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A Data Mining Transmission Switching Heuristic for Post-Contingency AC Power Flow Violation Reduction in Real-World, Large-Scale Systems

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Abstract

Transmission switching has proven to be a highly useful post-contingency recovery technique by allowing power system operators increased levels of control through leveraging the topology of the power system. However, transmission switching remains only implemented in limited capacity because of concerns over computational complexity, uncertainty of performance in AC systems, and scalability to real-world, large-scale systems. We propose a heuristic which uses a sophisticated guided undersampling procedure combined with logistic regression to accurately identify transmission switching actions to reduce post-contingency AC power flow violations. The proposed heuristic was tested on real-world, large-scale AC power system data and consistently identified optimal or near optimal transmission switching actions. Because the proposed heuristic is computationally inexpensive, addresses an AC system, and is validated on real-world large-scale data, it directly addresses the aforementioned issues regarding transmission switching implementation.

Keywords: Corrective transmission Switching, Contingency analysis, Large-scale power systems, Heuristics, Data mining

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1. Introduction

The robustness of the electrical power grid is one of the most vital features of our critical infrastructure. Therefore, research efforts which accurately model operation of the grid and validate its robustness are of great importance going forward. In particular, methods concerning post-contingency operations are noteworthy because they mitigate the harm which the grid may undergo following component failure. One notable analytical technique is contingency analysis, which allows operators to study the impacts of various contingencies and develop corrective measures which may be applied should such a failure occur. One example of a post-contingency corrective measure is transmission switching, also known as topology control, which we herein study.

In the past, the power grid has been modeled using a fixed configuration (Dehghanian et al., 2015). Using such a modeling paradigm, control on the grid is exerted only by making dispatch decisions. However, transmission switching allows system operators an additional method of control by physically switching transmission lines in and out of the grid. Previous research has demonstrated that transmission switching has a myriad of potential benefits. In one of the initial papers on the technique, Fisher et al. (2008) showed that transmission switching can produce significant reductions in generation fuel costs. Other works have echoed this conclusion with focuses on sensitivity analysis (Hedman et al., 2008; Ruiz et al., 2012) and contingency analysis (Hedman et al., 2009). In addition to cost, transmission switching has demonstrated usefulness in preventing loadshed (Escobedo et al., 2014; Dehghanian et al., 2015; Brown & Moreno-Centeno, 2020), improving system reliability (Korad & Hedman, 2013), and, as studied herein, reducing post-contingency violations (Li et al., 2017).

The herein studied problem, optimal transmission switching, lies within a class of computationally complex optimization problems in the area of power systems planning and operations. These problems are of substantial interest to the operations research community because of their challenging nature and their clear value to practitioners. Important recent work on transmission switching in particular includes novel formulations and valid inequalities (Kocuk et al., 2016), development of techniques to solve for transmission switching actions under stochastic conditions (Pichler & Tomasgard, 2016), application of transmission switching within the unit commitment problem (Schumacher et al., 2017), and accounting for variable renewable energy sources (Cavalheiro et al., 2018). A problem fundamentally related to transmission switching is transmission expansion planning (TEP), wherein optimal solutions suggest new transmission lines to be invested in and added to the power grid. Skolfield et al. (2022) derived path-based valid inequalities to ease the difficulty in solution of TEP, Ghaddar & Jabr (2019) solved TEP using semidefinite programming, and Moreira et al. (2021) developed a three-stage approach to solve TEP under climate uncertainty.

There are other problems in power systems planning and operations which are of similar interest to the operations research community. Such problems include power generation expansion, similar to TEP, wherein new generators are added to the power system (Lohmann & Rebennack, 2017; Pineda & Morales, 2016). Another related problem is in the planning and application of power grid defense Alguacil et al. (2014), in which transmission lines identified as critical are hardened from malicious or weather-related events. A third problem of interest is the optimal phasor measurement unit placement problem (Carvalho et al., 2018), which seeks to give full real-time visibility of the network at minimum cost. A class of problems regularly-studied by the operations research community are the unit commitment and security-constrained unit commitment problems, wherein generators are scheduled for operations either with or without consideration of potential critical contingencies (Lorca et al., 2016; Zheng et al., 2013, 2016; Zuniga Vazquez et al., 2022). Finally, a recent topic of interest from the academic community is in relation to electric vehicles, wherein operations research techniques can be used to account for power system operations impacted by vehicle charge and discharge scheduling (Umetani et al., 2017), inventory management (Sun et al., 2019), and relocation (Gambella et al., 2018).

We refer the reader to the work by Skolfield & Escobedo (2022), which provides a robust literature review on applications of operations research techniques in power systems.

This work develops a data mining method which identifies transmission switching actions to reduce post-contingency voltage magnitude and branch flow violations. The use of transmission switching to alleviate violations has been an issue of academic interest over recent years. Balasubramanian et al. (2016) analyzed switching actions by a major ISO for this expressed purpose. Zhao et al. (2019) developed a decomposition-based methodology to identify optimal switching actions to reduce violations in light-load settings. Khodaei et al. (2010) utilized transmission switching to alleviate violations within the context of security-constrained unit commitment. Li et al. (2020) developed sensitivity-based factors to identify switching actions to relieve violations. Shen et al. (2019) developed a multi-stage approach to reduce voltage violations with transmission switching. Most noteworthy to this work is (Li et al., 2017), in which several heuristics to identify switching actions to reduce violations were developed on real-world, large-scale power system data.

The proposed methodology applies a guided undersampling method proposed by (Sung et al., 2022) and then utilizes logistic regression to identify post-contingency transmission switching candidates to reduce AC power flow (ACPF) violations. Notably, these data mining methods are computationally inexpensive and can be quickly executed on real-world AC power system data, providing greater certainty regarding *both* AC system performance and large-scale implementation. This is notable because it addresses three of the four explanations mentioned in (Li et al., 2017) as to why transmission switching is currently being used only in limited capacity: computational complexity, uncertainty of impact on real-world large-scale power systems, uncertainty of impact when moving from DC to AC, and transient stability. These four items are substantiated in detail in the following paragraphs.

