A Systematic Approach for Dynamic Security Assessment and the Corresponding Preventive Control Scheme Based on Decision Trees

Chengxi Liu, *Member, IEEE*, Kai Sun, *Senior Member, IEEE*, Zakir Hussain Rather, *Member, IEEE*, Zhe Chen, *Senior Member, IEEE*, Claus Leth Bak, *Senior Member, IEEE*, Paul Thøgersen, *Senior Member, IEEE*, and Per Lund, *Senior Member, IEEE*

***Abstract*—This paper proposes a decision tree (DT) based systematic approach for cooperative online power system dynamic security assessment (DSA) and preventive control. This approach adopts a new methodology that trains two contingency oriented DTs on daily basis by the databases generated from power system simulations. Fed with real-time wide area measurements, one DT about measurable variables is employed for online DSA to identify potential security issues and the other DT about controllable variables provides online decision support on preventive control strategies against those issues. A cost effective algorithm is adopted in this proposed approach to optimize the trajectory of preventive control. The paper also proposes an importance sampling algorithm on database preparation for efficient DT training for power systems with high penetration of wind power and distributed generation. The performance of the approach is demonstrated on a 400-bus, 200-line operational model of the western Danish power system.**

***Index Terms*—Decision tree, dynamic security assessment, importance sampling, phasor measurement unit, preventive control**

NOMENCLATURE

CHP	Combined heat and power plant.
CPP	Central power plant.
DT	Decision tree.
RF	Random forest.
ODT	Observation decision tree.
PDT	Prevention decision tree.
OC	Operating condition.
G_CPP*x*	MW-output of central power plant *x*.
P_*x*_*y*, Q_*x*_*y*	MW- and MVar-power from bus *x* to bus *y*.
A_*x*_*y*	Voltage angle of bus *x* minus that of bus *y*.
$p_i(t)$	Probability of class *i* in node *t*.
$i(t)$	Impurity index of node *t*.
$\mathcal{S}$	Training database.
π_i	Prior probability of class *i*.
IS, NS	Importance sampling and normal sampling.
LS, TS	Learning set and test set.
C_i	Cost of reserve service from CPP *i*.
C_{Fi}	Fixed cost of reserve service from CPP *i*.
P_{UPi} , P_{DNi}	Prices of upward and downward generation rescheduling in CPP *i*.
ΔG_{UPi}, ΔG_{DNi}	MW-quantities of upward and downward generation rescheduling in CPP *i*.
ΔG_{UPi}^{max}, ΔG_{DNi}^{max}	Limits of upward and downward generation rescheduling in CPP *i*.
G_i^{min}, G_i^{max}	Min. and Max MW outputs in CPP *i*.
$\mathcal{G}$	Set of generators participating in the preventive control.
ΔP_{EX}	Mismatch between scheduled and actual international power exchange.
$P_{\{R\}}$	Price of international power exchange mismatch under range *R*.
C_{PEN}	Penalty of violating scheduled international power exchange.

Manuscript received February 7, 2013; revised May 23, 2013 and June 30, 2013. This work was supported in part by Danish Strategic Research Centre under *DSF 09-067255*, "Development of a Secure, Economic and Environmentally-friendly Modern Power System" (SEEMPS). Paper no. TPWRS-00169-2013.

C. Liu is with the Department of Energy Technology, Aalborg University, Aalborg Øst, DK-9220 Denmark and the Department of EECS, University of Tennessee, Knoxville, TN 37996 USA (e-mail:cli@et.aau.dk/cliu48@utk.edu).

Z. Chen and C. L. Bak are with the Department of Energy Technology, Aalborg University, Aalborg Øst, DK-9220 Denmark (e-mail: zch@et.aau.dk; clb@et.aau.dk).

K. Sun is with the Department of EECS, University of Tennessee, Knoxville, TN 37996 USA (e-mail: kaisun@utk.edu).

Z. H. Rather is with the Innovation Centre, kk-electronic a/s and the Department of Energy Technology, Aalborg University, Aalborg Øst, DK-9220 Denmark (e-mail: zahus@kk-electronic.com/ zhr@et.aau.dk).

P. Thøgersen is with the Innovation Centre, kk-electronic a/s, Aalborg Denmark (e-mail: patho@kk-electronic.com).

P. Lund is with the Energinet.dk, Fredericia, DK-7000 Denmark (e-mail: plu@energinet.dk).

I. INTRODUCTION

CONTINUOUSLY growing demand for electricity, driven by deregulated electricity markets, has forced modern power systems to operate closer to secure operating limits. Also, the increasing penetration of large scale renewable energy may impact transmission systems by bringing more uncertainties to grid operations. It becomes more challenging to protect a modern power system from insecurity by relying only on localized protection schemes. Hence, a power system should be secured proactively at the system level by advanced system protection schemes for online situational awareness and proactive wide area coordinating control [1]. For instance, an elaborated proactive system protection scheme may integrate both online DSA for identification of potentially insecure conditions and system level optimization and execution of control strategies for prevention of identified insecure conditions. Phasor measurement units (PMU) can provide high resolution real-time power system measurements

synchronized by global positioning system (GPS). Based on PMUs, wide area measurement systems (WAMS) have been built in many countries and would enable the development of aforementioned proactive system protection schemes.

Pattern recognition techniques, such as Artificial Neural Networks (ANN) [2], Support Vector Machine (SVM) [3] and Decision Trees [4]-[17] can be applied in DSA of power systems. Among them, some DT algorithms [18], especially those with the "white box" nature, have gained increasing interests because they not only provide the results of security assessment but also reveal the principles learned by DTs for security assessment. Those principles provide useful information required for the remedial actions against recognized insecure conditions. With the aid of WAMS and advanced computing resources, DTs may be integrated into online DSA tools for large interconnected complex power systems. For instance, reference [4] applies DTs in an online DSA method by adaptively updating the database to train DTs on daily basis for foreseen system conditions. In [5], a method for efficient database generation for DT training is introduced to enhance DT accuracy in DSA and decrease the computation burden in DT training. In [6], multiple optimal DTs are proposed to increase the accuracy for the assessment of static voltage security. In addition, DTs can also be used in adaptive protection [7], controlled islanding [8], [9], load shedding [10], loss of synchronization detection [11], quick restoration schemes [12] and energy markets [13]. In [14] and [15], DTs are used for preventive control (i.e. generation rescheduling) and for corrective control (i.e. load shedding) by determining the dynamic security regions. Then, the preventive control and the corrective control are optimized in terms of the fuel cost and the amount of load to be shed, respectively.

With the increasing penetration of renewable energy resources and other decentralized generation (DG), more uncertainties will be brought to the operation of transmission systems, since those resources are not as accessible for direct monitoring and control from control centers as conventional central power plants. Thus, a significantly increased number of scenarios need to be covered by DTs to address these uncertainties. However, it also becomes more important to minimize the computation burden with DT based online applications for real-time DSA and the associate sensitivity analysis. Most of the existing works apply DTs mainly for security assessment, whose predictors to be measured in real time are the system variables most effective in detecting security problems, e.g. line flows and angle differences. However, the DTs focusing on decision support for preventive control may employ a different set of predictors that are directly controllable, e.g. generation outputs, so it is advisable to build two DTs respectively for DSA and preventive control based on two sets of predictors selected separately.

The DT-based approach proposed in this paper aims at addressing the aforementioned problems. First, this paper studies the database preparation for training accurate DTs for power systems with high penetration of wind generation and other DG. Without losing generality, the paper focuses on a power system supported by three types of generation: traditional central power plant (CPP) generation, wind power generation and other DG mainly from combined heat and power plants (CHP). An importance sampling technique, considering the random distribution of various generation resources, is developed and applied in the proposed approach to enhance the information contained in the databases for DT training. Second, the approach is designed to be a systematic integration of cooperative online DSA and preventive control. The approach adopts a new methodology that offline trains two contingency-oriented DTs by databases generated from power system simulations. Fed with real-time wide-area measurements, one DT is employed for online DSA to identify potential security issues and the other DT provides system operators with the online decision support on allowed preventive control strategy to guide the operating point from a potentially insecure state to a secure state. Then the optimal control trajectory is searched out by minimizing the total economic cost incurred by generation rescheduling.

The rest of the paper is organized as follows. Section II presents the flowchart and stages of the proposed approach. Section III introduces the fundamental knowledge of DT. In Section IV, database preparation with due considerations to power systems with high penetration of wind power generation and other DG is described. An importance sampling technique is adopted and presented in the approach. Section V describes in detail the cooperative application of proposed two types of DTs to predict and prevent the potential insecure issues with the least economic cost implication. Then, the proposed approach is demonstrated in Section VI using an operational model of the western Danish power system, which is characterized by its large scale penetration of wind power generation and other DG. The concluding remarks are provided in Section VII.

II. Proposed Approach

The flowchart of the proposed DT-based systematic approach is shown in Fig. 1 and the proposed approach is executed in the following stages:

Stage I: Identification of the Security Boundary. Since wind forecasts are not highly accurate and DG is unpredictable, the power flow pattern in a next period is highly uncertain. However, a security boundary separating secure operating conditions (OCs) from insecure ones at each load level can be estimated and presented in multiple-dimensional space with coordinates of aforementioned stochastic variables, such as CPP generation, CHP generation and wind power generation.

