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Online Dynamic Assessment

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Abstract: A data mining approach using ensemble decisiontrees (DTs) learning is proposed for online dynamic security assessment (DSA), with the objective of mitigating the impactof possibly missing PMU data. Specifically, multiple small DTsare first trained offline using a random subspace method. Inparticular, the developed random subspace method exploits thehierarchy of wide-area monitoring system (WAMS), the locationalinformation of attributes, and the availability of PMU measurements,so as to improve the overall robustness of the ensemble to missing data. Then, the performance of the trained small DTs isre-checked by using new cases in near real-time. In online DSA,viable small DTs are identified in case of missing PMU data, anda boosting algorithm is employed to quantify the voting weightsof viable small DTs. The security classification decision for onlineDSA is obtained via a weighted voting of viable small DTs. A casestudy using the IEEE 39-bus system demonstrates the effectiveness of the proposed approach.

Index Terms: Boosting, data mining, decision tree, ensemblelearning, missing PMU data, online dynamic security assessment, random subspace method, transient stability.

I. INTRODUCTION

DYNAMIC security assessment (DSA) provides systemoperators with important information, e.g., transient securityof a specific operating condition (OC) under various contingencies.Given a knowledge base, decision trees (DTs) can identifythe attributes and the thresholds that are critical to assessingthe transient performance of power systems . With the advent of synchrophasor technologies, a significant amount ofeffort has been directed towards online DSA, by using PMUmeasurements directly for decision making . Upon a disturbance,by applying pre-determined decision rules to the PMUmeasurements of critical attributes, DTs can give security classificationdecisions in real-time.Previous studies on PMU measurement-based online DSAimplicitly assume that wide area monitoring systems (WAMS)provide reliable measurements. However, in online DSA, PMUmeasurements can become unavailable due to the unexpectedfailure of the PMUs or phasor data concentrators (PDCs), ordue to loss of the communication links. Recently, it has been widely recognized that PMU failure can be an important factorthat impacts the performance of WAMS. For example, AESO'snewest rules on implementing PMUs require that the lossor malfunction of PMUs, together with the cause and the expectedrepair time, has to be reported to the system operator in a timely manner. In the report, the deployment of redundancyis suggested by PMU manufacturers to reduce the impactof single PMU failure. Loss of PMUs has also been taken into account when designing WAMS and PMU placement .Moreover, the delivery of PMU measurements from multiple remote locations of power grids to monitoring centers could experiencehigh latency when communication networks are heavily congested, which could also result in the unavailability of PMU measurements. Therefore, it is urgent to design DT-based online DSA approaches that are robust to missing PMU measurements. Intuitively, one possible approach to handle missing PMU measurements is to estimate the missing values by using other PMU measurements and the system model. However, with existingnonlinear state estimators in supervisory control and data acquisition (SCADA) systems, this approach may compromise the performance of DTs. First, the scan rate of SCADA systems is far from commensurate with the data rate of PMU measurements,and thus using estimated values from SCADA data may result in a large delay for decision making. Second, SCADA systems collect data from remote terminal units (RTUs) utilizing a polling approach. Following a disturbance, it is possible that some post-contingency values are used due to the lackof synchronization, which can lead to inaccurate security classification decisions of DTs. It is worth noting that future fully

