INTELLIGENT ENSEMBLE LEARNING APPROACH FOR CONTROLLING SWITCHING TRANSIENTS IN CIRCUIT BREAKER SWITCHED CAPACITOR BANK

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Abstract: *In modern power systems, low-voltage pockets and poor power factor conditions commonly arise due to the dominance of inductive loads in Extra High Voltage (EHV) substations. These conditions increase reactive power demand, compromise grid efficiency, and reduce voltage stability. While conventional methods, such as transformer augmentation, load curve optimization, and reactive power compensation, can mitigate these issues, they are often costly and time-intensive. A practical and effective alternative involves the installation of shunt capacitor banks at EHV substation buses, which improves voltage regulation and power factor. However, switching these capacitor banks introduces severe transients, including high inrush and outrush currents and restriking voltages, which can significantly degrade circuit breaker performance and lifespan. To address this challenge, this paper presents an intelligent ensemble learning approach for controlling and mitigating switching transients associated with capacitor bank circuit breakers. A 132/11 kV substation model was developed in MATLAB/Simulink to simulate switching operations for capacitor banks of varying ratings (5, 10, 15, 20, and 25 MVAR). The framework integrates ensemble learning algorithms, bagging and boosting, to analyze transient waveform data and predict the health state of capacitor switching operations. These predictions dynamically assist control relays mechanisms, ensuring stable switching actions while suppressing harmful transient effects. The ensemble model effectively classifies switching conditions as healthy or unhealthy and predicts optimal switching actions to minimize transient intensity. Simulation results confirm that the proposed ensemble learning framework significantly reduces peak transient voltages and currents, improves voltage stability and power factor, and extends the operational life of circuit breakers. The approach provides a computationally efficient and scalable solution for enhancing capacitor bank switching performance in EHV substations.*

Keywords: **Ensemble learning, capacitor bank switching, circuit breaker transients, Bagging and Boosting, transient mitigation, EHV substation.**

1. INTRODUCTION

In modern power systems, maintaining an optimal power factor and voltage profile is essential for ensuring efficient grid operation and minimizing transmission losses. However, low-voltage pockets and poor power factor conditions frequently occur in Extra High Voltage (EHV) substations, primarily due to the predominance of inductive loads such as transformers, motors, and transmission lines. These loads increase the reactive power demand, which in turn degrades voltage stability and overall system performance [1]. Conventional mitigation techniques, such as transformer capacity augmentation, reactive power balancing, or load curve optimization, can alleviate these issues but are often costly, time-consuming, and operationally rigid. As a result, the installation of shunt capacitor banks at substation buses has emerged as a practical and efficient alternative for improving voltage regulation and maintaining a healthy power factor. Shunt capacitors inject reactive power locally, thereby enhancing voltage levels and reducing the reactive burden on the grid [2].

However, the switching of capacitor banks introduces severe transient phenomena, including high inrush and outrush currents, restriking voltages, and electromagnetic oscillations, which can adversely affect the performance, reliability, and lifespan of circuit breakers and other connected components. These transients can lead to mechanical wear, contact erosion, and in extreme cases, dielectric breakdown within the switching equipment. Therefore, intelligent monitoring and control mechanisms are crucial to ensure smooth capacitor bank operation while mitigating harmful transient effects [3]. To address this challenge, this paper presents an intelligent ensemble learning approach for controlling and mitigating switching transients in capacitor bank circuit breakers. The proposed system utilizes bagging and boosting ensemble algorithms to analyze transient waveform data and predict the health state of each switching operation. These predictions dynamically assist control relay mechanisms, allowing adaptive and predictive switching actions that ensure system stability and minimize transient stress. Additionally, the model's capability to classify healthy and unhealthy switching conditions facilitates proactive maintenance and fault prevention within substation automation systems.

The remainder of this paper is structured as follows: In Section II, existing methods for capacitor bank switching control, transient mitigation techniques, and recent applications of machine learning and AI in substation automation are reviewed. The proposed ensemble learning-based framework is described in Section III, including the substation modeling setup, feature extraction from transient data, and the implementation of bagging and boosting algorithms for switching condition prediction. The simulation results obtained from MATLAB/Simulink are presented and analyzed, evaluating transient suppression performance, voltage stability, and comparative analysis with traditional methods in Section IV. The key findings, practical implications, and potential future directions are summarized in the last section.