1 – Computational complexity: The first explanation for lack of widespread implementation of transmission switching is in regard to computational complexity or, equivalently, the scalability of algorithms. Mixed-integer nonlinear programs (MINLPs), such as the AC optimal transmission switching (ACOTS) problem, are notoriously difficult to solve. Because of this, researchers have primarily tested algorithms on small-scale networks and/or used linearizations to reduce the difficulty of the problem, which cast uncertainty over scalability and solution accuracy, respectively. These two approaches are discussed in greater detail in the following two paragraphs.

2 – Impact on large-scale systems: The second explanation is that the overwhelming majority of research on transmission switching studies small-scale systems. A handful of noteworthy research projects have vetted their approaches on large-scale systems. Works relevant to the herein studied problem include (Li et al., 2016, 2017, 2020; Shen et al., 2019) which each utilize transmission switching at a large scale to reduce violations. There have been other noteworthy research efforts which study real-world electric power systems but are not directly applicable to the application discussed here. Carrión et al. (2021) study a related problem of optimal static VAR compensator location at a large scale. Li et al. (2021) extend the traditional DC optimal transmission switching model with connectivity constraints and test on a large-scale system. Ramesh et al. (2021) utilize a decomposition technique to study the security-constrained unit commitment problem with switching and test their results on the Polish test system. Other recent noteworthy projects which utilize real-world sized test cases include (Han et al., 2022a; Mohseni-Bonab et al., 2022; Altun et al., 2020).

In contrast with the above, most works, including the bulk of works cited herein, test their approaches on small-scale systems such as the IEEE 118-bus test case which appear in test case archives such as (Christie, 2000). Real-world systems, however, have up to tens of thousands of buses, obscuring both the impact of complexity and scalability of current approaches. Given that most algorithms are tested on small systems, it remains unclear if these algorithms can be applied in the real world.

3 – Impact on AC systems: The third item addresses the concern that benefits derived from DC-based models may not translate to AC models. Because of the issues associated with solving problems such as the ACOTS, the majority of transmission switching research focuses on DC-based models. Indeed, excluding noteworthy examples (Soroush & Fuller, 2014; Bai et al., 2017; Li et al., 2017, 2016; Kocuk et al., 2017; Shi & Oren, 2015), the papers herein cited use linearizations to address the various transmission switching problem variants. This is worrisome because, as demonstrated in (Potluri & Hedman, 2012), transmission switching actions identified by DC models may be infeasible or result in negative outcomes when implemented in AC systems. Moreover, as aforesaid, most if not all of these models are only tested on unrealistically small networks, further clouding the issue of whether conclusions derived from DC models can be applied to AC systems.

4 – Transient stability Finally, we note that relatively recent research has shown that transmission line switching may introduce disturbances into power systems resulting in transient instability issues (Liu et al., 2011). Despite this fact, the overwhelming majority of research in this area fails to account for transient stability. There are a small group of noteworthy exceptions. Alhazmi et al. (2019) analyze the implications regarding stability and reliability of their transmission switching solutions, but do not account for them within the algorithm itself. Shi et al. (2019) introduce simple transient security constraints into a two-stage switching model. Han et al. (2022b) incorporate qualitative constraints to seek stability maintenance into their topology control model. Mak et al. (2017) propose a novel optimization model which incorporates constraints to seek transient stability and an algorithm which incorporates their new model to further ensure stability. While the above works take steps to reduce concerns regarding transient stability, to the authors knowledge, the methods described by (Dehghanian et al., 2015) and (Mak et al., 2017) are the only ones to systematically verify stability within the algorithm itself. Moreover, the framework proposed in (Dehghanian et al., 2015) can be combined with virtually any approach.

This work makes three primary contributions. First, to the authors' knowledge, our proposed heuristic is the first true data mining technique to classify strong AC transmission-switching actions using power flow information rather than a simple history of useful switching actions. Second, our method is unique in the literature in that it directly addresses three of the four issues regarding transmission switching implementation. Moreover, it can be directly combined with with the framework in (Dehghanian et al., 2015) to address the fourth issue. Finally, we make a much stronger empirical analysis than the analysis described in (Li et al., 2017), studying the impact of an exhaustive set of switching actions on real-world large-scale power system data, rather than a small subset of the actions or actions across a small system. A secondary contribution of this work is that we formalize the problem characterized in (Li et al., 2017).

We note that, in recent years, several papers claim to use "previous knowledge" in the context of a data mining framework, but fail to do so in the way data mining is understood. The authors in (Li et al., 2016) propose a heuristic where a lookup table containing contingency-specific switching solutions is used to select potential switching candidates. The authors in (Hedman et al., 2009) propose a similar heuristic where previously-successful switches are considered as potential switching actions. Finally, the authors in (Li et al., 2017) extend the approach in (Hedman et al., 2009) by splitting previously-successful switches into training and testing sets; these switches are subsequently validated accordingly. However, this method does not incorporate any additional information other than the switching action itself.

In contrast with the above methods, the herein proposed method incorporates information about the current status of the grid into a sophisticated data mining method to predict the *impact* of a given candidate switching action. Succinctly, the resulting method is a true data mining approach which exploits the set of available information to identify candidate switching actions.

The remainder of this paper is organized as follows. Section 2 presents and describes two optimization models for post-contingency ACPF violation reduction. Section 3 proposes our data mining heuristic using guided undersampling and logistic regression. Section 4 discusses the experimental setup and several implementation issues which are inherent to the proposed methodology and the herein studied problem. Section 5 presents our analysis and demonstrates that our proposed method identifies optimal and near-optimal switching solutions and is superior to existing heuristics based on distance to violation elements. Section 6 concludes the work.

