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Substation-level Circuit Topology Estimation Using Machine Learning

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***Abstract*—Modern distribution systems can accommodate different topologies through controllable tie lines for increasing the reliability of the system. Estimating the prevailing circuit topology or configuration is of particular importance at the substation for different applications to properly operate and control the distribution system. One of the applications of circuit configuration estimation is adaptive protection. An adaptive protection system relies on the communication system infrastructure to identify the latest status of power. However, when the communication links to some of the equipment are outaged, the adaptive protection system may lose its awareness over the status of the system. Therefore, it is necessary to estimate the circuit status using the available healthy communicated data. This paper proposes the use of machine learning algorithms at the substation to estimate circuit configuration when the communication to the tie breakers is compromised. Doing so, the adaptive protection system can identify the correct protection settings corresponding to the estimated circuit topology. The effectiveness of the proposed approach is verified on IEEE 123 bus test system.**

***Index Terms*—Adaptive protection, circuit configuration estimation, distribution system, machine learning.**

I. INTRODUCTION

Modern distribution systems (DS) can accommodate different circuit topologies for increasing the reliability of distribution systems. To this end, tie lines are installed at different locations of distribution circuits to provide an alternative source of power to the congested branches or branches hosting critical loads [1]-[2]. Each tie line has a breaker that can be controlled remotely from the DS control center to change the DS circuit topology. Estimating the prevailing circuit topology at the DS substation is of particular importance for different DS applications when the communication of the substation controller to the tie breakers is outaged or compromised due to cyber-attacks. One of the applications for which proper circuit topology estimation is critical is adaptive protection of distribution systems. An adaptive protection system is defined as a system that is responsive to the changes in the power system, e.g., its topology and generation profile, and can update protection relays' settings in real-time through the DS communication network [1]-[5]. An adaptive protection system highly relies on the communication network to identify the latest status of DS (e.g., circuit topology). However, when the communication links to some of the tie breakers are outaged due to physical damages or cyberattacks, the adaptive protection system fails to identify the prevailing circuit topology for calculating proper settings for the DS protection relays. Therefore, it is of paramount value to estimate the circuit topology using the available healthy communicated data [6]. The proposed algorithm uses the available measurements from the relays that still have communication to estimate the state of the other switches with lost communication. After topology estimation is performed, the adaptive protection system will use the topology to determine the appropriate protection settings for the relays.

In the literature, state estimation has been used as the common approach for circuit topology estimation in DS [7]. In [8], a weighted least square state estimator is utilized to identify the status of circuit breakers by accounting for their active and reactive power flow. A state estimation technique for topology processing and estimation is proposed in [9]. In [10], Bayesian estimation is introduced as a linear least square estimation problem for improving the performance of weighted least square state estimators that require extended number of sensors. Alternatively, data-driven and learning-based state estimation techniques have been proposed in [11]-[15] to improve the performance of conventional state estimation methods.

In this paper, the objective is to estimate the circuit topology when the adaptive protection system has limited access to a few of the protection relays and tie breakers in the system. Although

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the state estimation techniques can estimate circuit topology effectively, they require extensive communication to different locations of the circuit. This paper proposes the use of machine learning to estimate circuit topology at the substation when the communication links to the tie breakers are outaged. The proposed approach utilizes a support vector machine (SVM) and logistic regression (LR) as classifiers to identify the prevailing circuit topology of the distribution system. By doing so, the adaptive protection system can identify the correct protection settings corresponding to the estimated circuit topology. The proposed approach is verified on IEEE 123 node test system.

The rest of the paper is organized as follows: Section II discusses the proposed circuit topology estimation algorithm along with the preliminaries of LR and SVM. In Section III, the effectiveness of the proposed circuit topology estimation is performed on IEEE 123 bus test system. Section IV concludes the paper.

