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Analyzing the Static Security Functions of a Power System Dynamic Security Assessment Toolbox

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ABSTRACT

This paper presents the results from the iTesla offline workflow for a given set of contingencies applied to Nordic 44 power system model and are verified against the results from a similar workflow implemented separately using Python/Matlab that uses PSS/E analysis function. 21 (20 'N-1' and 1 'N-2') contingencies were created on the Nordic 44 power system model and was executed on 2928 snapshots (April to July 2015). This verification is only performed for the (static) steady state stability assessment results of the offline workflow. The generated decision trees (DTs) by the iTesla platform were verified for different network operating conditions. It was observed that the generated DT's are consistent for the given set of operating conditions. It would be beneficial to check how the rules generated from DT's with four months of data (April to July 2015) vary from the rules generated with one year of data (2015). The verification approach adopted provides a useful means to test and verify dynamic security assessment (DSA) tools' with an independent implementation of some of the tools' functions, this can be of value to other DSA tool developers.

1. Introduction

1.1. Motivation

The deployment of renewable energy sources increases network forecast uncertainty, making it difficult to accurately assess grid security levels during operation. The secure integration of generation from renewable energy sources (RES) into today's power systems requires an appropriate assessment of the security of the system in near real-time. The uncertainty associated with RES makes it unfeasible to tackle this problem via a brute-force approach, i.e. it is impractical to execute detailed static and dynamic simulations for all possible security problems.

An approach is to combine offline and online applications assessing different phenomena (steady-state violations determined by power flow computations or instabilities through dynamic simulations) with uncertainty. This allows bridging the gap between risk-based methods and traditional deterministic approaches, by introducing the concepts of probability and impact associated to the contingencies as well as the uncertainty of the energy consumption forecast and of the power production of RES.

Using this approach, the iTesla[1] project developed a platform for static and dynamic security assessment. The computations are performed with two complementary offline and online workflows. The offline workflow builds security rules and uncertainty models for use in the online workflow. Online, the security rules are applied to plausible grid operation states within the uncertainty margin of the forecasted network state, in order to identify the contingencies for which control actions are needed, while limiting the number of dynamic simulations to be performed online.

1.2. Literature review

The tools developed in [1,2] were able to manage several analysis applications within a single environment using a deterministic approach. Research projects have also dealt with the issue of security-assessment tool integration [3]. However, full integration of methods, models, tools, and analytics within a single platform is desirable. Computations based on different models may be inconsistent; the various outputs become fragmented, difficult to interpret and synthesize into a meaningful and actionable form. Therefore, it is becoming crucial to exploit an integrated environment that can manage different tools: static and dynamic analyses, contingency filtering and ranking, margins and control actions computation, and effective synthesis and

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[1] iTESLA (Innovative Tools for Electrical System Security within Large Areas), online: www.itesla-project.eu.

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0142-0615/

visualization of results.

The uncertainty of future power systems operating conditions due to RES integration and introduction of the electricity market causes two main effects: on one side, the need for techniques to perform an online dynamic security assessment (DSA) [4], and on the other side, new tools performing a probabilistic assessment of the operational risk are becoming necessary to exploit power systems flexibility [5,6]. The proposed iTesla platform combines traditional deterministic and probabilistic risk-assessment tools effectively and can fulfill the requirements.

1.3. Contribution

In this paper, the results from the iTesla offline workflow for a given set of contingencies applied to Nordic 44 power system model [7] are verified with the results from a similar workflow implementation separately using Python/Matlab that uses PSS/E's analysis functions. While this verification is only performed for the (static) steady-state stability assessment results of the offline workflow, to the authors' knowledge, this is the only paper proposing means for cross-validation of iTesla platform functions, or any other DSA's functions. The aim of this paper is also to contribute to the body of knowledge by proposing new means to test and validate DSA tools [8,9], which if imitated by DSA tool providers, can help in gaining confidence and credibility in the tools' functions and results.

2. Background

The iTesla platform is an open source and modular software that supports operators in power system security assessment from several hours ahead of operation up to near real time. The platform also determines and quantifies their efficiency when they are needed. The iTesla platform can consider the uncertainties affecting power injections, such as non-dispatchable RES and loads, and the dynamic behavior of the grid, thanks to a filtering approach that takes advantage of machine learning techniques. The computations are performed in two complementary workflows, namely the offline and the online workflows (see Fig. 1). The offline workflow builds (1) security rules and (2) uncertainty models for use in the online workflow: the security rules are applied to plausible states in the "uncertainty domain" of the forecast under analysis, to identify the contingencies for which control actions are needed, while limiting the number of accurate network simulations to be performed online. Both workflows include different computation modules, each fulfilling a specific technical function such as power flow (PF) computation or time-domain (dynamic) simulations.

2.1. Offline workflow

The offline workflow builds a database of historical and simulated network conditions that are used to compute security rules, which will

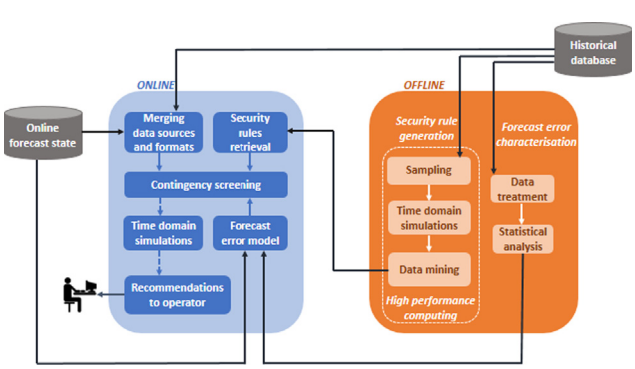

Fig. 1. iTesla workflow.