2. ACPF Violation Reduction Optimization Model with Transmission Switching

During post-contingency operations, system operators must be provided with corrective actions which are both quick to identify and can be implemented with confidence. We note that the execution of transmission switching to alleviate power system violations may represent a decreased burden on the system operator than actions such as a generation re-dispatch (Li et al., 2017). As an example, ISO New England lists twelve actions to return the system to "normal" status. These actions, in order listed by ISO New England, are as follows: adjusting phase shifting transformers, adjusting reactive power flows, enacting weather-sensitive transmission facility ratings, deviation from economic dispatch, opening of circuit breakers, manually tripping generators, transmission switching, exceeding generator maximums, load curtailment, capacity purchases, depletion of temporary reserves, and enacting enhanced facility ratings (ISO New England, Sep. 2022). It is frequently to the benefit of the system operator to avoid any of the above actions associated with a computationally expensive re-dispatch, particularly in the context of contingency response. In contrast, transmission switching, particularly when executed within the context of a data mining approach such as the one proposed herein, represents a computationally inexpensive solution to returning the grid to a violation-free status.

One of the traditional manners to derive corrective actions, and in particular transmission switching actions, is through the solution of optimization models such as those described in this section. As such, we herein describe the mathematical formulation of the ACPF optimization model for violation reduction with transmission switching (ACPF-VR-TS). Note that these problems were described qualitatively by the authors in (Li et al., 2017). However, this work is the first to formally characterize these problems as optimization models.

2.1. ACPF-VR-TS for Voltage Magnitude Violations

The ACPF-VR-TS model for voltage magnitude violation reduction is characterized as follows. We note that the notation utilized in this and the forthcoming subsection is defined in Appendix A.

$$\min \sum_{n\in N} V_n^+ + V_n^- \tag{1a}$$

subject to

$$P_i^g - P_i^d = \sum_{\langle i,j\rangle\in K} p_{ij} \qquad i\in N \tag{1b}$$

$$Q_i^g - Q_i^d = \sum_{\langle i,j\rangle\in K} q_{ij} \qquad i\in N \tag{1c}$$

$$p_{ij} = Z_{ij}(g_{ij}V_i^2 - V_iV_j(g_{ij}\cos\theta_{ij} + b_{ij}\sin\theta_{ij})) \qquad \langle i,j\rangle\in K \tag{1d}$$

$$q_{ij} = Z_{ij}(b_{ij}V_i^2 - V_iV_j(g_{ij}\sin\theta_{ij} - b_{ij}\cos\theta_{ij})) \qquad \langle i,j\rangle\in K \tag{1e}$$

$$V_n^- \geq V_n^{\min} - V_n \qquad n\in N \tag{1f}$$

$$V_n^- \geq 0 \qquad n\in N \tag{1g}$$

$$V_n^+ \geq V_n - V_n^{\max} \qquad n\in N \tag{1h}$$

$$V_n^+ \geq 0 \qquad n\in N \tag{1i}$$

$$\sum_{\langle i,j\rangle\in K} 1 - Z_{ij} = 1 \tag{1j}$$

Objective (1a) minimizes the sum of voltage magnitude violations. Constraints (1b) and (1c) model active and reactive power injections at bus i, respectively. Constraints (1d) and (1e) model the flow of active and reactive power from bus i to bus j, respectively, while accounting for transmission switching. Note that fixing all binary variables Z_{ij} to 1 reduces constraints (1b)-(1e) to the constraints which characterize the ACPF. Constraints (1f) and (1g) model the violation of the voltage magnitude lower bounds. Constraints (1h) and (1i) model the violation of the voltage magnitude upper bounds.

Finally, Constraint (1j) dictates that the number of allowable transmission line switches is equal to one. There are two primary practical explanations for this constraint. First, significant concerns exist regarding transient stability with multiple switching actions. Second, physical implementation of transmission switching requires substantial effort. This effort magnifies as the number of switches increases. We refer the reader to (Brown & Moreno-Centeno, 2020) for a detailed discussion on these two topics.

2.2. ACPF-VR-TS for Branch flow Violations

The ACPF-VR-TS model for branch flow violation reduction is characterized as follows.

$$\min \sum_{\langle i,j\rangle \in K} f_{ij} \tag{2a}$$

subject to

$$(1b)\text{–}(1e), (1j) \qquad \text{(2b)–(2e),(2j)}$$

$$f^i_{ij} \geq p^2_{ij} + q^2_{ij} - S^2_k \qquad \langle i,j\rangle \in K \tag{2f}$$

$$f^j_{ij} \geq p^2_{ji} + q^2_{ji} - S^2_k \qquad \langle i,j\rangle \in K \tag{2g}$$

$$f_{ij} \geq f^i_{ij} \qquad \langle i,j\rangle \in K \tag{2h}$$

$$f_{ij} \geq 0 \qquad \langle i,j\rangle \in K \tag{2i}$$

Objective (2a) minimizes the sum of branch flow violations. Constraints (2f) and (2g) model violation of thermal limits as a function of apparent power. Constraint (2h)-(2i) dictates that the flow violation for transmission line k is equal to either zero or the larger of the two violations at each end of the line.

3. Methodology

Traditionally speaking, optimal transmission switching actions are sought out by characterizing the power system in a steady state. That is, an optimal power flow (OPF) or optimal transmission switching (OTS) model is solved, and the switching actions are either obtained directly from the solution (when using OTS) or further derived from the solution (when using OPF). However, as discussed in Section 1 the solution of MINLPs is exceedingly computationally expensive. When considered in the context of real-time operations, this computational cost is unlikely to be to be satisfied. As such, less computationally-intensive methods are required, such as the one proposed in the forthcoming paragraphs.