Stage II: Importance Sampling. Considering the intermittency of wind power generation in wind farms and the variation of power generation in CPPs, importance sampling is used to bias a number of samples of OCs towards the security boundary by revising the sampling distribution function.

Stage III: Offline time domain (T-D) Simulation and DT Training. A large number of T-D simulations for each *"n*-1*"* contingencies and selected *"n-k"* contingencies are carried out to form a database, from which a series of operating guidelines are obtained by DTs.

Stage IV: Online Preventive Control. If online measurements violate pre-formulated guidelines, available preventive control

schemes can be concluded from DTs and the optimal control trajectory can be provided to system operators.

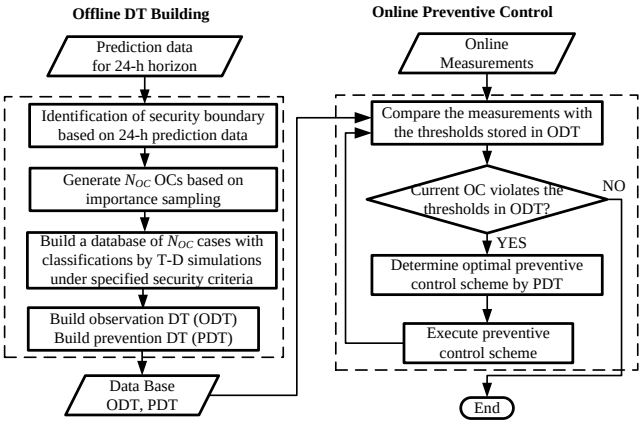


Fig. 1. Flowchart of DT-based DSA and preventive control approach.

III. Fundamental Knowledge of Decision Trees

A DT is a decision support tool which uses a binary structured tree graph or model to predict their possible consequences. The data mining algorithm used in DTs of the proposed approach is CART (Classification and Regression Trees), which was first developed by Breiman *et al.* in the 1980s [18]. It has been widely applied in many fields such as financial analysis, chemical constituent identification, and medical diagnostics and was introduced into the field of power systems by Wehenkel *et al.* in 1989 [19].

As shown in Fig. 2, given a case represented by set of measurements (i.e. $A,B,C,\ldots$) for a particular OC, the class (i.e. Secure or Insecure) of the case can be predicted by dropping the measurements of the case downward from the root node to a terminal node of a DT. The vector of predictors can be composed of both numerical variables (e.g. A) and categorical variables (e.g. B). Variables are called numerical variables if their measurements are real numbers, while called categorical variables if they take values from a finite set (e.g. **S**) which may not have any natural ordering.

A database composed of a number of cases is necessary for training DTs, which are randomly divided into a learning set (LS) and a test set (TS). The LS is used to grow a series of DTs at increasing sizes while the TS is used to evaluate their accuracies to decide the optimal DT. A DT is grown by recursive splits of the learning cases at its nodes. The fundamental idea of selecting each split is such that the learning cases in each descendant node are purer than the parent node. The optimal selection of splitting rules can be calculated by repeated attempts to minimize the overall GINI impurity index [18].

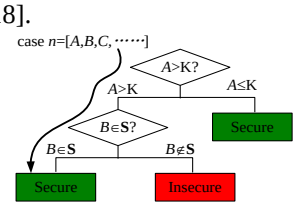


Fig. 2. A simple illustrative DT.

Prior adjusted probability is used effectively to control the splitting rules over the tradeoff between the class purity and class accuracy. The probability that a case lands in node t is

$$p_t = \sum_{i=1}^{J} \left(n_i / N_i\right) \pi_i \tag{1}$$

where π_i, N_i and n_i $(i = 1,\ldots,J)$ is the prior probabilities, the number of cases in LS, number of cases contained in node t for class i, respectively. Then the conditional probability of class i given that a case reached node t is defined in (2)

$$p_i(t) = \left(n_i / N_i\right) \pi_i / p_t \,. \tag{2}$$

So the probabilities $p_L(t)$, $p_R(t)$ that the cases in node t going to left descendent node t_L and right descendent node t_R are defined as (3) and (4) respectively

$$p_L(t) = p_t^{left} / p_t^{parent} \tag{3}$$

$$p_R(t) = p_t^{right} / p_t^{parent} \,. \tag{4}$$

As mentioned earlier, the optimal splitting rule δ is selected to maximize the decrease of impurity $\Delta i(\delta,t)$ after the split so as to minimize the overall impurity, as defined in (5), where $i(t)$, $i_L(t)$, $i_R(t)$ are the impurity indice of parent node, left descendant node and right descendant node respectively.

$$\max\left\{\Delta i(\delta,t)\right\} = \max\left\{i(t) - p_L(t) i(t_L) - p_R(t) i(t_R)\right\} \tag{5}$$

Hence, by adjusting prior probabilities π_i, one can adjust the splitting rules to find the overlapping region, as shown in yellow in Fig. 3. Accordingly, the regions in red and blue are with probability of exception lower than π_b and π_r respectively.

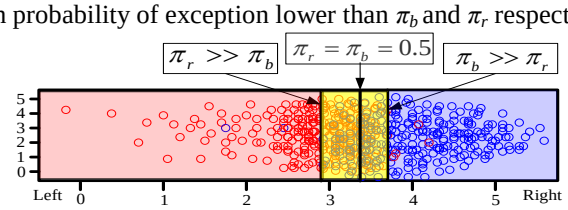


Fig. 3. The thresholds of DT w.r.t. prior probability adjustment.

Other extended techniques, such as random forest (RF), are adopted to improve the accuracy of classification in [20] and [21]. Random forest is a multitude of de-correlated DTs such that each tree depends on a sub-vector randomly selected from the full-vector of predictors. The output (Secure or Insecure) of RF model is the voting result from a large number of DTs, which may benefit from aggregation-based variance reduction. Bootstrap sampling is used in RF to assist in better estimating the distribution of the original dataset. For each DT in RF, about one third of the cases are left out from the bootstrap sampling called out-of-bag (OOB) data which can be used for testing the model. Details of RF algorithm can be found in [22]. The accuracies of RF and CART are compared later in this paper (see Table I for the results).

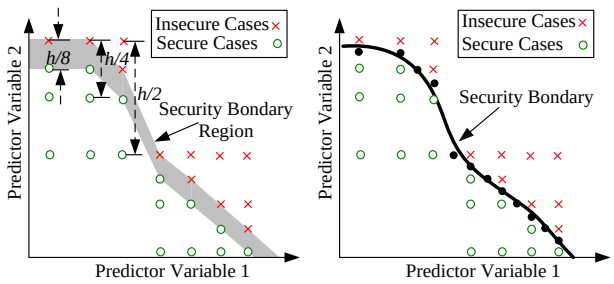
IV. Database Preparation for DT Training

For a two-class classification problem (Secure or Insecure), the concept of entropy, commonly accepted in the information theory, is used here to evaluate the information content in the database [23], as defined in (6).

$$Entropy(\mathcal{S}) = -p_S \log_2 p_S - p_I \log_2 p_I \tag{6}$$

where $\boldsymbol{S}$ is the training database, p_S, p_I are the proportions of S classified as secure and insecure respectively. So, a general prediction of security boundary and good representation of sampling OCs on both sides of the boundary are desirable.

In this paper, bisection method is adopted to approximately identify a region that contains the security boundary. Thus, only OCs adjacent to that region are simulated so as to significantly decrease the number of simulations. As illustrated in Fig. 4, the security boundary region is searched out by repeatedly bisecting the slot over Predictor Variable 2. In each iteration, the slot is selected in such a way that one end of the selected slot falls in secure region and the other end in insecure region and the repeated process should eventually converge at the security boundary. Then a security boundary is created by polynomial curve fitting of those points located between a secure and an insecure case.



(a) Bisection method (b) Curve fitting of security boundary

Fig. 4. The prediction of the security boundary.

Through this approach, the security boundary is traced in a multi-dimensional space of involved influencing factors. For example, CPPs which have relatively more flexible controllability can be used to compensate the uncertainties of wind power generation and other DG. During the search of security boundary in the space of CPP generation, wind generation and DG generation, other fixed important factors such as load and international power exchange should be maintained at their scheduled values.

However, it is important to mention that consideration of all possible generation uncertainties would result in a huge database. Given that the security boundary lies in the rare probability region, a database containing the sampling OCs within this rare probability region conveys more information, as the cases closer to the security boundary affect the process of making splitting rules much more than the cases away from the security boundary. So importance sampling is adopted to select the cases containing more information by revising the sampling distribution function *f(d)* towards the security boundary, so as to reduce the computational cost.