II. Machine Learning for Circuit Topology Estimation

Herein, the goal is to train a machine learning engine that estimates circuit topology with minimum information from the system. It is assumed that the machine learning engine only has access to data of a few of the protection relays or tie breakers. The data received from the protection relays and tie breakers including voltage, current, and active and reactive power are the inputs to the machine learning engine. The prevailing circuit topology is considered as the output of the machine learning engine. The number of circuit topologies depends on the number of tie lines and the utility practice. For example, in some utilities, it is preferred to only have radial branches and the formation of mesh loops is prohibited. The block diagram of the proposed circuit estimation method is shown in Fig. 1.
In this paper, the circuit topology estimation is defined as a classification learning problem. To this end, two different classification algorithms, namely, LR and SVM are used. In the following, these two algorithms are discussed in detail.

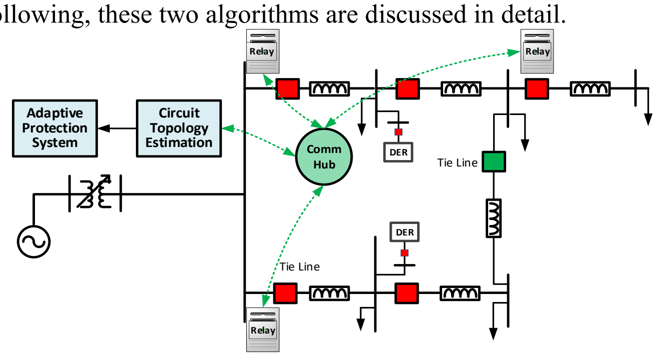


Fig. 1. Proposed circuit topology estimation block diagram.

A. Logistic Regression

LR is a linear classifier. The simplest LR case is known as binary classification where the output is typically a Boolean value. However, LR can have multiple output values, known as multiclass logistic regression (MLR). The output labels must be finite and known in advance. For example, to classify four kinds of circuit topologies, given some measurement features, the possible outputs are four classes, namely, c_1, c_2, c_3, and c_4. MLR in the one-vs-rest setup breaks it down into four simpler problems where each problem considers a single class as positive examples and all other classes as negative examples.

For all four problems, it is possible to use a binary classifier, such as LR, with the following output: The first classifier's output is denoted as $P(y=c_1|x)$, while the second, third and fourth outputs are $P(y= c_2|x)$, $P(y= c_3|x)$ and $P(y= c_4|x)$, respectively, and the most likely class is chosen as the model's recommendation [16].

B. Support Vector Machine

The main goal of SVM is to identify an optimal hyperplane that can separate the training data into two different categories labeled as $\{1,-1\}$ [6], [17]. Fig. 2 illustrates a classification problem with SVM. A linear hyperplane can be written as

$$y(\mathbf{x}) = \mathbf{w}^{\mathrm{T}}\mathbf{x} + b \tag{1}$$

where $\mathbf{x}$ is the vector of input data. The N input vectors $\mathbf{x}_1,\ldots,\mathbf{x}_N$ and their corresponding output targets $t_1,\ldots,t_N$, where $t_n \in \{-1,1\}$, construct the training set. An illustrative example is given in Fig. 2 where, $t_n = 1$ stands for red dots and $t_n = -1$ is for blue dots. $y(\mathbf{x})$ denotes the target values generated for the data input $\mathbf{x}$ that is excluded from the training set. As seen in Fig. 2, the red and blue dots located between $\mathbf{w}^{\mathrm{T}}\mathbf{x}+b=1$ and $\mathbf{w}^{\mathrm{T}}\mathbf{x}+b=-1$ margins can make the classification problem more challenging. To tackle this challenge, slack variables, $\xi_n \geq 0$ and $\xi_n \leq 0$ are utilized to. The slack variables are chosen as follows:

- For a red dot located on the $\mathbf{w}^{\mathrm{T}}\mathbf{x}+b=1$ margin, $\xi_n = 0$;
- For a red dot between $\mathbf{w}^{\mathrm{T}}\mathbf{x}+b=0$ and $\mathbf{w}^{\mathrm{T}}\mathbf{x}+b=1$ margins, $0 < \xi_n < 1$;
- For a red dot located on the $\mathbf{w}^{\mathrm{T}}\mathbf{x}+b=0$ margin, $\xi_n = 1$;
  For a red dot between $\mathbf{w}^{\mathrm{T}}\mathbf{x}+b=0$ and $\mathbf{w}^{\mathrm{T}}\mathbf{x}+b=-1$ margins, $\xi_n > 1$.