It is important to note that, as in (Li et al., 2017), we do not solve the models outlined in Section 2 via the use of an optimization solver. The primary reason for this is because of the computational difficulty associated with solving MINLPs. As such, most work addressing problems similar to those in Section 2 either use linearizations or solve across small systems. In contrast, this work seeks solutions to these models via a data mining-based heuristic in a manner tractable at a large scale without linearization. The following two paragraphs discuss an important feature of transmission switching which contextualizes the problem within a data mining framework – imbalanced data. Following this, we present our dual-component guided undersampling method, introduce the classification methodology, and formalize the proposed method.

It is well established in the literature that, regardless of objective (e.g., violation reduction or cost savings), there are typically only a small number of transmission switching actions which result in a substantial objective improvement. Thus, in a data mining context, identifying strong transmission switching actions should be viewed as an imbalanced-data classification problem. In a two-class setting, imbalanced data refers to a dataset where one class (the majority class) has cardinality substantially larger than that of the opposing (minority) class. In such settings, traditional classification algorithms can suffer poor performance because they can simply classify all instances as majority and still achieve a high classification rate. Therefore, when developing a data mining approach for transmission switching, one must take care to adequately handle the problems inherent to imbalanced data.

The proposed methodology addresses the imbalanced data problem as follows. First, we utilize a guided undersampling procedure (Sung et al., 2022) which undersamples the majority class using two instance-selecting techniques. The first technique, ensemble outlier-filtering, utilizes a unique ensemble classifier to remove both majority and minority outliers from the training data. The second technique, normalized-cut sampling, undersamples the majority class such that the density distribution of the majority class is preserved. After our guided undersampling method, we apply logistic regression to develop the classification boundary; i.e., to predict which transmission lines are strong candidates. The following subsections detail each of the components of the proposed methodology.

3.1. Ensemble Outlier-Filtering

The first component of the guided undersampling method used herein is ensemble outlier-filtering. From a data-analytic perspective, outlier removal is a critical component of building an effective classifier. However, when the training data is imbalanced, many outlier filtering techniques demonstrate poor performance. To address this, the authors in (Sung et al., 2022) proposed an ensemble outlier-filtering technique which utilizes the power of an ensemble classifier in which each training set is balanced. The ensemble outlier-filtering technique is described as follows. Note that, throughout the remainder of this section, an important value is the ratio of majority instances to minority instances, known as the imbalance ratio.

Given a set of n-dimensional data $X = X_{\mathrm{maj}} \cup X_{\mathrm{min}}$, with imbalance ratio $r = \frac{|X_{\mathrm{maj}}|}{|X_{\mathrm{min}}|}$, ensemble outlier-filtering proceeds as follows.

1. Partition the majority class X_{maj} into r subsets of equal size, where each subset has cardinality $|X_{\mathrm{min}}|$. Construct r distinct training subsets: X_{min} and one subset of X_{maj}.
2. Train r logistic regression classifiers, one for each subset of the training data.
3. Predict the class of every instance in X using the majority voting scheme: instance X_i is assigned to a class if it is predicted as such by at least $\frac{r}{2}$ classifiers.
4. Remove from the training data the outliers – instances whose predicted class differs from their true class.

One salient characteristic of the method described above is that it seeks to remove both minority and majority from the training data. While the removal of minority data may appear counterintuitive, as shown in (Sung et al., 2022), it is critical to strong imbalanced data classification performance.

3.2. Normalized-Cut Sampling

One traditional approach to imbalanced data classification is majority subsampling, in which a subset of the instances from the majority class is selected from the training data in an effort to address class imbalance. However, as described in (Sung et al., 2022), the user must take great care to construct their majority subsample, as they risk an inaccurate decision boundary if there are regions where the density distribution of the greater majority class does not persist. To address this, the authors in (Sung et al., 2022) proposed a new technique, normalized-cut sampling. This method utilizes the normalized-cut segmentation technique proposed in (Shi & Malik, 2000) to iteratively cluster the majority class such that the density distribution is preserved and the number of majority-class clusters is equal to the cardinality of the minority class. The medoids of the clusters are then selected as the majority class subsample.

Given training data $X = X_{\text{maj}} \cup X_{\text{min}}$, with $k = |X_{\text{min}}|$, the normalized-cut sampling procedure is described as follows.

1. Construct graph $G_1 = (V, E)$, where V denotes all majority instances and E contains edges between all node pairs in V. Set edge weights between node pair (i, j) as

$$\mathcal{L}_{ij} = \exp(||\mathbf{X}_i - \mathbf{X}_j||^2) \tag{3}$$

2. Initialize an empty set C.
3. For $i = 1 \dots k$
   (a) Utilizing the procedure from (Shi & Malik, 2000), bipartition G_i into clusters C_i^1 and C_i^2. Add these two clusters to C.
   (b) Construct G_{i+1} using the instances from the cluster in C with maximum cardinality (C_{max}).

(c) Update $C = C \setminus C_{\text{max}}$.

4. Form the majority subsample with the medoids of the clusters in C.

3.3. Logistic Regression

Logistic regression is a classification model which estimates the probability that a given categorical dependent variable belongs to a particular category (James et al., 2013). Given two categories, denoted numerically as 0 and 1, and a set of n-dimensional data $\mathbf{X}_i$ with target variable $Y_i \in \{0, 1\}$, the logistic regression model estimates the probability that the target variable is in category 1 as

$$P(Y_i|\mathbf{X}_i) = \frac{e^{\beta_0 + \sum_{j=1}^{n} \beta_j X_i^j}}{1 + e^{\beta_0 + \sum_{j=1}^{n} \beta_j X_i^j}}, \tag{4}$$

where β_0 is the intercept of the regression function and β_j is the multiplicative regression coefficient associated with the j-th dimension of the data. The regression coefficients are those which maximize the log-likelihood function

$$\begin{aligned} \ln L(\beta|Y) = &\sum_{i=1}^{m} Y_i \ln P(Y_i|\mathbf{X}_i) \\ &+ \sum_{i=1}^{m} (1 - Y_i) \ln(1 - P(Y_i|\mathbf{X}_i)), \end{aligned} \tag{5}$$

where m denotes the number of observations in the data set.