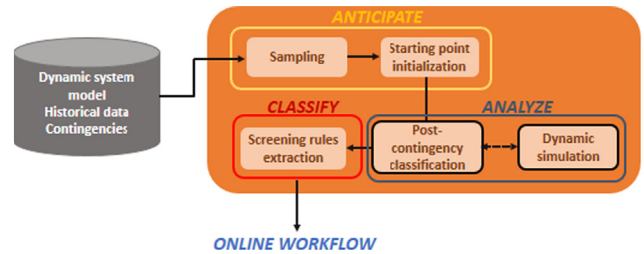

Fig. 2. Offline security assessment workflow.

serve to characterize future operating conditions as secure or unsecure. The process follows the triptych anticipate – analyze – classify as shown in Fig. 2.

Anticipate: To compliment historical data, a large number of additional plausible network states isbuilt (sampled), using the historical data. Uncertainties such as demand or wind power production are also modeled

Analyze: for each sampled network state, dynamic simulations are performed to quantify the impact of various contingencies (overloads, transient instability, etc.).

Classify: machine learning algorithms are used to compress the results from the analysis stage into a set of security rules (threshold values) discriminating secure from unsecure network states. These rules are used by the online platform to quickly classify unseen network states as safe/unsafe against a contingency.

2.2. Online workflow

During operation, the network forecasts are complimented with an uncertainty margin (loads, RES) and the iTesla online workflow allows to perform a fast security assessment within this margin. First, plausible network states are sampled within the margin of uncertainty of the forecast, and then, the states are checked against the security rules computed offline, characterizing them as secure/unsecure.

For potentially unsecure network conditions, an additional but get limited number of dynamic simulations are performed and analyzed. If needed, curative/remedial actions are generated in order to assist the network operator. Further details about offline and online workflow of iTesla platform can be found in [10] and [11].

3. Application of the offline workflow to the Nordic44 power system model

The outputs from the offline workflow of the iTesla platform for a set of contingencies applied to the Nordic 44 power system model are verified against the results obtained from a similar workflow implemented separately using Python.

3.1. Nordic44. Power system model

The Nordic-44 Bus test system is an equivalent representation of the Nordic grid (Sweden, Norway and Finland) as shown in Fig. 3. and was originally implemented in PSS/E and Modelica [7,12]. It consists of 44 buses, 61 generators with various control systems (exciter, turbine, governor and stabilizer), 67 transmission lines (420 kV and 300 kV) and 43 loads. The regions shown in this model are defined according to the Nordic electricity market bidding regions. The entire historical market data for 2015 was matched w.r.t the powerflow results for this model and the details can be found in [7]. These snapshots are provided in CIMv14, Modelica and PSS/E (Siemens PTI) files. The software developed to generate these snapshots are also provided in [6].

To perform a meaningful assessment, it was necessary to match and consolidate the historical market data to the physical description of the

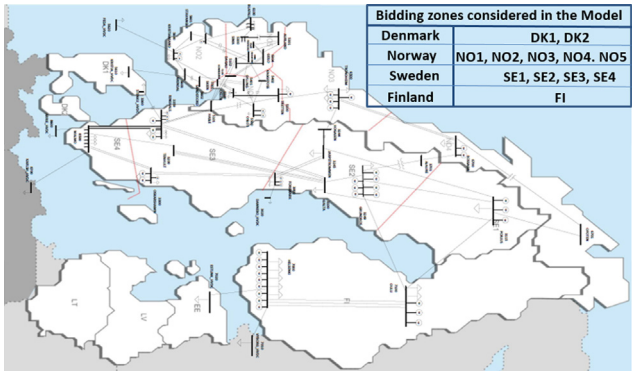

Fig. 3. Nordic 44 model mapped to the bidding zones of the Nordic Pool.

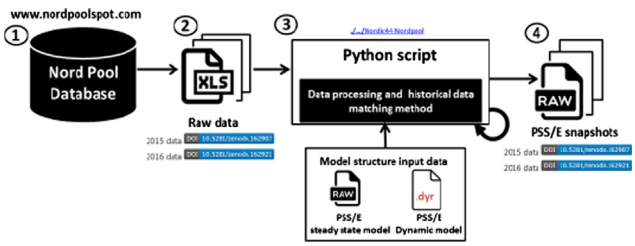

Fig. 4. Consolidation of the Nordic 44 snapshots.

Table 1
overload index parameters.

Variable	Description	Dimension	Units
f_x	Actual overload index	Scalar	–
N_l	Number of transmission lines	Scalar	–
S_{mean}	Mean apparent power flow	$\Re^{1\times Nl}$	MVA, p.u.
S_{max}	Max apparent power flow	$\Re^{1\times Nl}$	MVA, p.u.
w_f	Weighting factor of lines	$\Re^{1\times Nl}$	–
p	Exponent	Scalar	–

Table 2
under/over volatge index parameters.