Similarly, slack variables can be defined for the blue dots. In summary, the slack variable can be formulated as $\xi_n = \left|t_n - y(x_n)\right|$.

An SVM classifier tends to maximize the region between two $\mathbf{w}^{\mathrm{T}}\mathbf{x}+b=-1$ and $\mathbf{w}^{\mathrm{T}}\mathbf{x}+b=1$ margins. The misclassified points are handled through the slack variables. SVM's objective function can be defined as

$$C\sum_{n=1}^{N}\xi_n + \frac{1}{2}\parallel \mathbf{w} \parallel^2 \tag{2}$$

where $C > 0$ provides a trade-off between the slack variables impact and size of separating region. The Lagrangian is formulated as

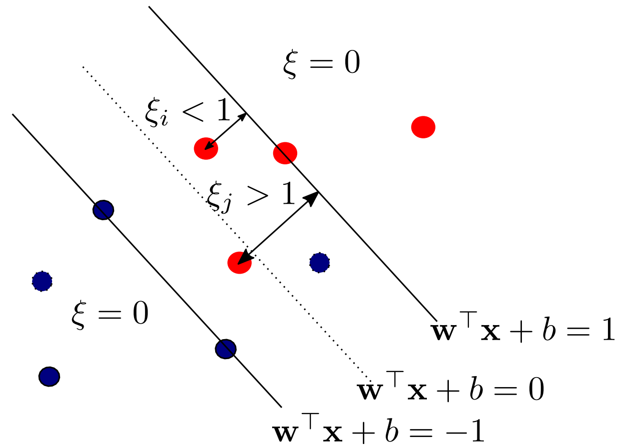


Fig. 2. SVM classification.

$$\begin{aligned} L(\mathbf{w}, b, \mathbf{a}) &= \frac{1}{2} \| \mathbf{w} \|^2 + C \sum_{n=1}^{N} \xi_n \\ &- \sum_{n=1}^{N} a_n \{ t_n y(\mathbf{x}_n) - 1 + \xi_n \} - \sum_{n=1}^{N} \mu_n \xi_n \end{aligned} \tag{3}$$

where $a_n \geq 0$ and $\mu_n \geq 0$ are the Lagrange multipliers. By separately calculating the first derivative of (3) with respect to $\mathbf{w}$, b, and ξ_n and making the results equal to zero one will have

$$\mathbf{w} = \sum_{n=1}^{N} a_n t_n \mathbf{x}_n \tag{4}$$

$$\sum_{n=1}^{N} a_n t_n = 0 \tag{5}$$

$$a_n = C - \mu_n \tag{6}$$

Using (4), (5) and (6), the Lagrangian equation is reformulated as

$$L(\mathbf{a}) = \sum_{n=1}^{N} a_n - \frac{1}{2} \sum_{n=1}^{N} \sum_{m=1}^{N} a_n a_m t_n t_m \mathbf{x}_n^\top \mathbf{x}_m \tag{7}$$

With $0 \leq a_n \leq C$ and $\sum_{n=1}^{N} a_n t_n = 0$.

The training points along with a_i form the support vectors. The optimal b is

$$b = \frac{1}{N_{\mathcal{M}}} \sum_{n \in \mathcal{M}} \left(t_n - \sum_{m \in \mathcal{S}} a_m t_m \mathbf{x}_m \mathbf{x}_n \right) \tag{8}$$

where $\mathcal{M}$ denotes data points inside the margin hyperplanes , $0 < a_n < C$, and $\mathcal{S}$ is the set of support vectors.