Note that the output of the logistic regression model from Equation (4) is the probability that a given datum $\mathbf{X}_i$ belongs to the class of focus. In our case, this value can be interpreted as the probability that a transmission switching action results in a substantial reduction in post-contingency violation. Therefore, we use this probability to rank the set of all transmission lines.

3.4. Proposed Methodology

The previous subsections detailed the two components of the guided undersampling method as well as a specific classification methodology. Given training data $X = X_{\text{maj}} \cup X_{\text{min}}$, the proposed method is formalized as follows.

1. Apply ensemble outlier-filtering to the training data X to obtain the clean subsample $X' = X'_{\text{maj}} \cup X'_{\text{min}}$

2. Apply normalized-cut sampling to X'_{maj} to further subset the majority class and obtain X''_{maj}, where $|X''_{\text{maj}}| = |X'_{\text{min}}|$
3. Train a logistic regression model on the clean and balanced training data $X''_{\text{maj}} \cup X'_{\text{min}}$ to derive the classification model

The logistic regression model which is trained in Step (3) can then be utilized as follows. Given an $m \times n$-dimensional data set where m is the number of transmission lines and n denotes the number of variables describing post-contingency ACPF information, the model trained in Step (3) can be directly applied to such data to predict which transmission lines are strong switching candidates. We elaborate on this process in the following section.

From a practical setting, the above-proposed methodology can be implemented as follows. The model should be trained and validated in an off-line setting to account for the computational time associated with the dimensionality of the data. Following this, whenever a contingency occurs, a post-contingency state should be established. The ISO can then gather the system information associated with this post-contingency state. This system information can be fed into the model as described above, each viable switching action predicted for impact, and the superior switching action implemented.

4. Experimental Setup

4.1. Test Case

The test case utilized for analysis herein consists of emergency management system snapshots from the Pennsylvania New Jersey Maryland Interconnection (PJM). These snapshots span 167 hours, each with a different load profile, and total of 8064 critical contingencies across the entire test case. For a detailed description on how these contingencies were identified, we refer the reader to (Li et al., 2017). The PJM system consists of approximately 15,500 buses, 2,800 generators, and 20,500 transmission lines. The total active power load is approximately 139 GW and the total reactive power load is approximately 22 GW.

4.2. Data Development

4.2.1. Exhaustive Search of Switching Actions

To develop the training data which drives the predictive model, we performed an exhaustive search (henceforth referred to as the "exhaustive search") of non-radial transmission switching actions across all critical contingencies from (Li et al., 2017) as described in the following paragraph. Because it is indeed exhaustive, this search guarantees that, for each contingency, we will identify the switching action that reduces the most violations (i.e., the optimal switching action). This is a salient point which allows this work to be the first to conduct a thorough analysis using the true optimality gap (as defined in Section 5.1) for the herein studied heuristics and for a problem of this size. We note that the exhaustive search is conducted using a series of AC power flow solutions before and after a switching action has occurred. The analysis of such actions allow for the data mining approach proposed in Section 3.4 to identify strong switching actions in seconds, rather than via an optimization methodology, dramatically reduce the computational cost associated traditional approaches as discussed in Section 3.

We perform the exhaustive search for each hour and critical contingency. For contingencies which did not include generator failure, all generator outputs remained at the pre-contingency level with the exception of the slack bus. For contingencies which simulate generator failure, re-dispatch was performed using a participation factor as outlined in (LI et al.). Finally, only a single corrective line switch is implemented. The procedure utilized to generate the data is thus described in the following steps. Given a power system instance with n non-radial lines, the exhaustive search proceeds as follows.

1. Run ACPF using given input data
2. Simulate contingency
3. Calculate re-dispatch (if necessary)
4. Run ACPF
5. Record system information

6. For $i = 1 \ldots n$
    (a) Perform line switch
    (b) Run ACPF
    (c) Record remaining violation magnitude (if any)

Note that, in Steps (5) and (6c), information gathered includes both voltage magnitude and branch flow violations. As such, the exhaustive search generates data for both problems outlined in Section 2. The exhaustive search outlined above was run systematically to include all critical contingencies identified in (Li et al., 2017) and all feasible line switches. Doing so yields a rich data set which can be exploited via the use of data mining techniques.

4.2.2. Data Features

There are several important pieces of data collected during step (5) which drive the prediction methodology. The first set of features describes the switching element. This set includes branch resistance, reactance, susceptance, thermal rating, and active and reactive power flow. Next, we gathered the magnitude of all violations within a set of distances, calculated using undirected distance, around the switching element. The third group of data we gathered were characteristics of the violation elements including bus type, active and reactive power demand, node degree, resistance, reactance, MVA rating, active power flow, and reactive power flow. Next, we measured the undirected distance from the switching element to each violation element, the distance from each violation element to the contingency element, and the distance from the switching element to the contingency element. Finally, we gathered distance data in a directed fashion, using the flow of active power to construct a directed graph. From this graph we identified distances identical to those described above.

We note that the model herein developed is sensitive to the set of features used to train it. As such, we conducted feature selection prior to training the model. We utilized the first 83 hours (approximately on half of the data set), to conduct a forward-stepwise procedure to select a set of features which minimized the optimality gap. As such, all forthcoming experiments were conducted on the remaining 84 hours of data described in Section 4.1.