2. LITERATURE REVIEW

The literature presents extensive research on capacitor bank switching transients and intelligent mitigation strategies in modern power systems. One study performed transient analysis on capacitor bank switching using a Power Factor Regulator (PFR) to enhance reactive power control and voltage stability [4]. Another explored the integration of Artificial Intelligence and Machine Learning technologies in power system applications, emphasizing their role in predictive maintenance and operational optimization [5]. A machine learning-based forecasting model was proposed to improve the efficiency of grid-integrated photovoltaic plants by optimizing capacitor bank usage [6]. Similarly, condition monitoring of DC-link capacitors in back-to-back converters using machine learning was demonstrated to enhance fault detection accuracy [7]. Advanced diagnostic approaches, such as convolutional neural networks combined with chaotic synchronization and empirical mode decomposition, were developed for fault identification in power capacitors [8]. Several works analyzed the impact of capacitor bank switching on harmonics and transient overvoltages in distribution networks, highlighting effective mitigation techniques [9]. Simulation-based investigations on the energization and de-energization of capacitor banks provided insights into transient overvoltage suppression [10]. Further simulation studies at 220/22 kV substations evaluated switching effects on system performance and equipment safety [11]. Research also examined the influence of DC components and mis-synchronization during inadvertent operation of high-voltage generator circuit breakers, providing a better understanding of transient phenomena [12].

Studies on medium-voltage capacitor bank switching in 132 kV substations emphasized practical mitigation approaches to limit overvoltages [13], while additional work on shunt reactor switching at high compensation levels analyzed its impact on system insulation and voltage recovery [14]. A comprehensive tutorial and case study presented an in-depth analysis of shunt capacitor bank switching transients, highlighting their causes, effects, and mitigation methods under different network configurations [15]. A method for reducing inrush current and transient overvoltage in three-phase capacitor banks was proposed using modified circuit arrangements to ensure smoother switching transitions and improved system protection [16]. Field experiments on 10 kV shunt capacitor bank switching compared ordinary and phase-controlled vacuum circuit breakers, demonstrating that phase-controlled switching significantly reduces transient severity and improves equipment lifespan [17]. A fuzzy-probabilistic model was introduced for circuit breaker condition assessment by analyzing the actuating coil's current signature, providing a reliable diagnostic framework for breaker health evaluation [18]. Analytical and simulation studies on 132 kV grid stations examined the impact of shunt capacitor bank switching transients and proposed effective mitigation strategies to prevent overvoltage stress and restrikes [19]. Further investigations analyzed the influence of DC components on circuit breaker operation, emphasizing their role in contact wear and delayed current zero crossing during fault conditions [20]. Another study reported cases of high-impedance bus differential misoperation due to circuit breaker restrikes, stressing the need for improved protective relay coordination and breaker transient management in high-voltage substations [21].

Collectively, these works contribute to a deeper understanding of transient mechanisms and form the foundation for developing intelligent, learning-based mitigation frameworks in modern power systems.

3. METHODOLOGY

The proposed 132/11 kV model substation employing the Ensemble Learning-based Basic Model is illustrated in Figure 1 below.

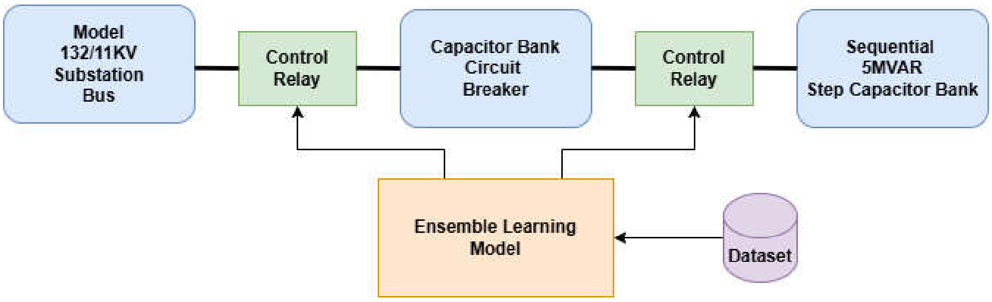

Figure 1: Block diagram of the Proposed 132/11KV Model Substation using an Ensemble Learning

The diagram illustrates a framework for integrating Ensemble Learning models and Explainable Artificial Intelligence (XAI) into the operation of a power system involving a sequential capacitor bank and circuit breaker setup. The process begins with the 132/11 KV substation bus model, which is connected to a capacitor bank circuit breaker through a control relay. The 132 KV model substation is energized by supplying power from a higher substation, thereby charging the 132 KV capacitor bank breaker, which in turn switches the sequential capacitor bank when needed. The circuit breaker, in turn, connects to the sequential capacitor bank, and both directions are monitored and managed through control relays. To enhance decision-making, operational data (inrush current, outrush current, re-striking voltage, and frequency) is collected and stored in a dataset, which feeds into an Ensemble Learning model. This model generates predictions regarding the operation of the capacitor bank and circuit breaker, aiming to optimize performance and mitigate risks such as switching transients, with an appropriate time delay to protect the system (depending upon the switching actions).