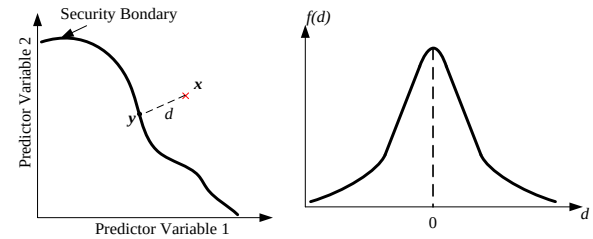
The Gaussian distribution $N(0,\sigma^2)$ with probability function *f(d)* is adopted to sample the OCs, as defined in (7)

$$f(d) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{d^2}{2\sigma^2}}. \tag{7}$$

where d is the 2-norm distance from the sampled OC point $\boldsymbol{x}$ to the security boundary $\boldsymbol{y}$, as defined in (8)

$$d = \left(\sum_{i=1}^{n} |x_i - y_i|^2 \right)^{1/2}. \tag{8}$$

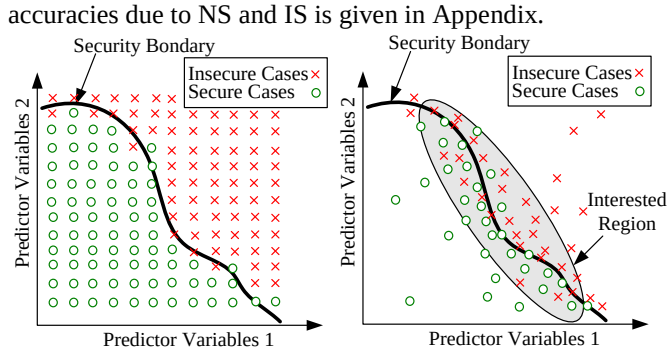
As shown in Fig. 5, the sampling OCs in the space of involved factors subject to Gaussian distribution. The cases close to the security boundary have higher probability to be selected for database than that away from the boundary. So a number of OCs are selected and biased to the interested region adjacent to the security boundary. The parameter σ, the standard deviation of the samplings, controls the degree of convergence to the security boundary.



(a) 2-norm distance to the boundary (b) Probability density function

Fig. 5. The probability function of sampling OCs

As illustrated by Fig. 6 on a comparison between two sampling methods, the number of cases given by importance sampling (IS) is significantly reduced but they still contain the critical information for differentiating insecure cases from secure ones. Assume that the splitting of databases created by normal sampling (NS) and that created by IS have the same boundary, i.e. the equally accurate results. However, the DT with IS usually suggests a lower value of accuracy due to two main reasons: i) a number of secure and insecure cases by IS overlap each other in the interested region, which makes clear splits more difficult; ii), a large number of apparent secure or insecure cases from NS outside the interested region, have minor effect on the final splits but are counted in the denominator of the accuracy ratio. A detailed analysis on the accuracies due to NS and IS is given in Appendix.



(a) Conventional sampling (b) Importance sampling

Fig. 6. The selection of operating conditions.

V. Preventive Control Scheme

When a power system at a given OC is detected to be vulnerable to a specific credible contingency, the operators are supposed to take preventive actions to ensure its security in post contingency condition. Generation rescheduling which involves shifting generation among centralized generators so as to restore the system from insecure state to secure state is usually adopted by operators.

For each OC among N_{OC} initially obtained OCs from IS, detailed T-D simulations for all the critical contingencies are executed. Specific security criteria such as transient instability,

transient voltage dip, insufficient damping on T-D simulation results are examined to determine the security classification for each case. In this research, two DTs are trained for each contingency. One is for observation of insecure condition called observation DT (ODT) and the other is for prevention of insecure conditions called prevention DT (PDT). The security boundary in the space of measurements is specified by the ODTs, while the PDTs provide directions of generation shift when the system is identified as an insecure state.

A. Observation Decision Tree (ODT)

In a database of N_{OC} cases, each case includes a vector of measurements to present an OC before the disturbance which serves as predictors and the results of T-D simulations after the disturbance (Secure or Insecure) which serve as the target for aforementioned predictors. For each OC, synchronized data from PMU measurements, including voltage, current and power are able to provide accurate predictor values. In addition, predictors also can be selected from SCADA system, if the values do not change frequently.

ODT is used to detect the current security state by providing accurate thresholds of security boundary and calculating out the security margins of current OC. Since the DT is trained from all measurable values as predictors, the data mining algorithm is able to seek out the accurate boundary in the space of dominant observable values. In other words, ODT is the subspace of the most dominant measurements before the disturbance that is able to accurately predict the post-disturbance security condition.

B. Prevention Decision Tree (PDT)

PDT is the decision tree which selects only the controllable variables as predictors from measurements, e.g. outputs of generators, power exchange across HVDC links. Although PDT has lower accuracy than ODT due to the fewer number of predicting values, it is capable of searching out the most effective controllable variables among all the measurable control parameters and providing the potential directions of control to draw the system back to a secure state.

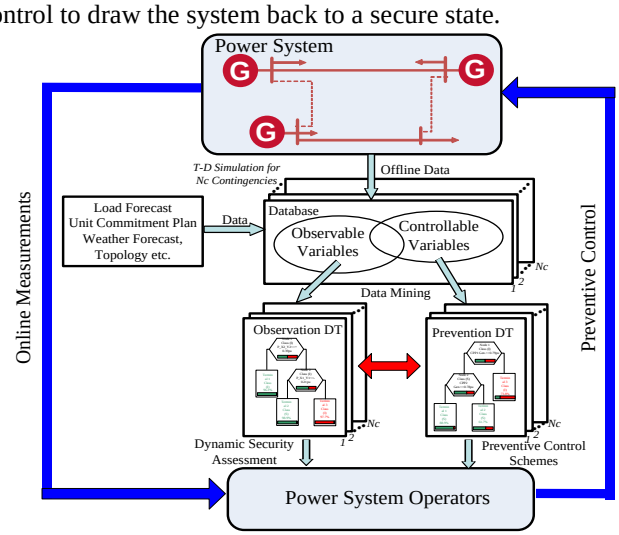
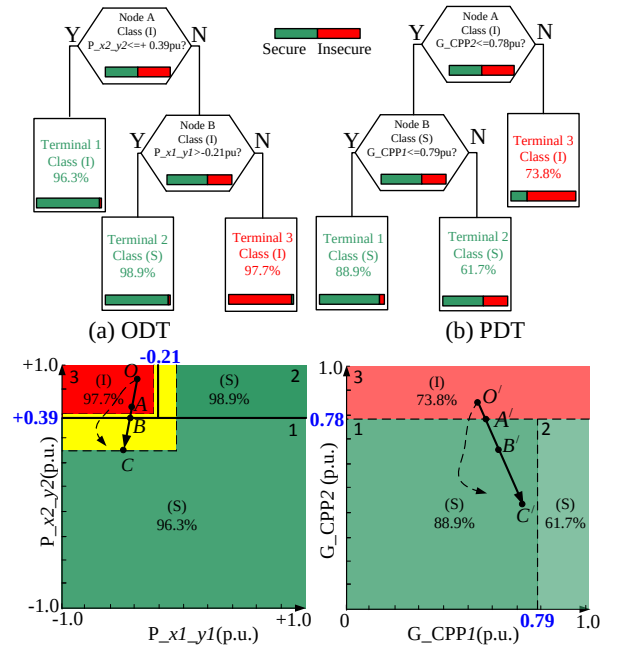


Fig. 7. Systematic approach for DSA and preventive control scheme

As shown in Fig. 7, this systematic approach offline trains two paralleled DTs for each critical contingency based on 24-hour horizon system prediction data, such as load forecast, weather forecast, unit commitment-based generation plan, network topology as well as the unavailability of system elements due to scheduled maintenance, etc. Fed with online measurements, ODT is employed for online DSA to identify the margins of predictors against their thresholds determined from DT training. If any online measurements of predictors violate the thresholds, ODT would provide situational awareness on insecurity if that contingency really happens. At the same time, PDT would provide system operators with preventive control schemes to drive the state to a new OC without insecurity under that contingency. Therefore, the parallel and cooperative utilization of PDT and ODT in the control schemes provides both the situational awareness and the preventive control against critical contingencies.

C. Control Strategy based on ODT and PDT



(c) 2-D nomogram of ODT (d) 2-D nomogram of PDT

Fig. 8. Illustration of observation DT and prevention DT.

As illustrated in Fig. 8, two 2-dimensional (2-D) nomograms in (c) and in (d) are adopted to represent the secure operating regions determined by ODT in (a) and the PDT in (b) from the predictors and their thresholds, respectively. When the current OC "*O*" is in the insecure region shown in Fig. 8(c), the direction of preventive control can be easily found in Fig. 8(d), i.e. to reduce generation in CPP*2*. Moreover, the variation in generators' outputs will definitely lead to the variation of the power flows in transmission lines, so the trajectory in PDT nomogram has its corresponding projection in ODT nomogram, for example the dashed lines in both Fig. 8(c) and Fig. 8(d).

Additionally, many constraints on OCs should still apply. For example, in order to maintain the international power exchange invariant, the sum of generation from involved CPP, CHP generation and wind power generation minus network loss and total load consumption must maintain as their

scheduled value, as defined by (9).

$$\sum_{i=1}^{n} Gr_i + \sum_{j=1}^{p} Dr_j + \sum_{k=1}^{m} Wr_k - Pr_{loss} - Pr_{load} = \sum_{i=1}^{n} Gs_i + \sum_{j=1}^{p} Ds_j + \sum_{k=1}^{m} Ws_k - Ps_{loss} - Ps_{load} \quad (9)$$

where n, p and m are the total number of involved CPP generators, CHP generators and wind power plants respectively. Gr, Dr, Wr, Gs, Ds and Ws are real-time values and scheduled values of CPP generation, CHP generation and wind power generation in each generation unit respectively.