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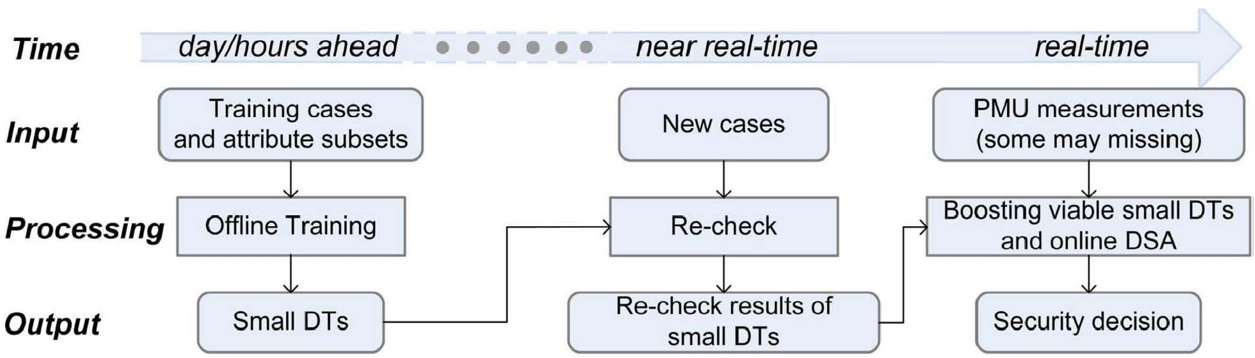
PMU-based linear state estimators can overcome the aforementioned limitations; but this is possible only when there is a sufficient number of PMUs placed in system. With this motivation, data-mining based approaches are investigated in this paper, aiming to use alternative viable measurements for decisionmaking in case of missing data. In DTs built by the classification and regression tree (CART)algorithm , missing data can be handled by using surrogate.However, a critical observation in this study is that when PMUmeasurements are used as attributes, most viable surrogate attributes have low associations with the primary attributes. Clearly, the accuracy of DSA would degrade if surrogate is used. This is because a DT is essentially a sequential processing method, and thus the wrong decisions made in earlier stages may have significant impact on the correctness of the final decisions. Thus motivated, this paper studies applying ensemble DT learning techniques, including random subspace methods and boosting, to improve the robustness to missingPMU measurements.



Three-stage ensemble DT-based approach to online DSA with missing PMU measurements.:

Aiming to develop a robust and accurate online DSA scheme, the proposed approach consists of three processing stages. Specifically, given a collection of training cases, multiple small DTs are trained offline by using randomly selected attribute subsets. In near real-time, new cases are used to re-check the performance of small DTs. The re-check results are then utilized by a boosting algorithm to quantify the voting weights of a few viable small DTs (i.e., the DTs without missing data from their attribute subsets). Finally,security classification decisions of online DSA are obtained via a weighted voting of viable small DTs. More specifically, a random subspace method for selecting attribute subsets is developed by exploiting the locational information of attributes and the availability of PMU measurements. Conventionally, the availability of aWAMS is defined as the probability that the system is operating normally at a specified time instant.

In this study, the availability of PMU measurements is defined similarly, i.e., as the probability that PMU measurements are successfully collected and delivered to a monitoring center. The developed random subspace method guarantees that a significant portion of small DTs are viable for online DSA with high likelihood. Further, a boosting algorithm is employed to assign the viable small DTs with proper voting weights that are quantified by using the results from performance re-check, leading to the high robustness and accuracy of the proposedapproach in case of missing PMU measurements. The proposed approach is applied to the IEEE 39-bus system with 9 PMUs. Compared to off-the-shelf DT-based techniques (including random forests (RFs) with and without using surrogate), the proposed ensemble DT-based approach can achieve better performance in case of missing PMU measurements. The rest of the paper is organized as follows. An introduction toDTs with application toDSAis given in Section II.Section III focuses on the random subspace method for selecting attribute subsets. The proposed three-stage approach is presented in detail in Section IV. A case study is discussed in Section V. Finally, conclusions are given in Section VI.