4.2.3. Training Data

To train the classification model outlined in Section 3, we took the top 100 switching actions according to the exhaustive search for each hour, critical contingency, and violation type. We took only the top 100 switches for three reasons. First, this allowed us to satisfy the memory requirements of the computational setup used to perform our experiments. Second, we note that even using the top 100 switching actions results in an imbalanced data set. Specifically, for voltage magnitude violations, approximately 2.5% of the top 100 switches result in an optimality gap of less than ten percent. For branch flow violations, only 5.7% switches result in such an optimality gap. Finally, we note that it has been established in the literature that one successful approach to majority subsampling is to focus on regions where the majority and minority classes overlap (Japkowicz, 2000).

4.3. Cross-Validation

Cross-validation is imperative for the development of any predictive model to properly assess the model's strength. However, it bears mentioning that cross-validation in this setting is different than in traditional contexts. In an effort to minimize bias from similar instances, each fold used during cross-validation consisted of all contingencies within a single hour out of the 84 hours used for testing as described in Section 4.2.2. The remaining data used to train the model consists of all contingencies within the remaining 83 hours. This resulted in an 84-fold cross-validation procedure. On average, each cross-validation iteration took approximately 25.59 minutes for model training and testing. In addition, each contingency in the test fold was tested individually for the performance metric described in Section 5.1. That is, rather than a single data point for each fold, testing generates a number of data points equal to the number of contingencies within the given hour.

4.4. Computational Environment

All computational experiments herein described for data generation (Section 4.2) were conducted in a distributed environment on computing nodes which had 22GB of RAM shared by two 2.8 GHz quad core Intel 503 Xeon 5560 processors using Texas A&M University supercomputing resources. The operating system was CentOS Linux version 7.6.1810. All power flows were solved using the MATPOWER toolbox (Zimmerman et al., 2011). All tasks related to model development, feature selection, and cross-validation were conducted on a machine equipped with 8 GB of RAM memory and a quad-core 1.8 GHz Intel i7-8565U processor. Ensemble outlier-filtering, normalized-cut sampling, and logistic regression models were implemented using the LIBLINEAR package Fan et al. (2008) within MATLAB.

We note that supercomputing resources were utilized not because of the computational time associated with model training nor prediction nor the cost of solution of the power flow problem itself. In contrast, the supercomputing resources were utilized due to the sheer number of scenarios studied herein. Specifically, as described in Section 4.1 there were over 8000 contingencies to test across the 167 hours. Of the roughly 20,500 transmission lines, on the order of 16,000 resulted in valid switching solutions, resulting in approximately 128 million power flows to solve. Though each such power flow can be solved in a fraction of a second either in a supercomputing infrastructure or a standard workstation, it was the number of cores available which made such an analysis feasible given the data provided. It merits mentioning that such data can be gathered within the context of a regularly-scheduled contingency analysis procedure.

5. Results

5.1. Performance Metric

To measure the effectiveness of our data mining heuristic, we utilize the optimality gap. This measure describes the relative difference between the percentage of violations reduced by the optimal switching action and the corresponding value from the best action chosen by the heuristic. We utilize the percentage of violations reduced because it dampens the impact of instances with a particularly large or small initial violation magnitude. As mentioned in Section 4.2.1, we note that the exhaustive search guarantees the identification of the optimal solution. Therefore, the forthcoming analysis using the optimality gap provides context on how closely a heuristic performs relative to the optimal solution. The optimality gap is calculated as follows

$$Gap\% = \frac{V^* - V^H}{V^*} \times 100, \tag{6}$$

where V^* denotes the percentage of violation reduction stemming from the optimal switching action as identified by the exhaustive search, and V^H denotes corresponding value stemming from the switching action proposed by the heuristic. Note that we calculate this value separately for voltage magnitude violations and branch flow violations.

5.2. The Data Mininig Heuristic Consistently Identifies Optimal or Near-Optimal Transmission Switching Actions

Table 1 shows the average and standard deviation of the optimality gap obtained for the top switching action according to Equation (4), fixed all other lines as closed, and solved the ACPF problem associated with that topology. The results are broken out by violation type.

Table 1: Summary statistics for optimality gap

Violation Type	Mean	St. Dev.
Voltage Magnitude	5.51%	17.60%
Branch Flow	5.89%	93.71%

Table 1 shows that the data mining heuristic produces strong performance in terms of optimality gap. Specifically, for both violation magnitude and branch flow violations, the average optimality gap of the top switch identified by the data mining heuristic is less than six percent, which is a very reasonable result in practice for real-world, large-scale systems. However, the branch flow violations produce a relatively large standard deviation. This is largely because of three instances, where the data mining heuristic produced optimality gaps substantially larger than 100%. Removing these three instances, the standard deviation drops to 17.5%, a much more reasonable value. The following paragraphs explore these results in greater detail.

Figure 1 shows a histogram of the optimality gaps attained by the data mining heuristic for the two types of violations. The first finding shown in Figure 1 is that the bulk of instances fall either at zero or less than 0.1%. This means that, for the bulk of instances herein studied, the data mining heuristic identified optimal or near-optimal switching actions.

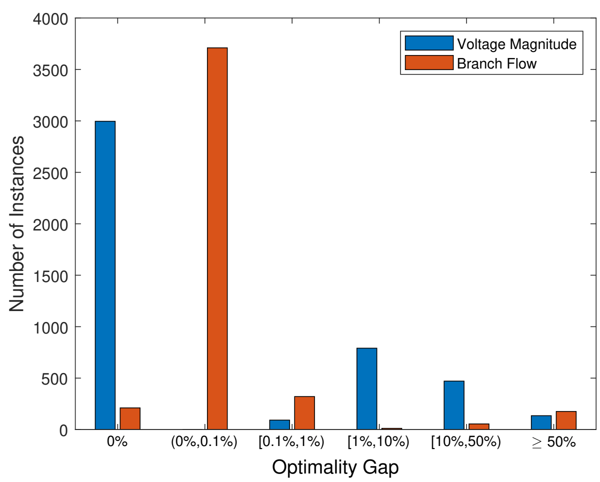

Figure 1: The data mining heuristic attains optimality gaps at or near zero in the overwhelming majority of instances

One additional important finding from Figure 1 is the number of scenarios with optimality gaps greater than 50%. Specifically there are 135 such scenarios for voltage magnitude violations and 176 such scenarios for branch flow violations. We note that these scenarios make up only approximately 1.7% and 2.2% of studied instances, respectively, further demonstrating the strength of the method.