Thus, the process-cum-direction of preventive control can be represented by the trajectory shown in Fig. 8(d) by the solid line in PDT nomogram. "*O*" and "*O'* " are the original insecure OC. "*A*" and "*A'* "represent the OC on the threshold of PDT, while "*B*" and "*B'* " represent the OC on the threshold of ODT. The thresholds in ODT are more accurate than the thresholds in PDT, so the regions below "*B*" and "*B'* " can be deemed as secure regions.

The block diagram shown in Fig 9 describes more clearly the detailed procedure of how ODT and PDT work in tandem to implement online DSA and preventive control scheme.

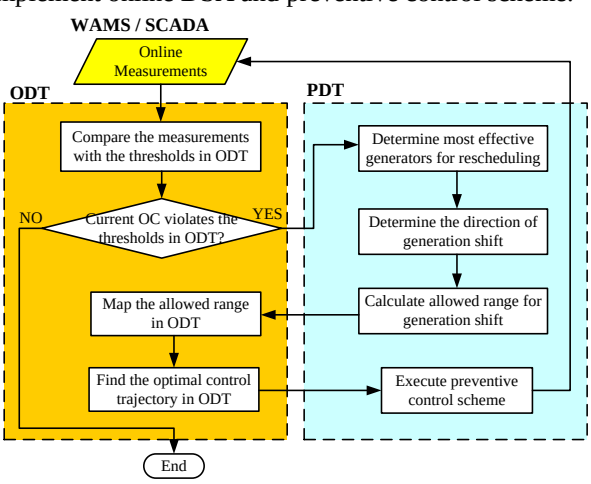


Fig. 9. Block diagram of the cooperative scheme with ODT and PDT.

D. Prior Probability for DT

As mentioned in Section III, prior probability is used to adjust the control guidelines over the tradeoff between dependability and security. By adjusting the ratio of prior probabilities of secure cases π_s and insecure cases π_i from 0.5/0.5 to 0.99/0.01, one can find the security boundary in 2-D ODT nomogram with higher security. Conversely, by adjusting the ratio π_s/π_i from 0.5/0.5 to 0.01/0.99, the security boundary with higher dependability can be found in 2-D ODT nomogram. The patch between these two boundaries is the fuzzy region, shown in yellow in Fig. 8(c). The regions below "*C*" and "*C'* " have high security since the probability of exception (i.e. insecure case) is below 0.01.

Therefore, by monitoring the OC in ODT nomogram, the operators are informed of the exact amount of generation rescheduling that should be adopted.

E. Optimization of Preventive Control

As mentioned earlier, PDT and ODT are able to provide operators with the allowed range of generation rescheduling. Then the optimal control trajectory is searched out by minimizing the total economic cost due to generation rescheduling, as $f(x,\lambda,\mu)$ defined in (10). A security constrained optimal power flow problem is formulated as

$$\text{min.} \quad f(x,\lambda,\mu) = c(x,\lambda) + p(x,\mu) \quad (10)$$

$$\text{s.t.} \quad g(x,\lambda,\mu) = 0 \quad \text{and} \quad h(x,\lambda,\mu) \le 0 \quad (11)$$

$$\lambda \in \mathcal{R} \text{ and } \mu \notin \mathcal{R}$$

where x represents the variables in power flow, λ and μ are control variables, e.g. generation outputs of CPPs involved in preventive control. $\mathcal{R}$ is a set representing the allowed range of generation rescheduling to maintain international power exchange invariant. Two items on right side of (10) are respectively the cost of generation rescheduling and the penalty on violation of scheduled international power exchange, (11) gives equality constraints i.e. power flow equations and inequality constraints representing operational constraints, i.e. security criteria.

VI. Case Study

A. Danish Power System

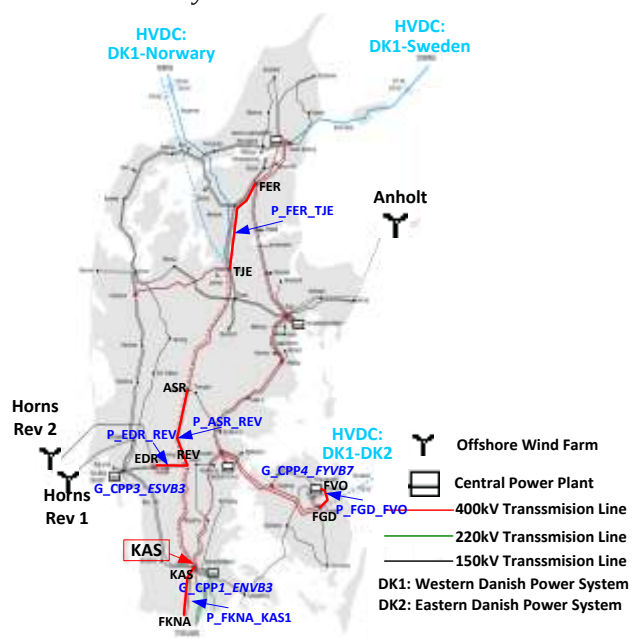


Fig. 10. Geographical map of western Danish power system.

The scheme proposed in this paper is tested on the operational detailed model of western Danish power system with about 400 buses, 200 lines, 8 CPP units and 150 CHP units. Denmark, which currently produces around 28% of electricity from wind, plans to realize 50% wind share of electricity production by 2025 with wind turbines, especially offshore wind farms. Currently onshore and offshore wind farms are integrated in the system with capacities of 2232MW and 369MW respectively. A new offshore wind farm (Anholt) with 400MW capacity is expected to be commissioned in 2013. Further, about 40% of today's total installed capacity in Danish system is decentralized generation units, such as onshore wind farms and CHP units. The geographical map of western Danish transmission system is shown in Fig. 10.

Cross border interconnections of western Danish power system to external grids are strong. So the abundance of hydro power generation in Norwegian and Swedish power systems can cooperate with the wind power generation in Denmark and Germany. The 400kV transmission system acts as the power transmission corridor, which is subjected to significant amount of active power transport.

Under the circumstances of such high penetration of wind generation and other DG, the wind forecast and the prediction of DG are not accurate, which lead to considerable mismatch between the predicted power flow and the actual power flow patterns in real time, so the online wide-area preventive control scheme in Danish grid is of great significance.

B. Analysis Tools

In this research, four tools have been used to develop the proposed approach: *DIgSILENT/PowerFactory* is used to create system OCs and perform power flow analysis and T-D simulations, which is interfaced with *Excel* via *DIgSILENT* Programming Language (DPL) to manage simulations and the results; *Salford Predictive Miner* [24] including CART and RF sub-packages is used for data mining; *MATLAB* is used for data collection, database creation and surface fitting.

C. Creation of DTs

The training of DTs should be based on a database which is built offline by screening N_C "*n*-1" contingencies and "*n-k*" typical contingencies from Danish transmission system operator's (Energinet.dk) historical record and experience on each OC. The "*n*-1" contingencies are the three-phase faults at the terminals of 400/150kV transmission lines with clearing time of 0.12 seconds. The database contains not only the predictor values, e.g. active power, reactive power, phase angle, voltage and current, before the disturbances calculated by power flow, but also the results of T-D simulations, i.e. secure (S) or insecure (I) based on criteria as given below:

- Transient stability: The system is considered as transient unstable for a given contingency, if the systems transient stability index (TSI) defined by (12) is lower than 10%, in which $\Delta\delta_{max}$ is the maximum angle separation of any two rotor angles in degree.

$$TSI = \left[(360 - \Delta\delta_{\max})/(360 + \Delta\delta_{\max})\right] \times 100\% \qquad (12)$$

- Short-term voltage security: The system is considered to be insecure if duration of any bus voltage going out of range from 0.8p.u. to 1.1p.u. is longer than 0.5sec.

Other criteria e.g. frequency drop, reactive power starvation, oscillation damping, etc. can also be included in this approach by simple modification in the programming. However, due to the severity status and special requirement of Danish power system, other specific criteria are not included for examination. Out of all possible contingencies, only a small proportion can result in the insecurity of power system and only those corresponding critical OCs violate the security criteria. Hence, only those critical contingencies will be selected to generate the contingency-oriented DTs. To demonstrate the proposed approach, the maximum load scenario is selected as the candidate scenario and the contingency selected is short circuit in 400kV *KAS_400_LAG* overhead line close to *KAS* substation, as tagged in Fig. 10.

Based on bisection search technique programmed by *DIgSILENT/DPL*, the approximate security boundary for contingency near *KAS* substation under maximum loading scenario is drawn by *MATLAB surface fitting toolbox*, shown in Fig.11. The upper side is predicted to be the insecure region and the lower side is predicted to be the secure region.

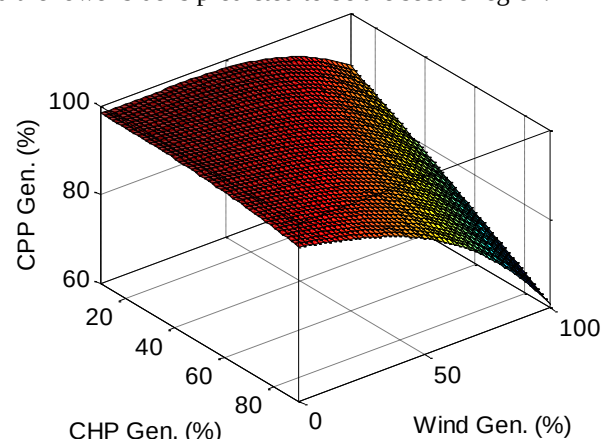


Fig. 11. The security boundary.