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II. BACKGROUND ON DTS

A decision tree is a tree-structured model that maps the measurements of the attributesx∈Xto a predicted valueŷ∈Y. In a DT, a test on an attribute (thus called the primary attribute of the internal node) is installed at each internal node anddecides which child node to drop the measurements into. Further, each leaf node of the DT is assigned a predicted value, and the measurements are thus labeled with the predicted value of the leaf node which it sinks into. The path from the root node to a leaf node specifies a decision region in the attribute space
corresponding to that leaf node. Specifically, the length of the longest downward path from the root node to a leaf node is defined as the height of a DT.
A. Application of DTs in DSA DTs with binary predicted values (i.e.,) are used in DSA. Specifically, represents that an OC is classified as insecure under a given contingency. The numerical attributes used by DTs in DSA include voltage magnitudes, voltage phase angles and power/current flows. Moreover, the index of contingencies is used as a categorical attribute. In DSA, a collection of training cases are first created by applying DSA packages (e.g., DSATools) to known OCs for a given list ofcontingencies. Then, the training cases , where , are used by the classification and regression tree (CART) algorithm to build a DT that fits the training data. Intuitively, if the DT fits the training data well and the newOCs in online DSA are similar to the OCs corresponding to the training cases, the trained DT can give accurate security classification decisions for the new OCs in online DSA. In this study, small DTs,which havesmall height are used. Generally, a small DT could have lower accuracy than a fullygrown DT, but is less prone to overfitting when the training data is noisy [14], and multiple DTs are usually combined togetherto improve the classification accuracy.
B. Handling Missing Data by Using Surrogate in DTs A surrogate split at an internal node is the one that "mimics"the primary split most closely, i.e., gives the most similar splitting results for the training cases. Usually, the similarity is quantified by the association between the surrogate split and the primary split [11]. The significance of a surrogate split that has a high association (i.e., over 0.9) with the primary split is that the DT could still use the surrogate split at this internal node to give almost the same decisions when the PMU measurement of theprimary attribute is missing. The performance of surrogate in DT-based DSA is evaluatedvia a case study, in which a single DT is built by using the same knowledge base for voltage magnitude violation analysis .

CASE STUDY ON THE SURROGATES OF DTS

node	primary attribute[1]	by modified CART		by CART	
		surrogate	assoc.	surrogate	assoc.
1	$V_{\{217\}}$	$V_{\{207\}}$	0.76	$V_{\{207\}}$	0.76
2	$Q_{\{204,207\}}$	$Q_{\{212,216\}}$	0.33	$Q_{\{207,209\}}$	0.50
3	$Q_{\{204,207\}}$	$V_{\{209\}}$	0.28	$Q_{\{207,209\}}$	0.64
4	$I_{\{211,204\}}$	$P_{\{008,011\}}$	0.62	$P_{\{209,211\}}$	0.83
5	$P_{\{210,201\}}$	$P_{\{211,062\}}$	0.87	$P_{\{231,201\}}$	0.87
6	$Q_{\{005,033\}}$	$Q_{\{801,999\}}$	0.71	$Q_{\{801,999\}}$	0.71
7	$P_{\{213,222\}}$	$Q_{\{207,211\}}$	0.85	$P_{\{222,223\}}$	0.85
8	$Q_{\{041,060\}}$	$I_{\{011,051\}}$	0.50	$I_{\{011,051\}}$	0.50
9	$P_{\{211,062\}}$	$P_{\{213,216\}}$	0.50	$I_{\{062,211\}}$	0.75
10	$P_{\{236,219\}}$	$Q_{\{230,052\}}$	0.42	$P_{\{236,207\}}$	0.68