If the training data is not linearly separable, one can transform he data into a higher dimensional space using a nonlinear function $\phi(\mathbf{x})$. Since the inner product of $\phi(\mathbf{x})$ in a higher dimensional space can be a computationally heavy calculation, one can use a kernel function to efficiently calculate the inner product in the original data space. The common kernels used for SVM classifiers are linear, polynomial, and radial basis functions (RBF) kernels. In this paper, linear and RBF kernels are used. RBF is formulated as

$$k(\mathbf{x}, \mathbf{x}') = \exp\left(-\frac{\left\| \mathbf{x} - \mathbf{x}' \right\|^2}{2\sigma^2}\right) \tag{9}$$

where σ is a tunable hyperparameter for the standard deviation. A kernel function can be represented as

$$k(\mathbf{x}, \mathbf{x}') = \phi(\mathbf{x})^\mathrm{T} \phi(\mathbf{x}') \tag{10}$$

Using the kernel function, (7) can be reformulated as

$$L(\mathbf{a}) = \sum_{n=1}^{N} a_n - \frac{1}{2} \sum_{n=1}^{N} \sum_{m=1}^{N} a_n a_m t_n t_m k(\mathbf{x}_n, \mathbf{x}_m) \tag{11}$$

Similarly, one can find a_i that with the training points form the support vectors. Moreover, the optimal b is

$$b = \frac{1}{N_{\mathcal{M}}} \sum_{n \in \mathcal{M}} \left(t_n - \sum_{m \in \mathcal{S}} a_m t_m k(\mathbf{x}_n, \mathbf{x}_m) \right) \tag{12}$$

where $\mathcal{M}$ is the set of data points inside the margin hyperplanes, $0 < a_n < C$, and $\mathcal{S}$ is the set of support vectors. Once the SVM optimization problem is solved, the optimal SVM decision function can be formulated as

$$y(\mathbf{x}) = sign\left(\sum_{n=1}^{N} a_n t_n k(\mathbf{x}, \mathbf{x}_n) + b\right) \tag{13}$$

C. Evaluation of Learning Algorithms

Precision and recall are two scorer objects that can evaluate a model's performance. Precision is the ratio of true positives (TP), divided by the sum of TP and false positives (FP). The precision is intuitively the ability of the classifier not to label as a sample as positive that is negative [17]-[18]. The precision formula is the following:

$$precision = \frac{TP}{(TP + FP)} \tag{14}$$

Recall is the ratio of TP, divided by the sum of TP and false negatives (FN). It measures the ability of the classifier to find all the positive samples. The formula for recall is:

$$recall = \frac{TP}{(TP + FN)} \tag{15}$$

Python with Scikit-learn library [16] is chosen to create the proposed circuit topology estimation algorithm. Scikit-learn includes various classification, regression, and clustering algorithms, as well as evaluation models. In this paper, F1 score is utilized. F1 score is interpreted as a weighted average of the precision and recall scorer objects. The F1 score is calculated using

$$F1 = 2 \times \left(\frac{precision \times recall}{precision + recall} \right) \tag{16}$$