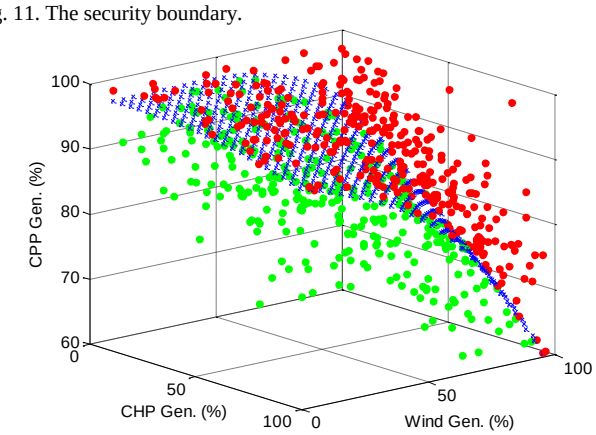


Fig. 12. The sampled OCs.

Then, importance sampling is utilized to bias the sampling towards this security boundary so that the cases closer to the security boundary would have higher probability to be selected for final refined database. Additionally, the number of cases in insecure region and secure region are controlled to be generally the same to maximize the entropy of the database. As shown in Fig. 12, given the standard deviation σ=0.1, 330 OCs each in secure region and insecure region for offline study are generated by importance sampling respectively, in which each spot represents an OC for the corresponding percentages of total CPP generation. Moreover, generator outputs are subjected to random distribution and wind farm outputs are based on the probability distribution density of forecast error with respect to forecasted wind power generation in Danish power system [25]. The process considering randomization on generator outputs while maintaining the total generation can assist the PDT to automatically find the most effective units to reschedule.

It is assumed that measurements are available from entire 400kV transmission system including all CPPs' generation outputs (G_CPP*x*). 660 power flow calculations (P_*x*_*y*,

Q_*x*_*y*) before the disturbance are conducted to create the predictors of the database and 660 T-D simulations are carried out for the results of security after the disturbance. 80% of the cases are randomly selected to form the LS, and the rest 20% form the TS. Finally, The PDT and an ODT created by CART are shown in Fig.13 and Fig.14, where inner and terminal nodes are respectively tagged with capital letters and numbers.

It is worth to mention that by considering phase angle differences between any two buses (A_*x*_*y*), the accuracy of DSA is improved. The comparison of accuracy between the measurement vectors with and without A_*x*_*y* shows the superiority of WAMS over SCADA by increasing the accuracy of about 3%, as shown in Table I. However, in a small power system with relative less line loading, the angle differences are relatively small which may result in erroneous judgment if it is not taken carefully during practical implementation. Some other advanced algorithms such as RF can also be used to predict the security with higher accuracy, as shown in Table I. However, the model trained by RF contains a large number of deep-grown DTs, which are difficult to be interpreted for preventive control. The combination of RF and preventive control is currently being pursued. As mentioned before, the values of accuracy still indicate with lower number than industrial requirement due to the implementation of importance sampling. A detail analysis regarding this issue is given in Appendix. Besides, one can easily adjust prior probability in the process of DT training to find the fuzzy region so as to significantly increase the reliability to achieve '3 nines' reliability standard [26].

TABLE I
THE PERFORMANCE OF DECISION TREES

Datasets	Insecure (I/S)	Secure (S/I)	Average (%)	Overall (%)
LS of ODT w/o A_*x*_*y* by CART	**257**/12	**252**/6	96.61	96.58
TS of ODT w/o A_*x*_*y* by CART	**73**/4	**51**/5	92.94	93.23
LS of ODT w/ A_*x*_*y* by CART	**255**/14	**256**/2	97.01	96.96
TS of ODT w/ A_*x*_*y* by CART	**76**/1	**52**/4	95.78	96.24
OOB test of ODT w/ A_*x*_*y* by RF	**299**/15	**338**/8	96.61	96.58
TS of ODT w/ A_*x*_*y* by RF	**76**/1	**53**/3	96.67	96.99

In Fig.13, ODT has five critical attributes of transmission lines, i.e. P_*FKNA_KAS1*, P_*FGD_FVO*, P_*FER_TJE*, P_*EDR_REV*, P_*ASR_REV*, and one critical attribute of generator output G_CPP*1_ENVB3*, which have been highlighted in Fig. 10. In Fig. 14, PDT has three critical attributes from three CPPs, i.e. G_CPP*1_ENVB3*, G_CPP*3_ESVB3*, G_CPP*7_FYVB7*. Most critical attributes selected by ODT for transmission lines belong to one backbone on Jylland Peninsula and one for the key transmission line on Fyn Island. All the critical attributes selected by PDT are generators in the southern part, close to the selected contingency. P_*FKNA_KAS1* is one of the paralleled key transmission lines connecting German grid.

D. Preventive Control Based on DTs

The ODT and PDT in Fig. 13 and Fig. 14 can be reproduced to 2-D nomograms to depict the space and its regions, as shown in Fig. 15 and Fig. 16. In each region the percentage of correctness and the serial numbers of the corresponding nodes are indicated. The red regions are insecure regions tagged by (I), while the green regions are secure regions tagged by (S). The thresholds in ODT in Fig. 13 are highlighted by solid lines and blue figures in 2-D nomograms in Fig.15. The yellow regions between dashed lines are the fuzzy regions, in which the prior probability of insecure cases is between 0.01 and 0.99. As shown in Table II, the ODT has higher classification accuracy than that of PDT because fewer variables are selected as predictors of PDT. However, the lower accuracy of PDT does not affect the reliability of preventive control because PDT can successfully search out the most effective controllable variables and provide the control directions. As shown in Fig. 16, the PDT nomogram is capable of informing the most influential CPPs (*ENVB3*, *FYVB7* and *ESVB3*) that need to be controlled and their control directions, i.e. to reduce generation in *ENVB3* and *FYVB7* and simultaneously to increase generation in *ESVB3*. Fig 17 shows the annual data of total CPP generation, total CHP generation and total wind generation represented by percentages based on their installed capacities [27]. At 09:00am, Feb. 2nd, 2011, the OC is detected to be in the insecure region, shown by the dot tagged with "OC" in Fig. 18.

TABLE II
THE PERFORMANCE OF DECISION TREES

Dataset	Insecure(I/S)	Secure(S/I)	Ave. (%)	Ove.(%)
LS of ODT	**257**/12	**252**/6	96.61	96.58
TS of ODT	**73**/4	**51**/5	92.94	93.23
LS of PDT	**184**/85	**199**/59	72.77	72.68
TS of PDT	**53**/24	**32**/24	62.99	63.91

In order to maintain the constant value of total generation in Denmark, the equation (13) must be respected.

$$\mathrm{G\_CPP1\_}ENVB3+\mathrm{G\_CPP3\_}ESVB3+\mathrm{G\_CPP4\_}FYVB7=Const. \quad (13)$$

Other constraints such as PQ-capacity limits of each generator and individual limits of CPP generation rescheduling should also be applied, as given in Table III.

Hence for this particular case as defined by (13), a surface boundary can be found, within which the total generation is maintained constant, respecting the abovementioned constraints, as shown in Fig. 18. The trajectories "A", "B" and "C" are some of the feasible control directions on the surface which would lead the system to the secure region.

As shown in Fig.15, the surface of generation rescheduling in the 3-D space of involved generators can be reproduced by its corresponding surface in 2-D ODT nomogram, which shows the effect of generation rescheduling with more clarity in the feasible region as shown in Fig. 19(a) which is the enlarged version of Fig. 15(e). The green spots on the surface represent the secure cases, while the red spots represent the insecure cases. It can be observed that the trajectories "A", "B" and "C" are the control directions which are able to reliably draw the system to the secure region.

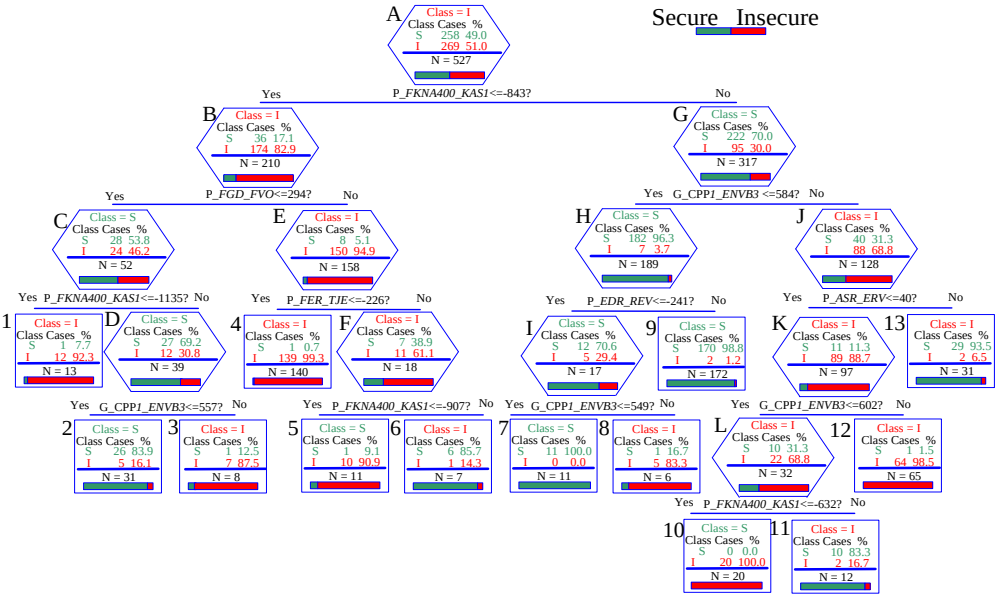


Fig. 13. The ODT for contingency near *KAS*.