However, different switching actions for different sizes of capacitor banks are carried out to ascertain the suitability of a circuit breaker engaged for capacitor switching. For instance, results for 5 MVAR, 10 MVAR, and 15 MVAR systems were found to be healthy, while the result for the 20 MVAR system was found to be unhealthy, as observed in the substations.

Also, as shown in Figure 1, the Ensemble Learning Model is trained to predict the system’s operating condition, classifying it as either healthy or unhealthy, for different capacitor bank sizes. Based on these predictions, it generates a control signal as logic “1” or “0”, corresponding to the system’s status.

For healthy conditions (5, 10, and 15 MVAR), the model outputs a logic “1” to the control relay, allowing the step capacitor bank to connect directly to the capacitor bank circuit breaker, thereby maintaining stable and healthy system operation.

In contrast, for unhealthy predictive states (20 MVAR and above), the model outputs a logic “0” to the control relay. In this case, the control relay initially disconnects the 20 MVAR or larger capacitor bank to protect the circuit breaker from excessive switching transients and potential damage. The system then automatically reverts to a lower step size of 15 MVAR capacitor bank, ensuring stability and continued healthy operation.

The Ensemble Learning Predictive Model is developed to enhance the accuracy, robustness, and generalization capability of the Ensemble Learning-based capacitor bank switching framework. Ensemble learning combines the predictive strengths of multiple base learners to form a single, more powerful model capable of handling complex, non-linear relationships within substation operating data. By integrating diverse learning algorithms, the ensemble model effectively reduces variance and bias, leading to improved prediction reliability in identifying optimal capacitor switching actions. This approach leverages both bagging and boosting techniques to capture complementary information from various base estimators, ensuring that the final decision is more stable under fluctuating load and reactive power conditions. Thus, the Ensemble Learning Predictive Model serves as a critical analytical layer for achieving intelligent, adaptive, and explainable control in the proposed 132/11 kV substation environment.

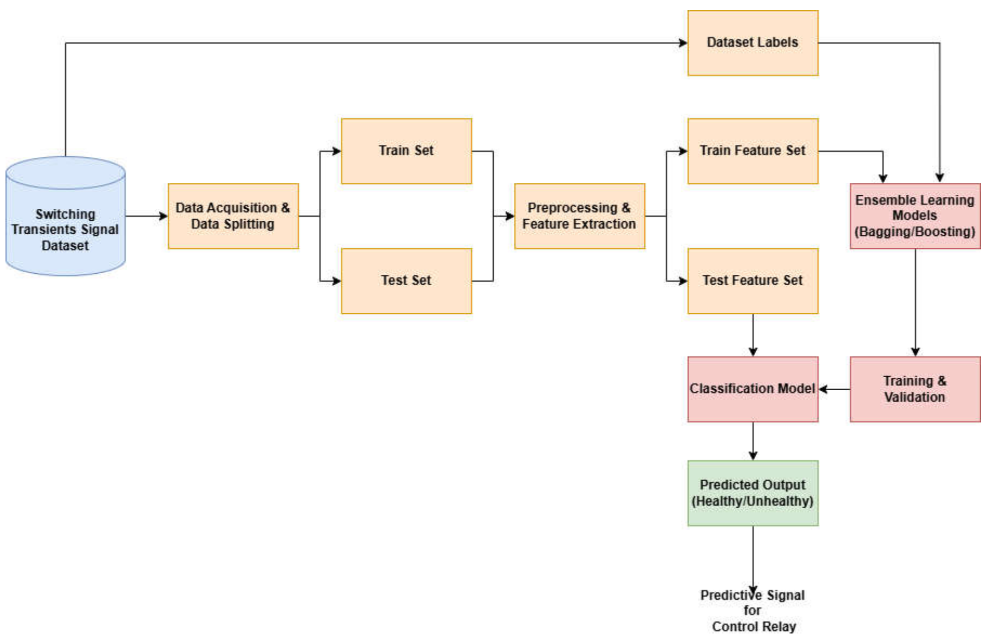

Figure 2: Predictive Classification Framework

Figure 2 depicts the proposed predictive classification framework is designed to classify substation operating conditions as healthy or unhealthy based on switching transient signal characteristics. This framework utilizes ensemble learning algorithms (Bagging and Boosting) to improve prediction accuracy, reduce model variance and bias, and provide robust decision support for automated control relay operation. The major stages of the framework are described below.