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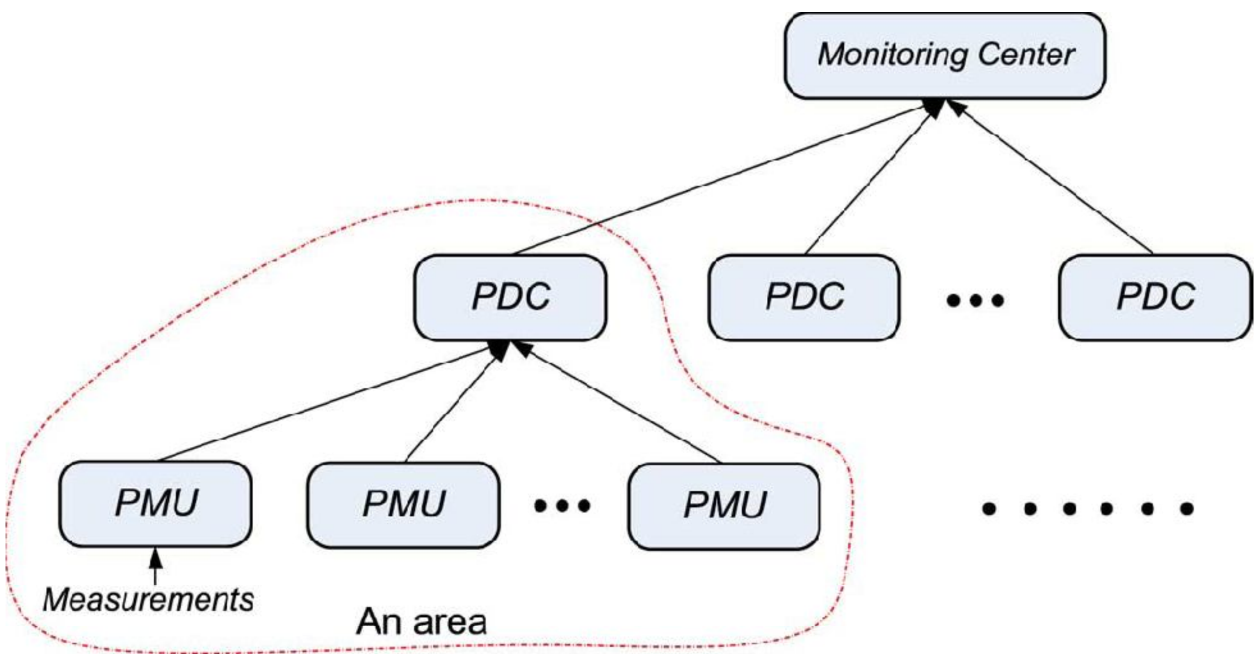
It is observed that co-located attributes (i.e., the attributes measured by the same PMU) would often be unavailable at the same time when the PMU fails, which implies that co-located attributes cannot be used as surrogate for each other in online DSA. Therefore, a modified CART algorithm in which co-located attributes are excluded from surrogate searching is used to build a single DT and identify the surrogate attributes. The results regarding the performance of the surrogates identified by both the modified CART algorithm and the CART algorithm are given in TABLE. Two key observations are drawn. First, the results obtained by the modified CART algorithm suggest thatall non-co-located surrogates have relatively low associations with the primary ones. The low association could be explained by the complex coupling structure of the attributes in power systems. According to the definition of surrogate, high association relies on the dependency between the surrogate and the primaryattributes, i.e., the surrogate attribute gives similar decisions to the primary attribute on all the training cases regardless of any other attribute. However, in power systems, one attribute (i.e., voltage magnitude, voltage phase angle or power/current flow) is coupled withmany other non-co-located attributes, as dictated by the AC power flow equations and the network interconnection structure. Second, it is observed in Table I that the surrogateattributes found by the CART algorithm are mostly co-located with the primary attributes. This observation signifies the redundancy between co-located attributes when used for splitting the training cases, and thus sheds lights on exploiting the locational information to create the attribute subsets, as described inSection III.

C. Ensemble DT Learning

Ensemble DT learning techniques (bagging, random subspacemethods, boosting, RF) combine multiple DTsto obtain better prediction performance. Studies have shown that using random subspace methods can lead to improved accuracy and generalization capability, if the DTs are trained from a variety of compact and non-redundant attribute subsets. Usually, the attribute subsets used by DTs are selected in a randomized manner. For example, in the random decision forest algorithm , each DT is built by using an attribute subset that is randomly selected from all possible candidate attribute subsets with equal weights. For online DSA.



Wide area monitoring system consisting of multiple areas.

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It is observed that additional system information on the attributes could be utilized to create and select the attribute subsets. First, the candidate attribute subsets could be significantly refined by exploiting the locational information of attributes. Further, by putting more weights on the attribute subsets that have higher availability when randomly selecting attribute subsets, the resulting small DTs would be more likely to be robust to possibly missing PMU measurements.

III. RANDOM SUBSPACE METHOD FOR SELECTING ATTRIBUTE SUBSETS

A key step of the random subspace method is to identify a collection of candidate attribute subsets and determine theweight that dictates how likely a candidate attribute subset is to be selected. In this study, by exploiting the locational information of attributes and the availability of PMU measurements, the random subspace method adheres to the following two guidelines:

• G1: Co-located attributes do not co-exist within an attribute subset.
• G2: The average availability of the selected attribute subsets should be sufficiently high.

Further, for a power system consisting of areas, the corresponding WAMS is assumed to have a hierarchical architecture .As each area of the power system has a PDC that concentrates the PMU measurements of this area and submits them to the monitoring center.

