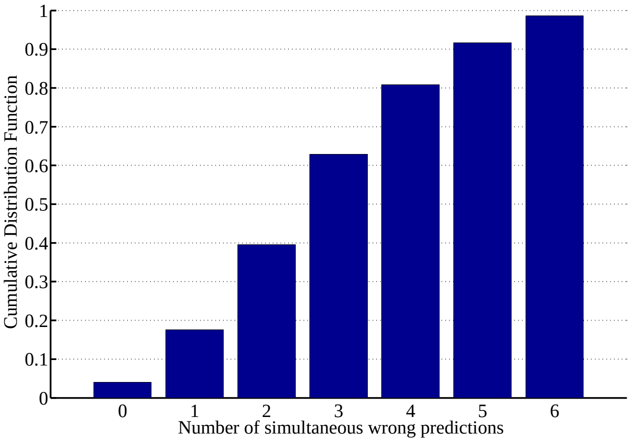

Fig. 5..Cumulative distribution function of the number of simultaneous wrong predictions

E. Scenario quality indexes

The quality of the forecasting tool can be measured by comparing the predicted scenarios with the scenarios effectively provided by the state estimator of the energy management system. Two comparison indexes have been defined for this purpose: (a) branch flow quality index and (b) bus voltage quality index.

The branch flow quality index BI is defined as the mean error of the branch flow S divided by the branch power flow limit S_{max}:

$$BI = \mathrm{E}\left[\frac{\left|S_{real} - S_{predicted}\right|}{\mathrm{S}_{\max}}\right] \tag{1}$$

The bus voltage quality index VI is defined as the mean error of pu bus voltages:

$$VI = \mathrm{E}\left[\left|\mathrm{V}_{real} - V_{predicted}\right|\right] \tag{2}$$

Both quality indexes are computed for each individual power system area, and for the total Spanish power system.

The impact of failing in one shunt device prediction has a local effect in the near bus voltages, but has very little impact in the overall area or total quality index. As Fig. 5 indicates, the probability of wrong forecasting several reactors/capacitors at the same time is very low, and thus, a low impact in the quality indexes.

Future research is being focused in evaluating the indexes to detect the main forecasting errors (coming from demand, wind power, voltage control resources or network topology) in the process of building the power system scenario, analysing their impact in running the security assessment tools.

VI. CONCLUSIONS

Short term forecasting of power system scenarios is required to foresee potential network problems and anticipate preventive or corrective measures to be taken under credible contingencies, thus increasing the reliability of the operation of the grid. This paper has presented a forecasting methodology to obtain the MVAR output of switched shunts devices (reactors and capacitors) for building power system scenarios with a short-term time scope (between 24 and 36 hours ahead). The discrete nature of the switched shunt elements suggests decision trees is appropriate to predict their value. The selection of potential explanatory variables has been discussed, and the methodology has been illustrated predicting the behavior of the shunt reactors and capacitors of the Spanish power system. A good generalization capability of the developed decision trees should be expected from the decision tree by equalling the forecasting efficiency of the trees applied to the training data set and the test data set (which is around 94%). Future research will be presented in additional papers. The main effort is concentrated in detecting the main forecasting errors (coming from demand, wind power, voltage control resources or network topology) and their impact in running the security assessment tools.

VII. ACKNOWLEDGMENT

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