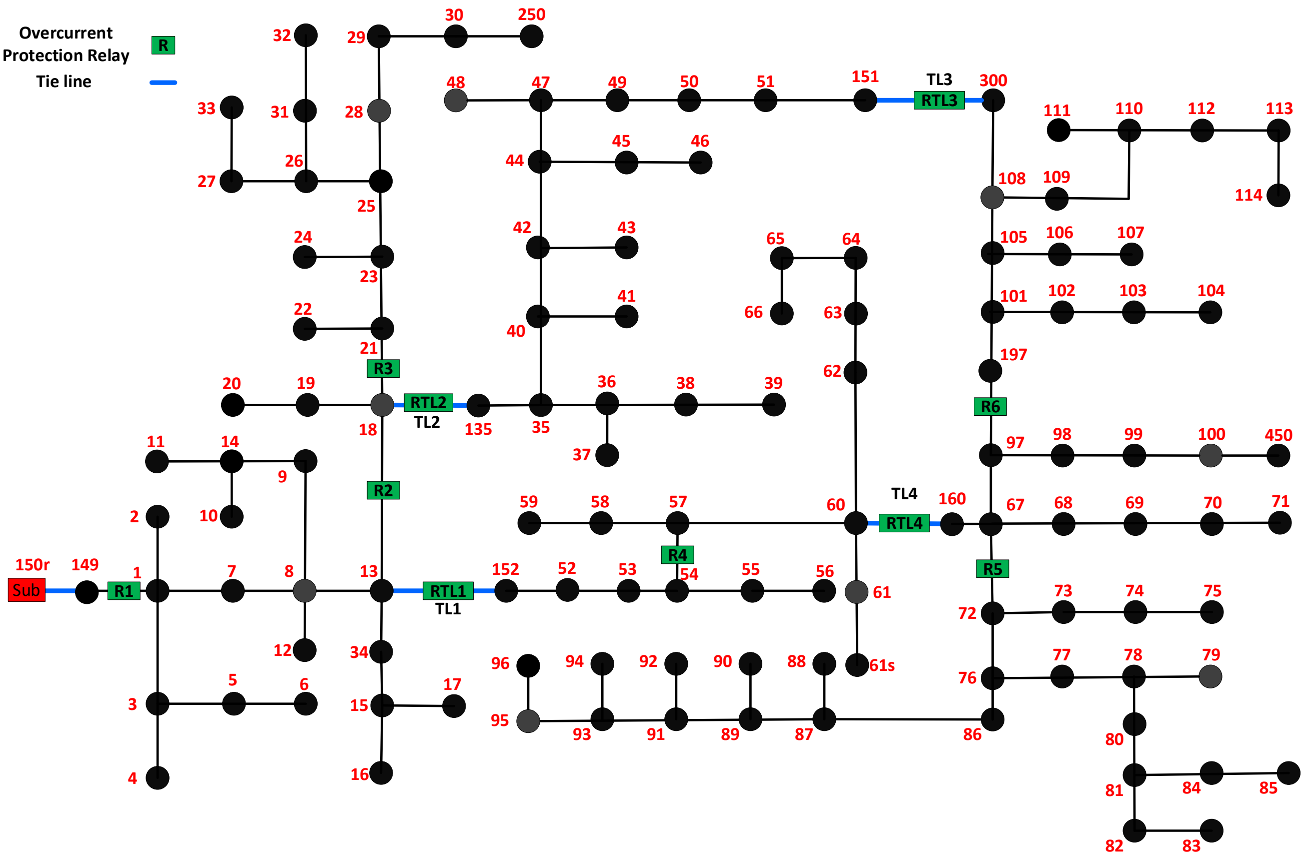


Fig. 3. IEEE 123 bus test system.

III. Simulation Results

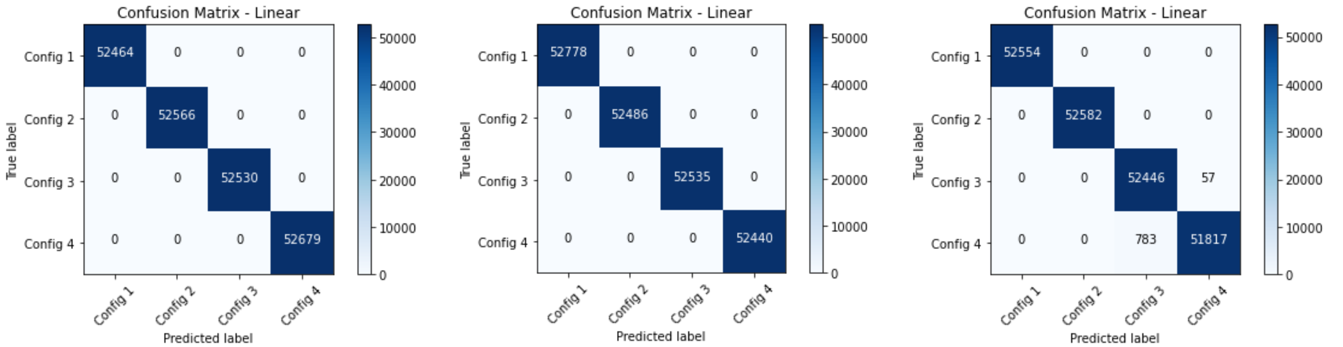
To evaluate the proposed method, a modified IEEE 123-bus test system is used. This circuit is shown in Fig. 3. The system has been modified by adding multiple relays with four tie-lines. This circuit allows the analysis of different circuit topologies for the adaptive protection system. The list of possible configurations is shown in Table I. These topologies are extracted based on the status of the tie breakers TL1, TL2, TL3, and TL4.

Table I. List of Topologies in IEEE 123 bus test system.