Variable	Description	Dimension	Units
v_x	Under/over Voltage index	scalar	–
N_b	Number of buses	scalar	–
v_{init}	Nominal voltage (pre-fault)	$\Re^{1\times Nb}$	V, p.u.
v_{mean}	Mean voltage (post-fault)	$\Re^{1\times Nl}$	V, p.u.
v_{max}	Max. voltage allowed in bus	$\Re^{1\times Nl}$	V, p.u.
v_{min}	Min. voltage allowed in bus	$\Re^{1\times Nl}$	V, p.u.
w_v	Weighting factor of buses	$\Re^{1\times Nl}$	–
q	Exponent	scalar	–

power network. Note that the aim here was to set a "base case", from which multiple snapshots of real measurements records could be mapped to the quantitative response from computations on a physical model of the grid, which include both steady-state and dynamic system response features.

The following steps are involved in the creation of the multiple snapshots of the Nordic 44 model as illustrated in Fig. 4.

A. The raw data was downloaded from Nord Pool webpage to MS-Excel files, 1 and 2 in Fig. 4.
B. A Python script computes the power flow with the constraint of minimizing the error between the power through the lines between the bidding regions. The method implemented in the python script performs several checks (e.g. convergence, limits etc.), and after completing these tasks, it computes the error between the Nord Pool measurement records and those obtained from the python script computations on the Nordic 44 model, 3 in Fig. 4.
C. The obtained PSS/E snapshots contain the power flow solutions that give the best match to the historical data from Nord Pool, 4 in Fig. 4.

3.2. Steady-state indexes for post-contingency classification

After performing a dynamic simulation for a specific contingency, an appropriate post-contingency severity index is determined in order to classify the impact of the contingency. To do so, a set of scalars (namely severity indexes), provide a measure of how severe the contingency is. The proposed indexes have been developed to satisfy requirements of fast computation (because several contingencies must be evaluated for each operating condition) and synthesis accuracy (provide a good measure of how **severe** the contingency is for different type of instabilities). These indexes therefore help to classify different time-domain simulations, this classification determines if a contingency will result in a *safe* operating condition or if there are *mild* or *severe* violations to specified operation criteria. The requirements mentioned before and the need for a simple methodology, differentiates the indexes proposed here to those described in [13,14] and [15].

An index is a scalar, vector, a matrix of numbers indicating specific properties, in this case, of the steady state stability of a power system. To assess a given operating condition under different contingencies, simulation outputs can be analyzed to determine if a particular contingency will result in an acceptable operating condition. The indexes are used to classify the condition of the system as safe or unsafe through specific operational criteria. The two static indexes are the overload and the under/over voltage index, which are summarized below. Further details about these static indexes is available in [16] .

3.2.1. Overload index

The time series of active and reactive power in the transmission network just after an outage has occurred can be calculated from simulation outputs. These calculations can be used to compare against the capacities of different devices in order to observe if the calculated post-fault time series of active and reactive power through the lines exceeds the capacity of any component in the network. If one or more components of the network are overloaded, the overload index can be used to measure the associated severity of the overload. The equation describing this index is

$$f_x = \sum_{i=1}^{N_l} w_{fi}\left(\frac{S_{mean,i}}{S_{\max,i}}\right)^p \tag{1}$$

where f_x is the overload performance index for the operating point x, N_l is the number of transmission lines, $S_{mean,i}$ and $S_{max,i}$ are the average and maximum power flows of the i_{th} line, respectively, w_{fi} is a weighting factor for each transmission line, which can be defined by the best judgment of the system operator, for instance $w_f = [1,1,\ldots,1]$ for unitary weight in all the lines. Finally, p is an exponent to reduce masking effects, which means that a high value of the exponent will scale the effects of an overload resulting in a higher index value. Definitions of each parameter is given in Table 1.

The final value of the over load index f_x is a scalar, and its interpretation is as follows:

$$\begin{aligned} f_x &= 1 \rightarrow \text{All lines are within the limits} \\ f_x &> 1 \rightarrow \text{At least one line has violated its limit} \\ f_x &>> 1 \rightarrow \text{A severe violation has occurred} \end{aligned} \tag{2}$$

3.2.2. Under/Over voltage index

Following a disturbance in the power network, e.g. a line outage, the power flow through the transmission lines is affected causing changes in other variables of the system. For instance, voltages across the system can be depressed or increased. Data from a simulation will

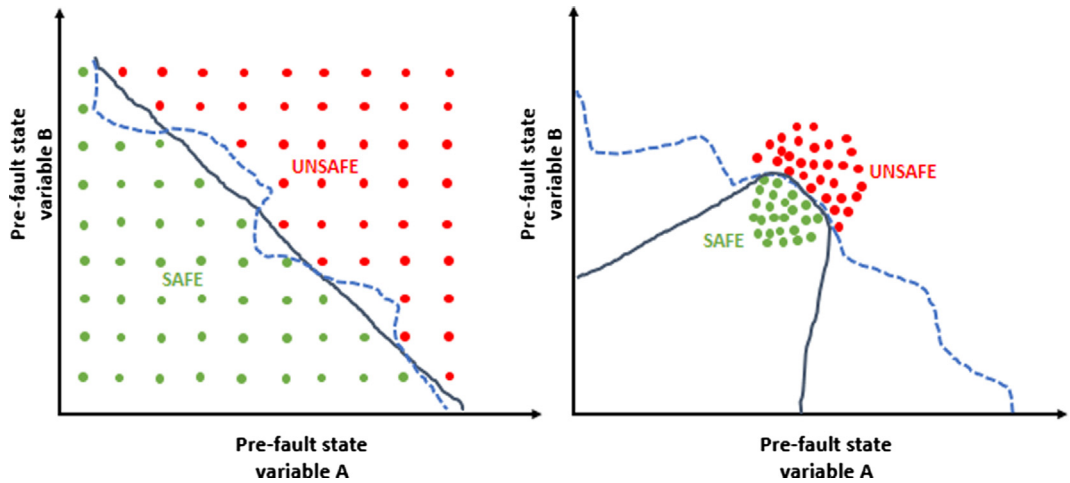

Fig. 5. Classification of operating points based on indexes.