A. Candidate Attribute Subsets

The candidate attribute subsets are created based on the three following specific rules:

1) Within a candidate attribute subset, all the attributes are from the same area.
2) In area, three categories of pre-fault quantities measured by PMUs are used as the numerical attributes:

• Category 1: voltage magnitude , for ;
• Category 2: active power flow , reactive power flow and current magnitude , for and ;
• Category 3: phase angle difference , for where denotes the collection of the buses with PMU installation within area , and denotes the collection of the neighbor buses of bus . An attribute subset of area is created by including one voltage or flow measurement from each bus and all phase angle difference measurements from this area.

3) The index of contingencies is included as a categorical attribute in any attribute subset. The criteria used in creating the attribute sets are elaborated below. By restricting the attributes of a subset to be the PMU measurements within the same area, the impact of some scenarios, i.e., when a PDC that concentrates PMU measurements within an area fails, is significantly reduced, since the small DTs using the PMU measurements from the other areas could still beviable. For a given bus, since Category 1 and Category 2 PMU measurements are co-located, it suffices to include only one of them in an attribute subset so that the redundancy within an attribute subset is minimal. Further, all measurable phase angle differences are included. This is because theoretical and empirical resulted to suggest that angle differences contain important information regarding the level of stress in OCs, and thus are more likely to be the attributes critical to assessing transient instability. It is also worth noting that the Category 2 attributes from two different buses are unlikely to be redundant, in the sense that they are the measurements from different transmission lines, given the fact that PMUs could provide power flow measurements and it is usually unnecessary to place PMUs at both ends of a transmission line to achieve the full observabilityof power grids. For convenience, let denote the collection of candidate attribute subsets of area . Then, the size of is where denotes the degree of bus , i.e., the number of buses that connect with bus . Then, is the collectionof candidate attribute subsets.

B. Randomized Algorithm for Selecting Attribute Subsets

It is plausible to develop the randomized algorithm so as to achieve maximum randomness of the selected attribute subsets by maximizing the entropy of the weight distribution .Without any other information of attribute, equal weights is usually used by existing random subspace methods. Here, by adhering to guideline G2, an additional constraint is that the average availability of the randomly selected attribute subsets is above an acceptable level . As a result, the weight distribution can

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be determined where denotes the availability of an attribute subset . According to the rules for creating the candidate attribute subsets, it is easy to see that each of the attribute subsets of an area consists of exactly two measurements from each PMU within this area. Therefore, the availability of an attribute subset of area , which was formally defined in Section I as the probability that the measurements of are successfully delivered to the monitoringcenter, equals that of the WAMS within area , i.e.,

In availability analysis of WAMS , it is usuallyassumed that the availability of PMUs, PDCs and communicationlinks are known (e.g., estimated from past operating data) and independent from each other. Under these assumptions, the availability of the WAMS within area is given bywhere , , and denote the availabilityof the PMU at bus , the communication link from the PMU at bus to the PDC, the PDC and the communication link from the PDC to the monitoring center, respectively. It is worth noting butare derived for the case and thus may not be directly applicable to the cases with measurement redundancy. For example, when multiple dual use PMU/ line relays are utilized in substations, the availability of bus voltage phasor measurements can be enhanced.

IV. PROPOSED APPROACH FOR ONLINE DSA WITH MISSING PMU MEASUREMENTS

First Small DTs are trained offline by using randomly selected attribute subsets. In case of missing PMU measurements in online DSA, viable small DTs are identified, and are assigned different voting weights. Specifically, the results of performance re-check in near real-time are utilized to quantify these voting weights. Finally, the security classification decisions for the new OCs in online DSA are obtained via weight voting of the viable small DTs.

A.Offline Training

B. Near Real-Time Performance Re-Check

In near real-time, a more accurate prediction of the imminent OC in online DSA can be made. Then, a collection of new cases are created in a similar manner to that in offline training and used to re-evaluate the accuracy of the small DTs. The re-check results are then utilized by the boosting process in online DSA. In case of variations between the OCs used in offline training and the new OCs in online DSA, near real-time re-check is also a critical step to make sure that the small DTs still work well.