Configuration	TL1	TL2	TL3	TL4
1	Close	Open	Close	Close
2	Close	Close	Open	Close
3	Close	Close	Close	Open
4	Open	Close	Close	Close

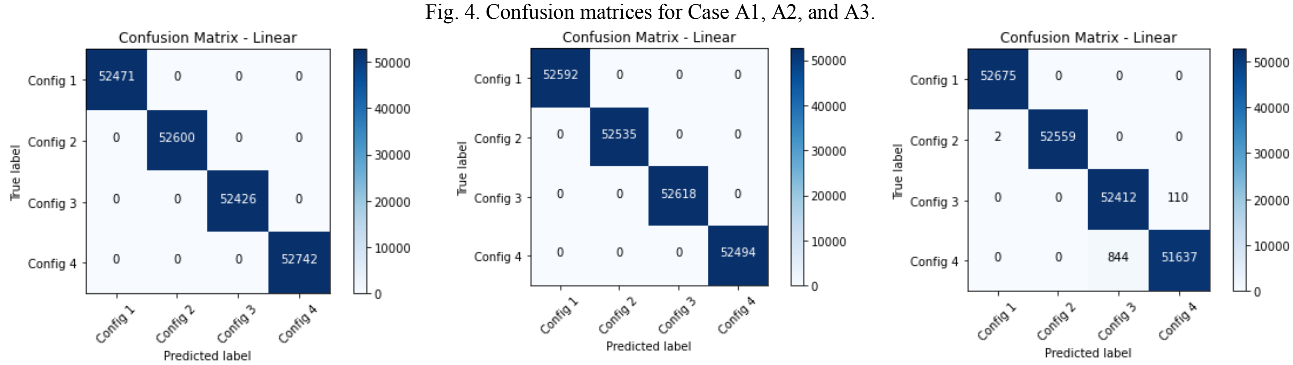
Each configuration has 105120 data samples, to resemble a full year of data, distributed into five-minute intervals. The data is gathered by simulating the system in OpenDSS. The data set is first standardized and equally split into testing and training data. The data from the first 6-month of the year is used for training, while the data of the second 6-month is used for testing. The data was then modeled by two classifiers, LR and SVM. For SVM, linear and RBF kernels are utilized. The kernel functions were defined based on the scikit learn Python library [16]. It is assumed that the adaptive protection system has only access to a limited number of relays and identifies the circuit configuration using the available information. At each relay, the local voltage, current, and active and reactive powers are measured and transmitted to the adaptive protection system.

The performance of ML algorithms is verified using the following test cases: In Case A, the data received from the relays is noiseless. In Case A1, it is assumed that adaptive protection system has access to the data of relays R2, R4, and R6. In Case A2, it is assumed that the adaptive protection system has access to the data of relays R4 and R6. However, in Case A3, the adaptiv e protection system only has access to the data of relay R6. In Case B, a 3% noise level is applied to the measurements. The noise is modeled using a Gaussian distribution function. In Case B1, it is assumed that the adaptive protection system has access to the data of relays R2, R4, and R6. In Case B2, it is assumed that the adaptive protection system has access to the data of relays R4 and R6. However, in Case B3, the adaptive protection system only has access to the data of relay R6. In Case C, a 5% noise level is applied to the measurements. The noise is modeled using a Gaussian distribution function. In Case C1, it is assumed that the adaptive