Data Acquisition and Data Splitting

The process begins with the acquisition of switching transient signal data from the model 132/11 kV substation. These signals include voltage and current transient waveform parameters during different capacitor switching events. The collected dataset is then divided into two subsets, a training set for model development and a testing set for performance evaluation. This data splitting ensures that the predictive model is trained effectively while maintaining generalization capability for unseen conditions.

Preprocessing and Feature Extraction

Raw switching signals often contain noise and redundant information. Therefore, preprocessing steps such as filtering, normalization, and signal segmentation are applied to improve data quality. Subsequently, feature extraction techniques are used to derive meaningful parameters from the transient signals, such as peak voltage, rise time, inrush current amplitude, Total Harmonic Distortion (THD), and energy content. These features provide quantitative representations of system behavior and form the foundation for machine learning model training.

Feature Set Formation

Following preprocessing, the extracted features are organized into training and testing feature sets. Each feature vector corresponds to a labeled data instance that represents either a healthy or unhealthy switching condition. The training feature set is used to build and optimize the ensemble learning models, while the testing feature set is reserved for evaluating predictive performance under real or simulated switching scenarios.

Ensemble Learning Model (Bagging and Boosting)

Ensemble learning methods are designed to improve the predictive performance of machine learning models by combining multiple base learners to produce a more accurate and stable prediction outcome. Among the various ensemble techniques, bagging and boosting are two of the most widely used approaches due to their complementary strengths in reducing variance and bias, respectively. At the core of the framework lies the ensemble learning mechanism, which combines multiple weak learners to enhance prediction reliability.

Training and Validation

The ensemble model undergoes a training and validation phase, where hyperparameters such as learning rate, tree depth, and number of estimators are optimized. Cross-validation techniques are employed to prevent overfitting and to ensure that the model's predictions generalize well across various operating states. The model's performance is evaluated using standard metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis.

Classification and Predictive Output

Once trained, the classification model predicts the condition of the substation's switching event based on incoming transient signal data. The output is categorized as Healthy (acceptable switching transients within standard limits) or Unhealthy (excessive transients, violating ANSI standards (related IEEE C37.06)). The predicted class serves as a decision signal for the control relay or switching controller.

Predictive Signal for Control Relay

Finally, the predicted output is converted into a predictive control signal, which guides the substation's switching mechanism. If the system is classified as unhealthy, the control logic automatically initiates corrective measures, such as switching back to a previous step capacitor bank to 15MVAR step capacitor bank (e.g., from 20 MVAR to 15 MVAR) in case of Basic Modelling and apply control logic to bypass the nominal control relay and insert capswitcher in case of Advanced Modelling to restore system stability and compliance with ANSI standards. This real-time predictive control mechanism enables intelligent, autonomous decision-making, ensuring system health, power factor stability, and transient mitigation.

4. EXPERIMENTAL RESULTS AND DISCUSSION

The experimental analysis was carried out on a MATLAB/Simulink-based model of a 132/11 kV substation to evaluate the performance of the proposed ensemble learning framework during capacitor bank switching operations. Various capacitor bank ratings, 5 MVAR, 10 MVAR, 15 MVAR, 20 MVAR, and 25 MVAR, were simulated to observe the corresponding transient behaviors under different operating conditions. The transient responses, including inrush current, outrush current, and restriking voltage, were closely analyzed to assess the health status of the switching operation. The ensemble learning model, integrating bagging and boosting algorithms, was employed to classify the switching conditions as healthy or unhealthy based on extracted transient signal features. The following section presents a detailed discussion of the simulated transient waveforms, model predictions, and their comparison with conventional switching operations. For capacitor bank switching using the proposed ensemble learning approach, a MATLAB Simulink model has been developed and is illustrated below in Figure 3.