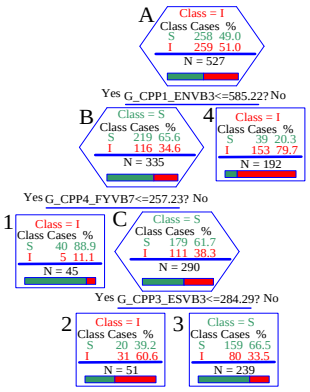


Fig. 14. The PDT for contingency near *KAS*.

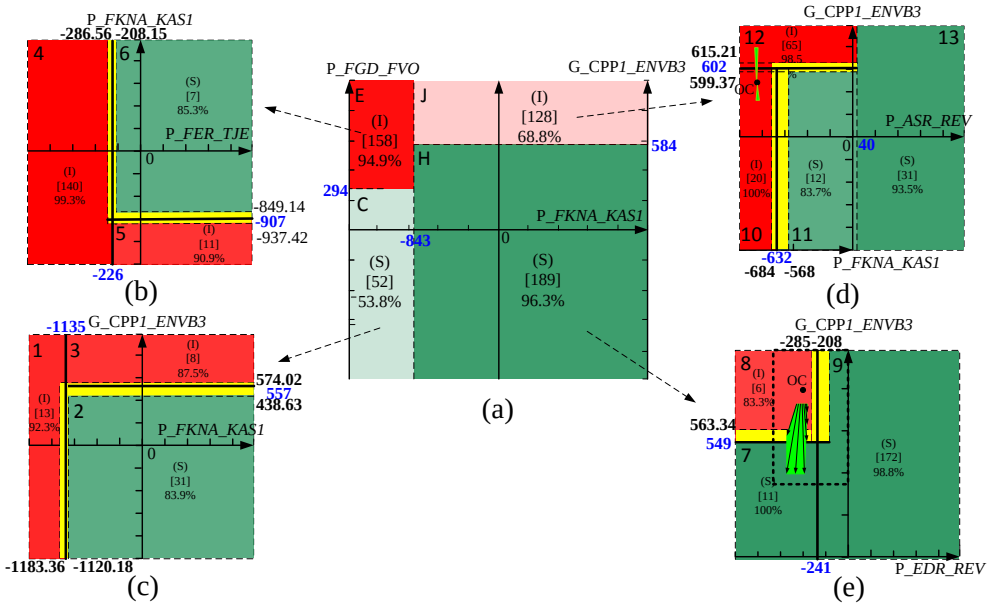


Fig. 15. The 2D-nomogram of ODT

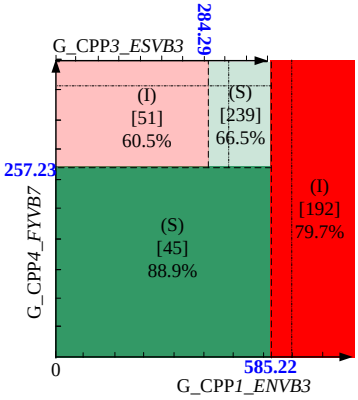


Fig. 16. The 2D-nomogram of PDT.

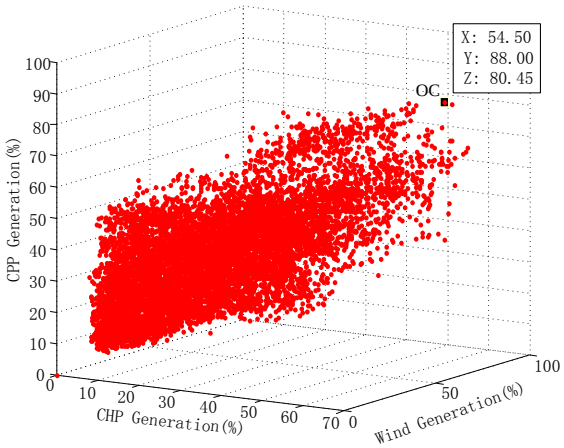


Fig. 17. Annual data of generation.

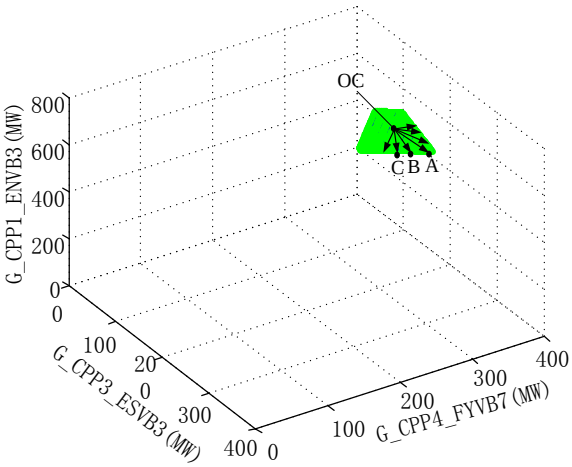
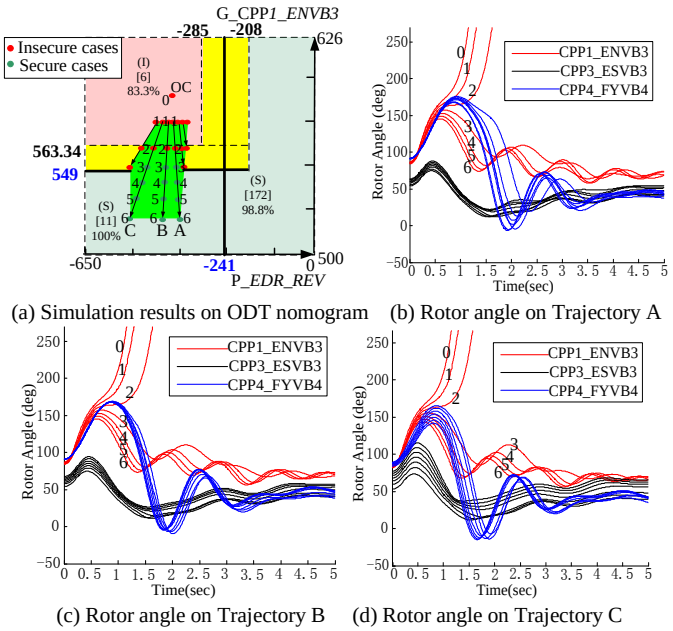


Fig. 18. Control constraint surface.



(a) Simulation results on ODT nomogram (b) Rotor angle on Trajectory A

(c) Rotor angle on Trajectory B (d) Rotor angle on Trajectory C

Fig. 19. Rotor angles curves of involved generators in Trajectories A~C.

The prediction of DT is followed by its verification through T-D simulations. Only the criterion of transient stability is violated in this case, so Fig. 19(b) (c) and (d) show the rotor angle curves of the involved generators for OCs tagged with "0" to "6" on the control trajectories "A", "B" and "C" respectively, in which the disturbance near *KAS* takes place at 0sec, and lasts for 0.12sec.

The results successfully verified the prediction of power system security as well as the guidelines of preventive control scheme. By rescheduling the generators instructed by this systematic preventive control scheme, the power system insecurity can be averted.

According to the actual regulations of Danish power system, (giving considerations to the prices of domestic reserve services and the penalty in cases of international exchange mismatch) further optimization on the trajectory of preventive control is conducted to minimize the total cost incurred by generation rescheduling, as defined in (14).

$$\min . C = \sum_{i \in \mathbf{G}} C_i + f\left(\Delta P_{EX}\right) \tag{14}$$

1) Cost of reserve services

$$C_i = C_{Fi} + P_{UPi} \cdot \left|\Delta G_{UPi}\right| + P_{DNi} \cdot \left|\Delta G_{DNi}\right|, \ \forall i \in \mathcal{G} \tag{15}$$

where

$$\Delta G_{UP_i} = \begin{cases} Gr_i - Gs_i & \text{if } Gr_i > Gs_i \\ 0 & \text{else if } Gs_i \le Gr_i \end{cases} \tag{16}$$

$$\Delta G_{DNi} = \begin{cases} 0 & \text{if } Gr_i \ge Gs_i \\ Gr_i - Gs_i & \text{else if } Gr_i < Gs_i \end{cases} \tag{17}$$

$$\text{s.t.} \quad G_i^{\min} \le Gr_i \le G_i^{\max} \tag{18}$$

$$\text{s.t.} \quad 0 \le \Delta G_{UPi} \le \Delta G_{PRi}^{\max} \text{ and } \Delta G_{PRi}^{\min} \le \Delta G_{DNi} \le 0 \tag{19}$$

As defined in (15)~(17), the cost of reserve services is composed of fixed cost C_{Fi} and variable cost depending on the actual quantity of generation rescheduling in effect, either upward or downward. The amount of generation rescheduling in each generator should also subject to the P-Q capacity and the limitations of the maximum available generation reserves in both directions, defined in (18) and (19).