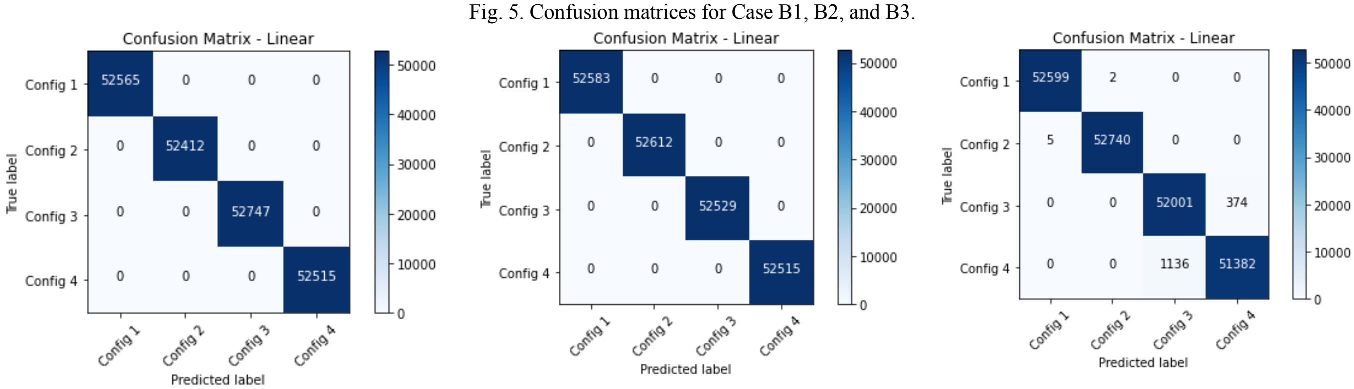
(a) (b) (c)

Fig. 4. Confusion matrices for Case A1, A2, and A3.



(a) (b) (c)

Fig. 5. Confusion matrices for Case B1, B2, and B3.



(a) (b) (c)

Fig. 6. Confusion matrices for Case C1, C2, and C3.

protection system has access to the data of relays R2, R4, and R6. In Case C2, it is assumed that the adaptive protection system has access to the data of relays R4 and R6. However, in Case C3, the adaptive protection system only has access to the data of relay R6. Note that revenue-grade meters are generally calibrated to be accurate within 0.5%, so this study includes analyzing up to a fairly substantial level of measurement noise.

The F1 scores for all cases with different learning algorithms and Kernel functions are shown in Tables II to IV. The F1 scores in the below tables show that the circuit topology estimation algorithm has better accuracy when it has information access to more relays. Moreover, noise on data slightly impacts the performance of learning algorithms. Among the machine learning techniques, SVM with a linear kernel renders relatively higher accuracy. The confusion matrices for Cases A1, A2, and A3 using SVM with linear kernel function are shown in Fig. 4. The confusion matrices for Cases B1, B2, and B3 using SVM with linear kernel function are shown in Fig. 5. The confusion matrices for Cases C1, C2, and C3 using SVM with linear kernel function are shown in Fig. 6.

Table II. F1 scores for Case A1, A2, and A3.

Case A1		
LR	SVM with RBF	SVM with Linear Kernel
0.999	0.999	1.0
Case A2		
LR	SVM with Linear Kernel	SVM with RBF
0.999	0.999	1.0
Case A3		
LR	SVM with Linear Kernel	SVM with RBF
0.990	0.997	0.996

Table III. F1 scores for Case B1, B2, and B3.

Case B1		
LR	SVM with RBF	SVM with Linear Kernel
0.999	0.999	1.0
Case B2		
LR	SVM with Linear Kernel	SVM with RBF
0.999	0.999	1.0
Case B3		
LR	SVM with Linear Kernel	SVM with RBF
0.989	0.997	0.995

Table IV. F1 scores for Case C1, C2, and C3.

Case C1		
LR	SVM with RBF	SVM with Linear Kernel
0.999	0.999	1.0
Case C2		
LR	SVM with Linear Kernel	SVM with RBF
0.999	0.999	1.0
Case C3		
LR	SVM with Linear Kernel	SVM with RBF
0.987	0.996	0.993

IV. CONCLUSIONS

This paper introduces an ML-based circuit topology estimation to be used for adaptive protection systems. An adaptive protection system relies on the communication system infrastructure to identify the latest status of the power grid (e.g., circuit topology or generation level of distributed energy resources). However, when the communication links are outaged due to physical damages or cyberattacks, the adaptive protection system may lose its awareness of the status of the system. Therefore, it is of paramount value to estimate the circuit status using the available healthy communicated data. The developed circuit topology estimation technique was verified on IEEE 123 bus test system. The case studies show that the proposed technique has a high accuracy for classifying the prevailing circuit topology. Among the utilized machine learning algorithms, SVM with a linear kernel function renders the best score. It is also shown that the impact of measurement noises on the accuracy of the proposed technique is minimal.

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