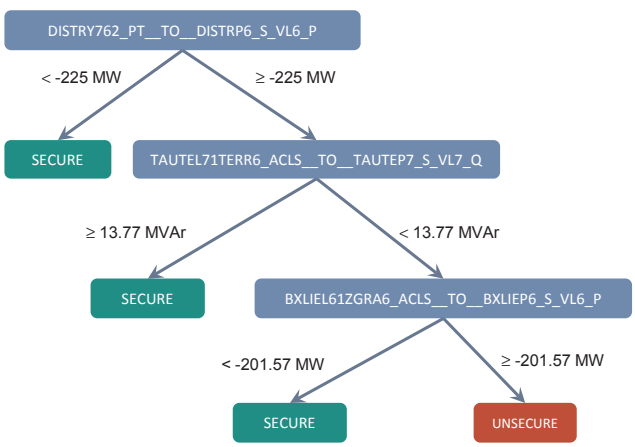

Fig. 6. Decision Tree for the considered contingency.

contain such information and can be used to determine if any device has violated the acceptable operational limits. For the case of bus voltages, it is possible to measure the severity of the violations (under and over operational limits) as follows:

$$v_x = \sum_{i=1}^{N_b} wv_i \left(\frac{v_{init,i} - v_{mean,i}}{\Delta v_i} \right)^q, \Delta v_i = \frac{v_{\max,i} - v_{\min,i}}{2} \tag{3}$$

where v_x is the performance index for the operating point x. It indicates if any bus in the system has surpassed the operational limits. N_b is the number of buses to be analyzed, $v_{init,i}$ is the initial voltage at the ith bus before any disturbance has occurred (pre-fault value), $v_{mean,i}$ is the average voltage of the post-fault data at the ith bus. w_{vi} is a weighting factor of the ith bus, which can be defined by the best judgment of the system operator, for instance $w_v = [1, 1, \ldots, 1]$ for unitary weight in all buses. $v_{max,i}$ and $v_{min,i}$ are the upper and lower voltage limits for the ith bus, respectively and q is an exponent to reduce masking effects, which means that a high value of the exponent will scale the effects of violations in the voltage limits resulting in a large index value. Definitions of each parameter is given in Table 2.

The final value of the over load index v_x is a scalar, and its interpretation is as follows:

$$\begin{aligned} &v_x = 1 \rightarrow \text{ All buses are within the limits} \\ &v_x > 1 \rightarrow \text{ At least one bus has violated its limit} \\ &v_x >> 1 \rightarrow \text{ A severe violation has occurred} \end{aligned} \tag{4}$$

Table 3
List of contingency cases.

Number	Description	Type
1	Outage of one line between Hasle (5101) and Ringhals (3359)	N-1
2	Outage of one line between Hagafoss (6001) and Sylling (5401)	N-1
3	Outage of one line between Hagafoss (6001) and Kaggefoss (5402)	N-1
4	Outage of one line between Blafall (6100) and Kvilldall (6000)	N-1
5	Outage of one line between Hjalta (3100) and Grundfors (3249)	N-1
6	Outage of one line between Ringhals (3359) and Hjalta (3100)	N-1
7	Outage of one line between Ringhals (3359) and Malmo (8500)	N-1
8	Outage of one line between Malmo (8500) and Oskarshamn (3300)	N-1
9	Outage of one line between Oskarshamn (3300) and Forsmark (3000)	N-1
10	Outage of one line between Forsmark (3000) and Jarpstrommen (3245)	N-1
11	Outage of one line between Hjalta (3100) and Porjus (3115)	N-1
12	Outage of one line between Trondheim (6500) and Rossaga (6700)	N-1
13	Outage of one line between Kvilldal (6000) and Kristiansand (5600)	N-1
14	Outage of one line between Geilo (5304) and Eidfjord (5305)	N-1
15	Outage of one line between Geilo (5304) and Kongaberg (5103)	N-1
16	Outage of one line between Geilo (5304) and Dagali (5102)	N-1
17	Outage of one line between Dagali (5102) and Hasle (5101)	N-1
18	Outage of one line between Geilo (5304) and Aurland (5301)	N-1
19	Outage of one line between Hasle (5101) and Krogsberg (5103)	N-1
20	Outage of one line between Oulu (7100) and Helsenki (7000)	N-1
21	Outage of two lines between Tenhult (3200) and Hjalta (3100)	N-2

-The number given in the brackets is the corresponds bus number in the PSS/E model