2) Penalty due to mismatch of international power exchange

$$\Delta P_{EX} \approx \sum_{i \in \mathbf{G}} \Delta P_{UPi} + \sum_{i \in \mathbf{G}} \Delta P_{DNi}, \ \forall i \in \mathcal{G} \tag{20}$$

$$f\left(\Delta P_{EX}\right) = \begin{cases} P_{<50} \cdot \Delta P_{EX} & \text{if } \left|\Delta P_{EX}\right| \in (0,50] \\ P_{<100} \cdot \Delta P_{EX} + C_{PEN1} & \text{if } \left|\Delta P_{EX}\right| \in [50,100) \\ P_{\ge 100} \cdot \Delta P_{EX} + C_{PEN2} & \text{if } \left|\Delta P_{EX}\right| \in [100,\infty) \end{cases} \tag{21}$$

Assuming that the network loss is invariant during preventive control, the imbalance between generation and load introduced by generation rescheduling in Denmark is compensated by German power system, as defined by (20). For mismatch between actual and scheduled power exchange larger than 50MW or 100MW, penalties C_{PEN1} or C_{PEN2} are applicable respectively, as defined in (21). As given in Table III, the prices of reserve services from participating generators in Denmark and the cost of international power exchange with Germany are assumed based on typical data.

TABLE III
THE PRICES OF RESERVE SERVICES AND INTERNATIONAL POWER EXCHANGE

Price	CPP1_ENVB3	CPP3_ESVB3	CPP4_FYVB4
G_i^{max} (MW)	626	378	372
G_i^{min} (MW)	188	98	110
ΔP_{UPi}^{max} (MW)	+39	+113	+32
ΔP_{DNi}^{max} (MW)	-75	-64	-38
C_{Fi} (DKK)	2230	1940	1880
C_{UPi} (DKK/MW)	535	390	450
C_{DNi} (DKK/MW)	328	208	236
Price	**International Power Exchange with Germany**		
$C_{<50}$ /$C_{<100}$ /$C_{\ge 100}$	400 / 450 / 500 (DKK/MW)		
C_{PEN1}/ C_{PEN2}	100,000 / 500,000 (DKK)		

Fig. 20 shows the cost of preventive control along trajectory A, B and C. After optimization, trajectory A is found to be the most economical trajectory and the optimal objective OC after rescheduling is below the threshold of reliable security boundary between "3" and "4" on trajectory A. The minimum cost is 42,392 Danish Kroners (DKK).

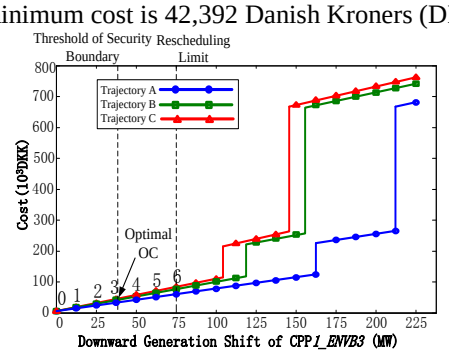


Fig. 20. Rotor angles curves of involved generators in Trajectories A, B and C.

To evaluate the overall reliability of this approach, multiple contingency-oriented DTs are created for eight most critical *n-1* contingencies which have been screened out by critical clearing time (CCT) calculations of Danish power system in [28]. The size, overall accuracies of LS and TS of these DTs are shown in Table IV. Among these contingencies, only five events violate the transient stability or short-term voltage security criteria. For each contingency, 20 insecure OCs are randomly generated. 98% of the random generated insecure OCs can be controlled and guided back to the secure

region (across the fuzzy region), if international power exchange is maintained as invariant. The remaining 2% OCs can certainly be controlled by varying the international exchange power with Germany, however at the cost of penalty.

TABLE IV
VERIFICATION OF THE MOST CRITICAL CONTINGENCIES

Con. No.	Fault Event	Switch Event	DT Size	Ove.(%) of LS	Ove.(%) of TS	Suc. Rate
1	KAS	KAS_400_LAG	13	96.58	93.23	**20**/20
2	KAS	KAS_400_REV	14	97.54	94.66	**19**/20
3	LAG	LAG_400_SVS	18	96.03	93.13	**19**/20
4	LAG	LAG_400_MAL	17	96.39	95.52	**20**/20
5	TRI	FER_400_TRI	n/a	n/a	n/a	n/a
6	TRI	MAL_400_TRI	21	97.87	96.52	**20**/20
7	NVV	NVV_400_VHA	n/a	n/a	n/a	n/a
8	NVV	FER_400_NVV	n/a	n/a	n/a	n/a
Tot.						**98.0%**

VII. CONCLUSION AND DISCUSSION

This paper presents a DSA method based on contingency-oriented DTs with high accuracy and proposes an online systematic preventive control scheme based on cooperative application of parallel DTs, i.e. ODT and PDT. The scheme was demonstrated on the operational model of western Danish power system. The verified results have shown that the generation rescheduling guided by DTs is able to reliably control and bring the system back to security region hence prevent the possible power system insecurity. The proposed cost effective optimization for preventive control is capable of finding the optimal control trajectory.

During this control strategy, the cost of generation rescheduling adopted domestically is significantly less compared to the penalty on violating the prescheduled exchange across international tie lines. However, in some specific cases, especially for peak load OCs where local generators might be operating close to their limits, and for large exchange to neighboring countries, curtailment on power exchange across international tie lines becomes inevitable to maintain system security.

APPENDIX

Assuming that all cases by IS are within the overlapping region, the accuracy percentages calculated by different sampling methods are expressed by equations in Table V, where m_I and m_N are the numbers of misclassified cases by IS and NS respectively; N_1 and N_2 are the numbers of cases sampled inside the overlapping region and outside the overlapping region, respectively; δ is the rare-event probability that OCs locates in the overlapping region, which is from the statistical data of industry. Normally, $m_I > m_N$, $N_1 < N_2$, and $\delta << 1$, so the accuracy percentage with database prepared by IS indicates lower values, as shown in (22).

TABLE V
EXPRESSIONS OF PERCENTAGE OF ACCURACY

Sampling methods	Accuracy (%)
Internal test with N_1 samples by IS	$(1-m_I/N_1)*100$
Internal test with N_1+N_2 samples by NS	$[1-m_N/(N_1+N_2)]*100$
Industrial data	$\{1-\delta m_N/[\delta N_1+(1-\delta)N_2]\}*100$

$$1-\frac{m_I}{N_1} < 1-\frac{m_N}{N_1+N_2} < 1-\frac{\delta m_N}{\delta N_1+(1-\delta)N_2} \quad (22)$$

ACKNOWLEDGMENT

Authors would like to thank Energinet.dk (Danish national TSO) for providing the data of western Danish power system.