To put these results in context, we note that, as mentioned in Section 4.1, the data upon which the herein proposed approach was developed consists of 167 distinct load profiles. Each a snapshot of the existing system operated by PJM. As such, the methodology is robust to changes in the system load. Moreover, if dramatic changes in the system should occur which significantly impact the load profile, it is simply a matter of data generation and model re-training to incorporate these changes into the herein proposed approach.

5.3. The Data Mining Hueristic Attains an Optimality Gap Substantially Smaller than that of a Distance-based Heuristic

While Section 5.2 showed that the data mining heuristic produced strong performance in its own right, it is also important to compare against the strongest-performing existing methods. The authors in (Li et al., 2017) developed distance-based heuristics which constitute the strongest-performing methods which are viable at a large scale for the problems outlined in Section 2. Specifically, the authors in (Li et al., 2017) developed a heuristic which obtains solutions based on the distance from the candidate branch to the violation element (CBVE). However, CBVE only identifies switches in the area around the violation element rather than focusing on characteristics of the switches themselves. Therefore, the following experiments utilize a candidate pool – a group of switching candidates from which the best switch is selected. We note that, to achieve best performance, we re-conducted feature selection as described in Section 4.2.2 using a candidate pool of ten. In the interest of full disclosure, we note that the authors in (Li et al., 2017) also developed a heuristic using the distance from the switch to the contingency element. However, in our experiments, this method was effectively dominated by CBVE. We therefore excluded it from our analysis.

Table 2 summarizes the performance of the two heuristic methods in terms of the optimality gap using a candidate pool of size ten. Specifically, Table 2 shows the mean and standard deviation of the optimality gap for the proposed data mining method, denoted DM-10, against that of the distance-based metric, CBVE, when using a candidate pool of size ten. These results are broken out by the type of violation.

Table 2: Summary statistics for optimality gap using a candidate pool of size ten

Violation Type	Method	Mean	St. Dev.
Voltage Magnitude	DM-10	3.41%	15.91%
	CBVE	28.94%	8.91%
Branch Flow	DM-10	0.04%	0.81%
	CBVE	1.58%	10.04%

Table 2 shows that the data mining heuristic outperforms the distance based heuristic across the board. In regard to voltage magnitude violations, the proposed heuristic attains an average optimality gap over eight times smaller than that of the distance-based heuristic. Regarding branch flow violations, the average optimality gap using the data mining heuristic is almost forty times smaller than that of the distance-based heuristic; the standard deviation is 12 times smaller using the same comparison. These results show that, at a high level, the data mining heuristic has extremely strong performance against distance-based heuristics in terms of the optimality gap. The remainder of this section explores these results in greater detail.

Figure 2 plots the empirical cumulative distribution function (ECDF) of the optimality gaps obtained for voltage magnitude violation reduction by both the proposed data mining heuristic and the distance based heuristic. An ECDF plots the fraction of data points that are less than or equal to a certain value for all possible values of the metric of interest. We use this plot because it characterizes the fraction of instances for which each heuristic achieves a certain performance.

There are two findings from Figure 2. First, for the data mining heuristic, there is a vertical line at zero which reaches almost 92% of instances. This means that, in approximately 92% of studied instances, the proposed heuristic identified the optimal switch. In contrast, the distance-based heuristic had no

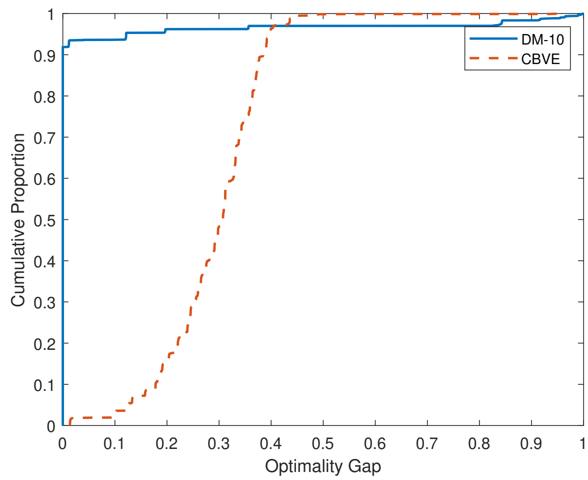

Figure 2: DM-10 dramatically outperforms CBVE for voltage violation reduction in terms of the optimality gap

such instances where the optimal switch was found within the candidate pool. This can be seen when the blue line diverges from the red line. These results show that, for the test case studied here, the data mining heuristic dramatically outperforms the distance-based heuristic in identifying optimal or near-optimal solutions.

The second finding is the relative performance between the data mining heuristic and the distance-based heuristic. Specifically, the proposed data mining heuristic attains an acceptable optimality gap of less than ten percent in over 93% of instances and and optimality gap of less than 25 percent in over 96% of instances, respectively. In contrast, the distance-based heuristic only attains such performance in and 3.3% and 29% of instances, respectively. We can therefore conclude that, for the test case studied here, the data mining heuristic dramatically outperforms the distance-based heuristic in the reduction of voltage magnitude violations.

Next, we conducted an identical analysis to the one described above studying the impact of the two heuristics on branch flow violations. Figure 3 shows the ECDF for both the data mining heuristic and the distance-based heuristic.