3.3. Classification

We define the three classes in which time-domain simulations can be classified:

$$1 = \psi_x < k_o \text{safe} \tag{5a}$$

$$1 < \psi_x < k_o \text{mild} \tag{5b}$$

$$1 < \psi_x > k_o \text{severe} \tag{5c}$$

where ψ_x is a real integer representing one of the static indexes and k_o is a real integer that represents the boundary which define the class of time domain simulation as *safe*, *mild* and *severe* limit violation. Defining the precise value of k_o is not simple, it is subject to the system under analysis and the settings used in the static index such as limits and the masking exponent. If for a given contingency the bounds of a static index are within the *safe* (5a) or *mild* (6b) classification, further

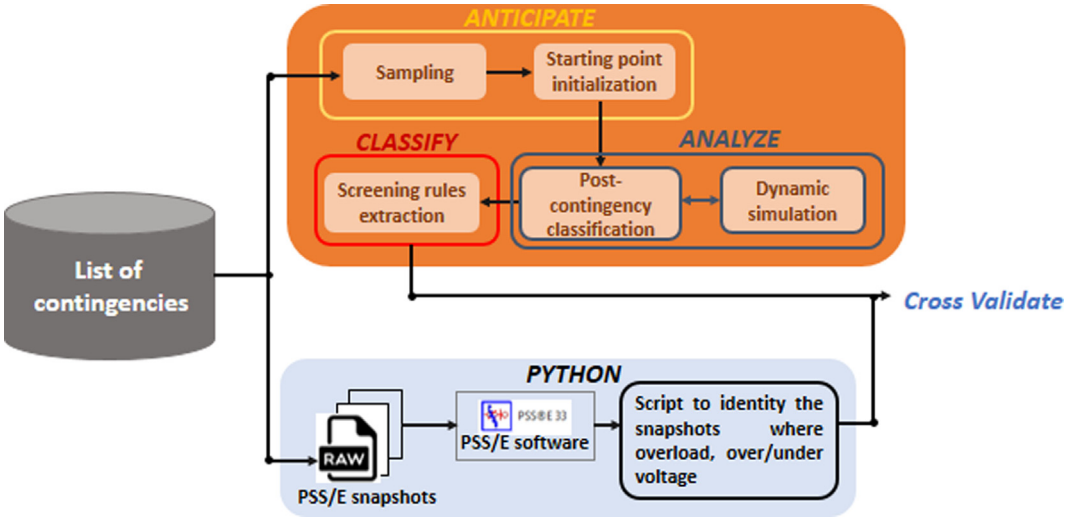

Fig. 7. Validation workflow.

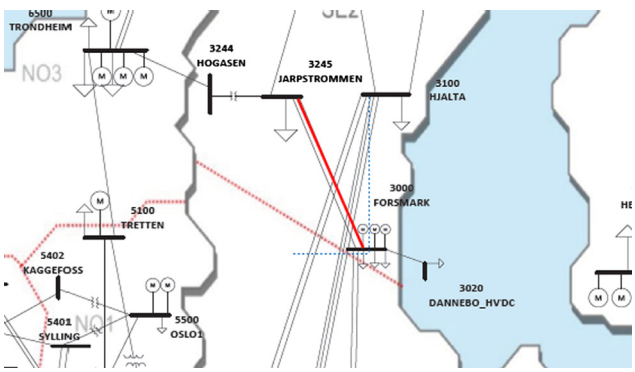

Fig. 8. Geographical location of the selected transmission line (red). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

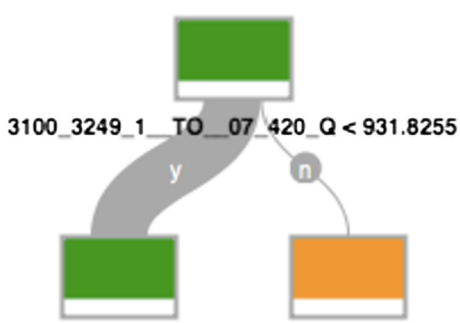

Fig. 9. Monte Carlo Like Approach (MCLA) DT.

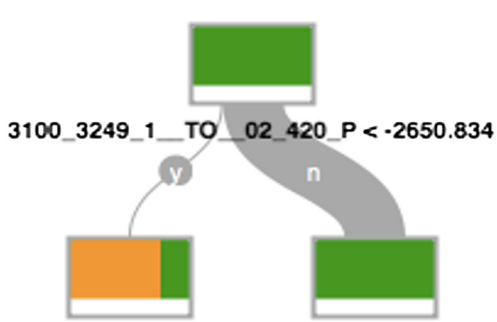

Fig. 10. Worst Case Approach (WCA) DT.

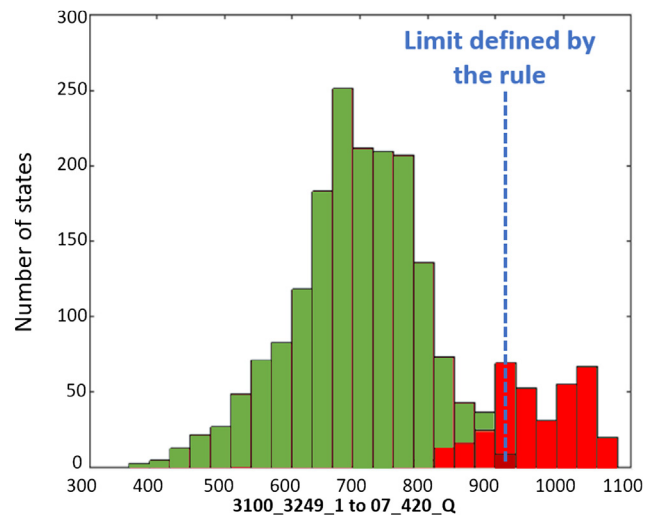

Fig. 11. Superimposed histograms of acceptable cases (green) and unacceptable cases (red) for the learning dataset. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

assessment of the simulation results is not required. On the contrary, if the contingency is classified as *severe* (7c), the simulation results require a deeper inspection, e.g. the application of a dynamic index. In this form, static indexes serve to classify time domain simulations under different contingencies.