REFERENCES

[1] V. Madani *et al.*, "IEEE PSRC report on global industry experiences with system integrity protection schemes (SIPS)," *IEEE Trans. Power Syst.*, vol. 25, no. 4. pp. 2143-2155, Oct., 2010.
[2] Q. Zhou, J. Davidson, and A. A. Fouad, "Application of artificial neural networks in power system security and vulnearability assessment," *IEEE Trans. Power Syst.*, vol. 9, no. 1. pp. 525-532, Feb., 1994.
[3] S. Kalyani, and K. S. Swarup, "Classification and assessment of power system security using multiclass SVM," *IEEE Trans. Systems, Mans, and Cybernetics*, vol. 41, no. 5. pp. 753-758, Sep., 2011.
[4] K. Sun, S. Likhate, and V. Vittal *et al.*, "An online dynamic security assessment scheme using phasor measurement and decision trees," *IEEE Trans. Power Syst.*, vol. 22, no. 4. pp. 1935-1943, Nov, 2007.
[5] V. Krishnan, J. D. McCalley, and S. Henry *et al.*, "Efficient database generation for decision trees based power system security assessment," *IEEE Trans. Power Syst.*, vol. 26, no. 4. pp. 2319-2327, Nov, 2011.
[6] R. Diao, K. Sun, and V. Vittal *et al.*, "Decision tree-based online voltage security assessment using PMU measurements," *IEEE Trans. Power Syst.*, vol. 24, no. 2. pp. 832-839, May, 2009.
[7] E. E. Bernabeu, *et al.*, "Methodology for a security/dependability adaptive protection scheme based on data mining," *IEEE Trans. Power Del.*, vol. 27, no. 1. pp. 104-111, Jan. , 2012.
[8] N. Senroy *et al.*, "Decision tree assisted controlled islanding," *IEEE Trans. Power Syst.*, vol. 21, no. 4. pp. 1790-1797, Nov. , 2006.
[9] R. Diao, V. Vittal, K. Sun, *et al*, "Decision tree assisted controlled islanding for preventing cascading events", *IEEE PES Power Systems Conference & Exposition*, Seattle, March 15-18, 2009.
[10] E. M. Voumvoulakis *et al.*, "Decision trees for dynamic security assessment and load shedding scheme," in *Proc. Power Eng. Soc. General Meeting*, Montreal, QC, Canada, Jun. 2006.
[11] K. Mei, and S. M. Rovnyak, "Response-based decision trees to trigger one-shot stabilizing control," *IEEE Trans. Power Syst.*, vol. 19, no. 1, pp. 531–537, Feb. 2004.
[12] Y. Hou, C. C. Liu, and K. Sun *et al.*, "Computation of milestones for decision support during system restoration," *IEEE Trans. Power Syst.*, vol. 26, no. 3. pp. 1399-1409, Aug. , 2011.
[13] K. A. Papadogiannis, N. D. Hatziargyriou, "Optimal allocation of primary reserve services in energy markets," *IEEE Trans. Power Syst.*, vol. 19, no. 1. pp. 652-659, Feb., 2004.
[14] I. Genc, R. Diao, and V. Vittal *et al.*, "Decision tree-based preventive and corrective control applications for dynamic security enhancement in power systems," *IEEE Trans. Power Syst.*, vol. 25, no. 3. pp. 1611-1619, Aug., 2010.
[15] I. Genc, R. Diao, and V. Vittal, "Computation of transient stability related security regions and generation rescheduling based on decision trees," in *Proc. PES General Meeting*, Minneapolis, MN, USA, Jul. 2010.
[16] R. Diao *et al.*, "Design of a real-time security assessment tool for situational awareness enhancement in modern power systems," *IEEE Trans. Power Syst.*, vol. 25, no. 2. pp. 957-965, May, 2010.
[17] I. Kamwa *et al.*, "Development of rule-based classifier for rapid security assessment of wide-area post disturbance records," *IEEE Trans. Power Syst.*, vol. 24, no. 1. pp. 258-270, Feb., 2009.
[18] L. Breiman, J. Friedman, R. A. Olshen, and C. J. Stone, Classification and Regression Trees. Belmont, CA, Wadsworth, 1984.
[19] L. Wehenkel *et al.*, "An artificial intelligence framework for on-line transient security assessment of power systems," *IEEE Trans. Power Syst.*, vol. 4, no. 2. pp. 789-800, May, 1989.
[20] I. Kamwa, S. R. Samantaray, and G. Joos, "Catastrophe predictors from ensemble decision-tree learning of wide-area severity indices," *IEEE Trans. Smart Grid*, vol. 1, no. 2, pp. 144-158, Sep., 2010.
[21] I. Kamwa *et al.*, "On the accuracy versus transparency trade-off of data-mining models for fast-response PMU-based catastrophe predictors," *IEEE Trans. Smart Grid*, vol. 3, no. 1, pp. 152-161, Mar., 2012.
[22] L. Breiman, "Random forest," *Mach. Learn.* vol. 45, pp. 5-32, 2001.
[23] E. A. Unger *et al.*, "Entropy as a measure of database information," in *Proc. 6th Annu. Computer Security Applications Conf.*, 1990, pp. 80–87.
[24] CART Tree-Structured Non-Parametric Data Analysis [Online]. Available: http://www.salford-systems.com/en/products/spm

[25] W. Hu, Z. Chen, and B. Bak-Jensen, "Stochastic optimal wind power bidding strategy in short-time electricity market," *International Review of Electrical Engineering*, vol. 7, no. 1. pp. 186-197, Feb., 2012.

[26] Electric Advisory Committee: 'Smart grid: enabler of the new energy economy'. US Department of Energy, Dec. 2008 [Online]. Available: http://energy.gov/sites/prod/files/oeprod/DocumentsandMedia/final-smart-grid-report.pdf

[27] Hourly Danish power system data [Online]. Available: http://www.energinet.dk/EN/El/Engrosmarked/Udtraek-af-markedsdata/Sider/default.aspx

[28] C. Liu, Z. Chen, and C. L. Bak *et al.*, "Transient stability assessment of power system with large amount of wind power penetration: the Danish case study," in *Proc. the 10th International Power and Energy Conf.*, Ho Chi Minh City, Vietnam, Dec., 2012.

BIOGRAPHIES

Chengxi Liu (M'10) received his B. Eng. and M. Sc. degrees in College of Electrical and Electronic Engineering, Huazhong University of Science and Technology (HUST), China, in 2005 and 2007 respectively. He has working experience of three years in industry in China and Hong Kong S.A.R.. He is at present pursuing the Ph.D. degree in electrical engineering at the Department of Energy Technology, Aalborg University, Denmark, and he is a visiting scholar in the Department of EECS, University of Tennessee, USA. His research interests include wide area power system protection and control, wind power integration as well as the application of artificial intelligence.

Kai Sun (M'06-SM'13) received the B.S. degree in automation in 1999 and the Ph.D. degree in control science and engineering in 2004 both from Tsinghua University, Beijing, China. He was a postdoctoral research associate at Arizona State University, Tempe, from 2005 to 2007, and was a project manager in grid operations and planning areas at EPRI, Palo Alto, CA from 2007 to 2012. He is currently an assistant professor at the Department of EECS, University of Tennessee in Knoxville.

Zakir Hussain Rather (M'11) received Master of Technology (M.Tech) degree in Power Systems from Indian Institute of Technology (IIT) Delhi, India and bachelor's degree in Electrical Engineering from Jammu University, India. He has industrial experience of around three years in power sector. He is working with kk-electronic a/s based in Denmark and is currently engaged with industrial PhD at Department of Energy Technology, Aalborg University, Denmark. His areas of interest include power system security and stability, renewable energy integration, wide area monitoring and control, HVDC and FACTS devices.

Zhe Chen (M'95–SM'98) received the B.Eng. and M.Sc. degrees from Northeast China Institute of Electric Power Engineering, Jilin City, China, and the Ph.D. degree from University of Durham, U.K. Dr Chen is a full Professor with the Department of Energy Technology, Aalborg University, Denmark. He is the leader of Wind Power System Research program at the Department of Energy Technology, Aalborg University and the Danish Principle Investigator for *Wind Energy* of *Sino-Danish Centre for Education and Research*. His research areas are power systems, power electronics and electric machines; and his main current research interests are wind energy and modern power systems. He has more than 300 publications in his technical field. Dr Chen is an Associate Editor (Renewable Energy) of the IEEE Transactions on Power Electronics, a Fellow of the Institution of Engineering and Technology (U.K.), and a Chartered Engineer in the U.K.

Claus Leth Bak (M'95–SM'98) was born in Århus, Denmark, on April 13th, 1965. He received the B.Sc. with honors in Electrical Power Engineering in 1992 and the M.Sc. in Electrical Power Engineering at the Department of Energy Technology at Aalborg University in 1994. After his studies he worked as a professional engineer with Electric Power Transmission and Substations with specializations within the area of Power System Protection at the NV Net Transmission Company. In 1999 he got employed as an Assistant Professor at ET-AAU, where he is holding a Professor position today. His main Research areas include Corona Phenomena on Overhead Lines, Power System Modeling and Transient Simulations, Power System Protection and HVDC-VSC Offshore Transmission Networks. He is the author/coauthor of app. 100 publications. He is a member of Cigré C4.502, Cigré SC C4 and Danish Cigré National Committee. He is an IEEE senior member.

Paul Thøgersen (M'92–SM'03) was born in Thy, Denmark, on June 29, 1959. He became M.Sc. EE. in 1984, and Ph.D. in 1989, at Aalborg University, Denmark. He was employed as an assistant professor at Aalborg University from 1988 to 1991. From 1991 to 2005 he worked at Danfoss Drives a/s, first as a research and development engineer and later as manager of technology, mainly responsible for the drives control technology area. Since 2006, he has been manager of the modeling and control group, which is a part of the kk-electronic a/s development department. He has always kept a close relationship to Aalborg University, resulting in various co-authored papers and participation in more than 10 PhD project advisory groups. He received the Angelo Award in 1999 for his contributions to the development of industrial drives, and he is a senior member of IEEE.

Per Lund (M'95–SM'02) is Chief Engineer at Energinet.dk, the Danish TSO owned by the Danish Climate and Energy Ministry. For the last six years he has been focusing his research activities on the Danish Cell Controller Pilot Project, which seeks to create the prototype of the future Danish intelligent power system. During this period, Dr. Lund has in parallel worked with advanced PMU/WAMS technologies such as Early Warning Systems based on Voltage Angel Stability prediction, and contributed to the development of National Grid Codes for fossil fired power stations. He earned his M.S. and Ph.D. degrees in Electrical Engineering from the Technical University of Denmark in 1983 and 1985 respectively. He is author or co-author of more than 20 publications in international journals and conference proceedings and has a general background in power system planning in large utility-owned systems. For a period of 13 years Dr. Lund worked worldwide as a senior engineer at Danish Power Consult, a former Danish based international consulting engineering company. The assignments abroad and at various industrial clients in Denmark ranged from feasibility studies concerning the introduction of wind farms in diesel powered island systems, transmission system reinforcements and expansions, power system loss reduction to specialized transient analysis of shaft or gear wheel breakdown in combined cycle generation plants following major faults in the electrical transmission system. From his previous 6 year employment in the Planning Department of the former Danish Electricity Consortium Elsam A/S he has gained comprehensive experience in utilizing computer programs for steady state and transient stability analyses used in the design and planning of power transmission systems. He has developed the SETPOS program system. Dr. Lund is a Senior Member of the IEEE and a certified European Engineer.