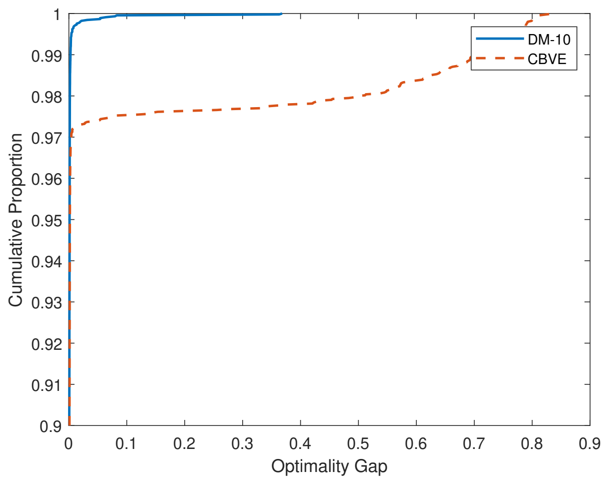

Figure 3: DM-10 performs more strongly in branch flow violations than CBVE

Figure 3 shows that, while the two heuristics are much more competitive in the case of branch flow violation reduction, the data mining heuristic is still the superior method. The first finding from Figure 3 is that both heuristics have a long vertical line at or near zero. This shows that both methods have strong performance in this case. Specifically, the data mining heuristic attains an optimality gap of less than 0.1% in over 92.8% of instances. The distance-based heuristic attains such a performance in over 89.5% of instances. If we increase the threshold to an optimality gap of one percent, the data mining heuristic identifies such a switch in over 99.6% of solution and the distance-based heuristic identifies such a switch in over 97.2% of solutions. These results, and those described by Figure 2 show that the proposed data mining heuristic definitively outperforms the distance based heuristic for the test case studied here.

6. Conclusion

This work developed a data mining heuristic to identify transmission switching candidates to reduce post-contingency voltage magnitude and branch flow violations. We used real-world large-scale AC power system data to generate a robust data set to feed into our logistic regression model with guided undersampling. The resulting heuristic demonstrated considerable performance in identifying strong transmission switching solutions, even given the substantial size of the PJM system. Our methodology shows the ability of data mining methods to substantially reduce the workload associated with identifying strong transmission switching candidates for post-contingency violation reduction. While the specific predictive model (i.e., the features chosen during feature selection and the regression coefficients) may not be specifically applicable to every system, the methodology herein proposed should generate a model which exhibits strong performance on alternate data sets.

We first showed that the data mining heuristic has strong performance in terms of accuracy. Specifically, using only the top switch identified by the data mining heuristic, the proposed methodology attained an average optimality gap of 5.5% for voltage magnitude violations and 5.9% for branch flow violations. Moreover, for both violation types, the bulk of studied instances (92% and 93%, respectively) result in optimality gaps of less than 0.1%. We therefore conclude that the data mining heuristic can regularly identify optimal or near-optimal solutions. We also showed that the data mining heuristic substantially outperforms distance-based heuristics in terms of accuracy. Using a candidate pool of only ten switches, the proposed heuristic outperformed an existing distance-based heuristic in terms of average optimality gap by over eight times for voltage magnitude violations and over 35 times for branch flow violations. These findings show that data mining methods such as the data mining heuristic with guided undersampling developed herein are noteworthy techniques which can identify optimal and near-optimal candidate switching actions for the herein studied problem with extremely high regularity.

One potential area of future study is the integration of transient stability integration into or alongside the herein studied method. As discussed in Section 1, the proposed methodology can be paired with that of (Dehghanian et al., 2015) in order to fully validate transmission switching actions. Moreover, it is possible that transient stability of the system can be integrated into the prediction step itself using sophisticated methods. An additional area of future work is in the area of data visualization. It would be beneficial to develop tools which, within the context of real-time contingency response, could identify either (1) areas of critical concern or (2) areas with significant improvement due to transmission switching, and highlight them and the associated impact in real-time. Such tools could be used in the context of other approach such as the one proposed by Li et al. (2017).

Our method demonstrates the strong performance that data mining methods can achieve in regard to power systems operation. Specifically, our proposed method is one of few which uses data mining techniques to address power systems operations. Moreover, ours is the first true data mining technique applied to transmission switching in a large-scale AC context. As mentioned previously, transmission switching is only implemented in limited capacity because of concerns over computational complexity, uncertainty of AC performance, and scalability to real-world systems. Because our data mining heuristic is computationally inexpensive, addresses an AC system problem directly, and has been rigorously tested on real-world large-scale data, it addresses these three issues directly. Given the performance of our model, it should be strongly considered in the use of post-contingency violation reduction. More importantly, it should motivate the study and development of new data mining techniques to address this and similar power systems operations problems.

Appendix A. Nomenclature

Parameters

g_{ij}, b_{ij}	Real/imaginary components of admittance of transmission line $\langle i, j\rangle$
p_n^d, q_n^d	Active/reactive power demand at bus n
p_n^g, q_n^g	Active/reactive power output at bus n
S_{ij}	MVA rating for line $\langle i, j\rangle$
$V_n^{\min}, V_n^{\max}$	Min/max voltage magnitude at bus n

Sets

$\langle i,j\rangle \in K$	Set of transmission lines
$n \in N$	Set of buses

Decision Variables

g_{ij}, b_{ij}	Real/imaginary components of admittance of transmission line $\langle i,j\rangle$
p_n^d, q_n^d	Active/reactive power demand at bus n
p_n^g, q_n^g	Active/reactive power output at bus n
S_{ij}	MVA rating for line $\langle i,j\rangle$
$V_n^{\min}, V_n^{\max}$	Min/max voltage magnitude at bus n

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