3.4. Security rule generation

The simulation and index computation results are compressed into a set of security rules that are used by the online workflow to quickly classify unseen network states as *safe* or *unsafe*. Examples of a classification is shown in Fig. 5. Note that a security rule is obtained for each contingency and security phenomenon (overloads, transient stability, etc.).

These security rules (boundary) are mapped against physical variables (active power, reactive power, voltage etc.,), which are predominantly influenced by the set of contingencies/security index pairs considered. Security rules are expressed as DTs [17], which have the advantage of being easy to interpret and suitable for integration as linear constraints into optimization tools. These DTs are generated by the "DataMaestro" software [18] that was integrated in the iTesla

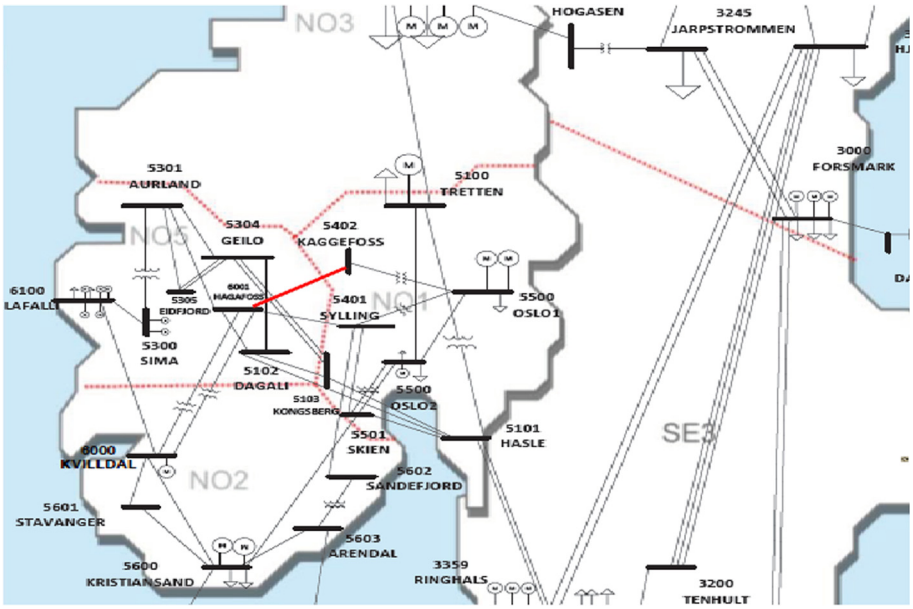

Fig. 12. Geographical location of the selected transmission line (red). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

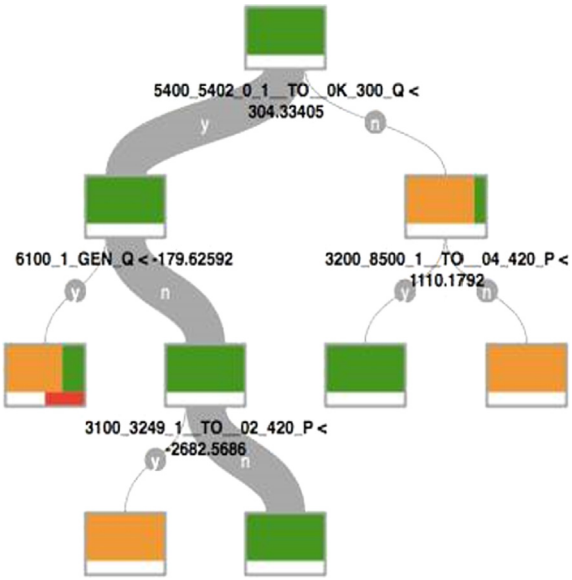

Fig. 13. Monte Carlo Like Approach (MCLA) DT.

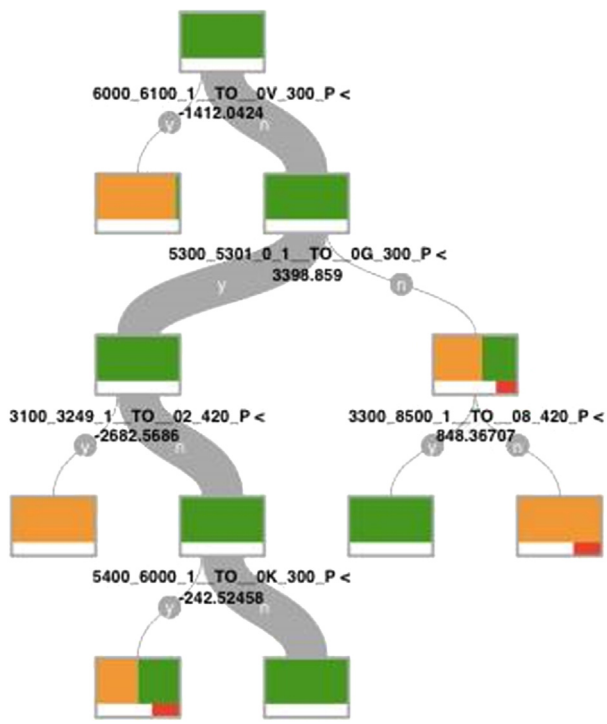

Fig. 14. Worst Case Approach (WCA) DT.

platform. These DTs help to characterize the power system security for pre-defined contingencies and minimize the amount of network simulations in the online workflow. An example of the decision tree created for a given contingency is shown in Fig. 6.