C. Online DSA

The results of near real-time re-check are utilized to choose a few viable small DTs to be used in online DSA and calculate the corresponding voting weights via a process of boosting small DTs. In order to make best use of existing DTs, the viable small DTs in online DSA include the small DTs without any missing PMU measurement and nonempty degenerate small DTs.

1) Degenerate Small DTs:A degenerate small DT is obtained by collapsing the subtree of an internal node withmissing PMU measurement into a leaf node. Specifically, a small DT degenerates to a non-empty tree if the PMU measurements used by the internal nodes other than the root node are missing, an example of which is illustrated in Fig. 3. Further, since each internal node of the original small DT is also assigned a decision in building the DT, the new leaf node of the degenerate small DT is assigned the same decision as the original internal node. Therefore, for a non-empty degenerate small DT, the re-check results on the new cases could be easily obtained.

2) Weighted Voting of Viable Small DTs: Let be the collection of viable small DTs. Then, weighted voting of the viable smallDTs in is utilized to obtain the security classification decisions of online DSA, due to the following two reasons. First, in case that some small DTs degenerate to empty trees and the accuracy of non-empty degenerate small DTs degrades, weighted voting could improve the overall accuracy compared tomajority voting, provided that the voting weights are carefully assigned based on the re-check results of the viable small DTs. Second, even though all the small DTs are viable, choosing the small DTs with proper voting weights based on their accuracy can still be a critical step to guarantee accurate decisions. This is because small DTs trained offline fit the training cases that are created based on day-ahead prediction, while the re-check results on the new cases containmore relevant information on assessing the

D. Further Discussion

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Through detailed complexity analysis, it is shown that the low computational complexity of the online processing renders that the time criticality of online DSA would not be compromised when the proposed approach is used. Specifically, the computationally intensive part of the online processing stage is the boosting process that consists of calculating the data weights , solving and calculating the votingweights of small DTs. According to (16), calculating the data weights requires evaluating for the new cases, which could be easily obtained from the re-check results of the small DTs. Therefore, it is easy to see that the complexity in calculating the data weights is Solving boils down to searching for the small DT in that has the least weighted misclassification error. Since the re-check results of the small DTs in for the new cases are already known, the optimal small DT could be found by comparing the weighted misclassification errors of the small DTs

V. CONCLUSION

A data-mining approach has been proposed to mitigate the impact of missing PMU measurements in online DSA. In particular, the various possibilities of missing PMU measurements in online DSA can make off-the-shelf DT-based techniques (a single DT, RF, etc.) fail to deliver the same performance as expected.The proposed ensemble DT-based approach exploits the locational information and the availability information of PMU measurements in randomly selecting attribute subsets, and utilizes the re-check results to re-weight the DTs in the ensemble.

These special treatments developed from a better characterization of power system dynamics guarantee that the proposed approach can achieve better performance than directly applying off-the-shelf DT-based techniques.

REFERENCES

[1] L.Wehenkel, T.VanCutsem, andM.Ribbens-Pavella, “An artificial intelligenceframework for online transient stability assessment of power systems,” IEEE Trans. Power Syst., vol. 4, no. 2, pp. 789–800, May1989.

[2] S. Rovnyak, S. Kretsinger, J. Thorp, and D. Brown, “Decision trees forreal-time transient stability prediction,” IEEE Trans. Power Syst., vol. 9, no. 3, pp. 1417–1426, Aug. 1994.

[3] K. Sun, S. Likhate, V. Vittal, V. Kolluri, and S. Mandal, “An onlinedynamic security assessment scheme using phasor measurements and decision trees,” IEEE Trans. Power Syst., vol. 22, no. 4, pp. 1935–1943,Nov. 2007.

[4] R. Diao, K. Sun, V. Vittal, R. O’Keefe, M. Richardson, N. Bhatt, D.Stradford, and S. Sarawgi, “Decision tree-based online voltage security assessment using PMU measurements,” IEEE Trans. Power Syst., vol.24, no. 2, pp. 832–839, May 2009.

[5] R. Diao, V. Vittal, and N. Logic, “Design of a real-time security assessmenttool for situational awareness enhancement in modern power systems,” IEEE Trans. Power Syst., vol. 25, no. 2, pp. 957–965, May2010.