Two approaches are used to generate DTs in the offline workflow for each contingency/security index pair. In the Worst Case Approach (WCA), the set of candidate attributes of the DT can only be related with computed power variables. While in the Monte Carlo Like Approach (MCLA), the set of candidate attributes of the DT can also consider other type of network variables (e.g. voltage). Further details about these approaches is available in [10].

4. Validation of the results from offline workflow

The results from the iTesla offline workflow for a given set of contingencies were applied to the Nordic 44 power system model and verified against simulations performed using PSS/E. This validation was carried out in the following methodology.

A. iTesla – Offline Workflow:
   1. Simulation of contingencies
   2. Identify the output reported by each index of interest
   3. DT generation
B. Python + PSS/E:
   1. Simulation of contingencies
   2. Extract the output from PSS/E depending on index of interest
C. Cross Validation:
   1. Cross validate the results from A and B

```
[itesla@ns6375582 ~]$ itools print-security-indexes-synthesis --workflow workflow-3
+--------------+-----------------+-----------------+--------------+
| Contingency | TSO_OVERVOLTAGE | TSO_UNDERVOLTAGE | TSO_OVERLOAD |
+--------------+-----------------+-----------------+--------------+
| 5304_5305_1 | 2925/0          | 2925/0          | 2918/7       |
| 6500_6700_1 | 2925/0          | 2925/0          | 2914/11      |
| 3359_5101_1 | 2925/0          | 2925/0          | 2919/6       |
| 3000_3245_1 | 2925/0          | 2925/0          | 2914/11      |
| 5102_5304_1 | 2925/0          | 2925/0          | 2918/7       |
| 3000_3300_1 | 2925/0          | 2925/0          | 2918/7       |
| 5103_5304_1 | 2925/0          | 2925/0          | 2918/7       |
| 7000_7010_1 | 2925/0          | 2925/0          | 2919/6       |
| 3100_3200_1 | 2925/0          | 2907/18         | 2918/7       |
| 3100_3249_1 | 2925/0          | 2907/18         | 546/2379     |
| 5101_5102_1 | 2925/0          | 2925/0          | 2890/35      |
| 5401_6001_1 | 2925/0          | 2925/0          | 2916/9       |
| 5402_6001_1 | 2925/0          | 2925/0          | 2880/45      |
| 3300_8500_1 | 2925/0          | 2924/1          | 2909/16      |
| 5101_5103_1 | 2925/0          | 2925/0          | 2883/42      |
| 3359_8500_1 | 2925/0          | 2925/0          | 2918/7       |
| 3100_3115_1 | 2925/0          | 2835/90         | 1902/1023    |
| 5301_5304_1 | 2925/0          | 2925/0          | 2837/88      |
| 6000_6100_1 | 2925/0          | 2925/0          | 2806/119     |
| 3100_3359_1 | 2925/0          | 2924/1          | 2920/5       |
| 5600_6000_1 | 2925/0          | 2925/0          | 2914/11      |
+--------------+-----------------+-----------------+--------------+
```

Fig. 15. Screenshot showing the results computed by iTesla offline workflow for steady state index validation.

Table 4
Comparsion of results from iTesla offline workflow and Python + PSS/E.

Contingency	iTesla Overload	Python Overload	Unmatched Cases	% Matching
1	7	7	0	100.00
2	11	12	1	99.92
3	6	6	0	100.00
4	11	11	0	100.00
5	7	7	0	100.00
6	7	8	1	99.88
7	7	7	0	100.00
8	6	7	1	99.86
9	2379	2431	52	99.98
10	35	35	0	100.00
11	9	9	0	100.00
12	45	40	5	100.13
13	16	16	0	100.00
14	42	45	3	99.93
15	7	7	0	100.00
16	1023	1049	26	99.98
17	88	98	10	99.90
18	119	127	8	99.94
19	5	5	0	100.00
20	11	11	0	100.00
21	7	5	2	99.60

2. Analyze and contrast the created DT in A with the system response observed from that contingency in B

This methodology was used to validate the (static) steady-state stability assessment (Overload, Over/Under voltage indexes) of the offline workflow.

4.1. Cross validation

21 contingencies were created and simulated using the Nordic 44 bus system in the iTesla platform. These contingencies were applied to 2928 snapshots and each snapshot indicates the operating point based on the hourly data posted on the Nord pool from April 2015 to July 2015. The outputs from the contingencies were computed from a simulation program available in the platform. The selected contingencies contain transmission lines whose average loading is more than 65% of their nominal rating. Table 3 lists the 20 'N-1' contingencies and one 'N-2' contingency used in the cross validation. These contingencies were also created and simulated in PSS/E to compare the results to those of the iTesla offline workflow as shown in Fig. 7.

Because of space constraints, the cross-validation workflow is explained in detail with one contingency and results of the remaining contingencies is shown in Fig. 15.

4.1.1. N-1. Forsmark to Jarpstrommen

This transmission line is in SE2 region of Sweden as shown in Fig. 8.

For this contingency, the overload index in the platform reported the overloading in 11 snapshots of the available 2925 snapshots. The DTs generated from the offline workflow is shown in Fig. 9. and Fig. 10. It can be observed from the figures that the size of DTs is same for both approaches, but the MCLA DT clearly differentiates *safe* and *unsafe* operating points; while the WCA DT classifies as *safe* operating points in the *unsafe* region (green shaded region in the orange box in Fig. 10). So, in the sequel, only the DT generated by the MCLA approach is considered.

A Python script was developed to automate the same process applied by the iTesla offline workflow. The power system simulations and other computations in this case were performed by PSS/E. The results from executing indicated overloading in 11 snapshots, which match the results from the iTesla platform.

Next, the rules generated from the offline workflow of the iTesla platform were verified by performing manual simulations in PSS/E and it was found that the generated rule holds good for this contingency. This was determined by checking that the reactive power flow on one of the circuits is below 931.8255 Mvar.

This is consistent with the operational rule that shows that the import flow of the region is limited. This import flow is heavily correlated with this variable as long as the underlying 420 kV topology does not change. The rule's performance is satisfactory when applied to the learning dataset, as shown in the below Fig. 11.

4.1.2. N-1. Hagafoss to Kaggefoss

This transmission line is in Norway and it connects the NO1 and NO5 regions as shown in Fig. 12. For this contingency, the overload index in the platform reported the overloading in 45 snapshots of the available 2925 snapshots.

The DTs generated from the offline workflow is shown in Figs. 13 and 14. It can be observed from the figures that the size of DT generated by the MCLA approach is bigger than the DT generated by WCA approach. It should be noted that the MCLA DT clearly differentiates *safe* and *unsafe* operating points in all the nodes except for one; while the WCA DT classifies as *safe* operating points in the *unsafe* region (green shaded region in the orange box in Fig. 14). So, in the sequel, only the DT generated by the MCLA approach is considered.

The results from executing Python + PSS/E workflow indicated overloading in 40 snapshots. The remaining snapshots 5 snapshots were checked manually and it was found that they have 99.99% loading due to which it is not classified as overload.

Next, the rules generated from the offline workflow of the iTesla platform were verified by performing manual simulations in PSS/E and it was found that the generated rule holds good for this contingency. This was determined by checking that the active power reactive power flow on two circuits and reactive power generated from a generator.

This is consistent with the operational rule that shows that the import flow of the region is limited. This import flow is heavily correlated with these variables as long as the underlying 420 kV topology does not change.

The screenshot of iTesla platform in Fig. 15. shows the results from the steady state stability indexes for all the 21 contingencies applied to the Nordic 44 system.

It should be observed from Fig. 12 that only 2925 snapshots are shown instead for 2928. This is because 3 snapshots expose overloads in them even before the execution of contingency. So, the iTesla platform executed only 2925 snapshots.

Finally, a percentage of matching was quantified to determine any differences between the results from iTesla offline workflow and those

obtained using Python + PSS/E, Table 4 provides the results.

It can be observed from the table that for some contingencies, the number of overloads reported by offline workflow differs with the number of overloads reported by Python + PSS/E workflow. These snapshots were checked manually and it was found that the transmission lines are loaded to 99.99% and PSS/E did not flag them as overloaded. This discrepancy in the number of significant figures between iTesla offline workflow and PSS/E was determined to be the main issue with matching. It can also be observed from the above table that average percentage of matching in results between iTesla offline workflow and PSS/E is 99.6%. Thus, it can be observed that the results from iTesla offline workflow are matching the results obtained from the Python + PSS/E implementation for overload index. Similarly, the results from the over and under voltage indexes of the platform were also verified using this methodology.

5. Future work

The methodology reported in this paper validates only the (static) steady-state stability assessment functions (Overload, Over/Under voltage indexes) of the offline workflow but not those of the dynamic stability assessment (voltage stability, small signal stability and transient stability indexes). There are many challenges that need to be addressed when performing a proper validation study for DSA. First, both "application" and "functional" testing cases need to be developed to provide a starting point for analysis. This will be reported in a companion paper [19]. However, due to time limitations it was not possible to explore the source of differences when computing the time domain simulations using Dymola and PSS/E. The use of the testing codes to validate the DSA functions of the offline workflow of the iTesla platform will be subject of future work.

6. Conclusions

The results from the iTesla offline workflow for a given set of contingencies applied to Nordic 44 power system model are verified against the results from a similar workflow implemented using Python + PSS/E. The generated DTs by the iTesla platform were verified for different network operating conditions. It was observed that the generated DT's are consistent for the given set of operating conditions. However, it should be noted that DT's can become more efficient and consistent if they are trained on diverse scenarios (i.e. well-defined contingencies and a large learning set). Hence, it would be beneficial to check how the rules generated from DT's with four months of data (April to July 2015) vary from the rules generated with one year of data (2015). This could help in validating the generalization capability of the generated trees.

While the cross-validation performed in this paper only took into account the (static) steady-state stability assessment results of the offline workflow, to the authors' knowledge, this is the first paper proposing such means for functional testing of DSA tools' functions with an independent implementation of the tools' functionalities being tested. This contributes to the body of knowledge on DSA, if similar efforts are imitated by DSA tool providers, this can help in gaining confidence and credibility in the tools' functions and results.

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