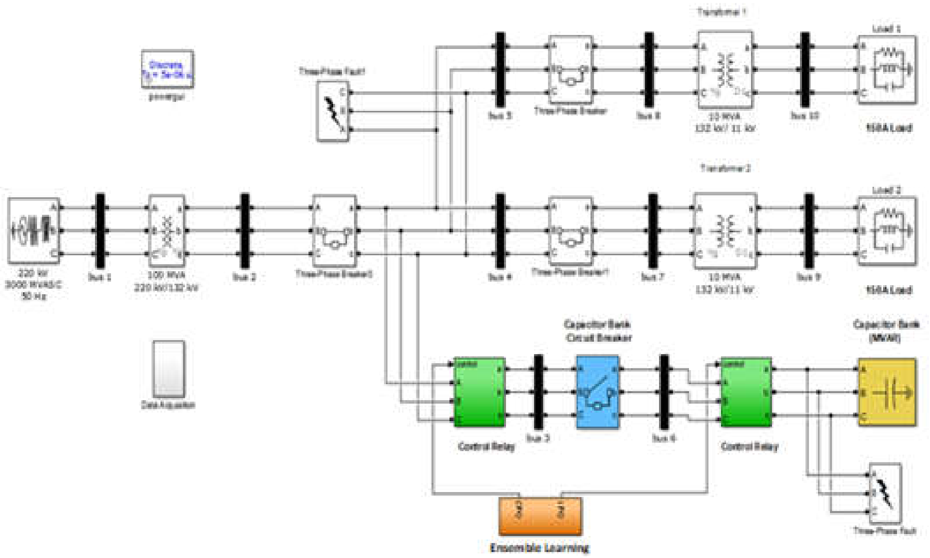

Figure 3: MATLAB Simulation model for the proposed capacitive switching

In the exclusive switching configurations, it is observed that the status of the 5 MVAR, 10 MVAR, and 15 MVAR capacitor banks is found to be healthy. Subsequently, a detailed transient magnitude evaluation was carried out for the 20 MVAR and 25 MVAR capacitor banks, where critical stress conditions are more evident. The voltage and current responses at Bus 3 and Bus 6 have been observed and analyzed under different switching operations.

Expert knowledge of voltage and current switching transients is crucial for training the proposed ensemble learning-based techniques. This expertise is utilized to model and classify the switching operations of different capacitor bank sizes, 5 MVAR, 10 MVAR, 15 MVAR, 20 MVAR, and 25 MVAR, under both healthy and unhealthy circuit breaker conditions. Capacitor banks of other ratings, beyond these sizes, are subsequently used for testing and performance evaluation of the ensemble learning framework to ensure robustness and generalization.

The various switching operations are performed and summarized in Table 1. For simulating the various capacitor bank sizes switching, a sequential 5MVAR step capacitor bank is used. For example, a 20 MVAR capacitor bank is divided into four 5 MVAR step capacitor bank units, a 25MVAR capacitor bank into five 5MVAR step capacitor bank units, and so on. Each section is switched on sequentially with a 0.2 s delay between operations to lessen transient disturbances.

Table 1: List of possible switching operations

Case No	Switching Operations
Case 1	Healthy Capacitor Bank Switched ON
Case 2	Healthy Capacitor Bank Switched OFF
Case 3	Capacitor bank breaker switching OFF in case of a fault in capacitor bank
Case 4	Capacitor bank breaker switching OFF in case of fault on 132 KV Bus or very near to Bus

All four switching operation scenarios are simulated in MATLAB and discussed in detail in the following sections.

Case 1: Healthy Capacitor Bank Switched ON

The switching transients of voltage and current captured at Bus 6 for (a) the 20 MVAR and (b) the 25 MVAR capacitor banks are shown in Figure 4 (a) and (b) through their respective output waveforms. In this scenario, the healthy capacitor bank is energized at t = 0.2 s.

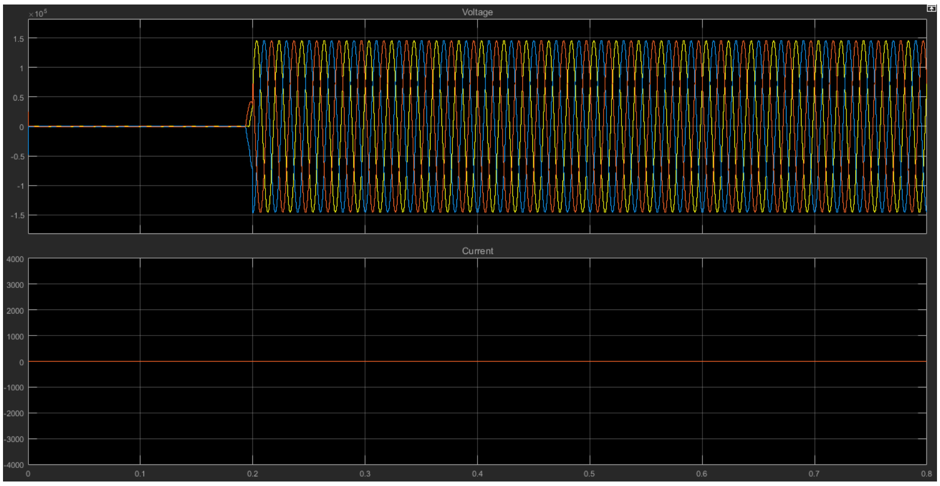

Figure 4: a) Voltage–Current Transient Response of Healthy capacitor bank switched ON for 20 MVAR capacitor bank

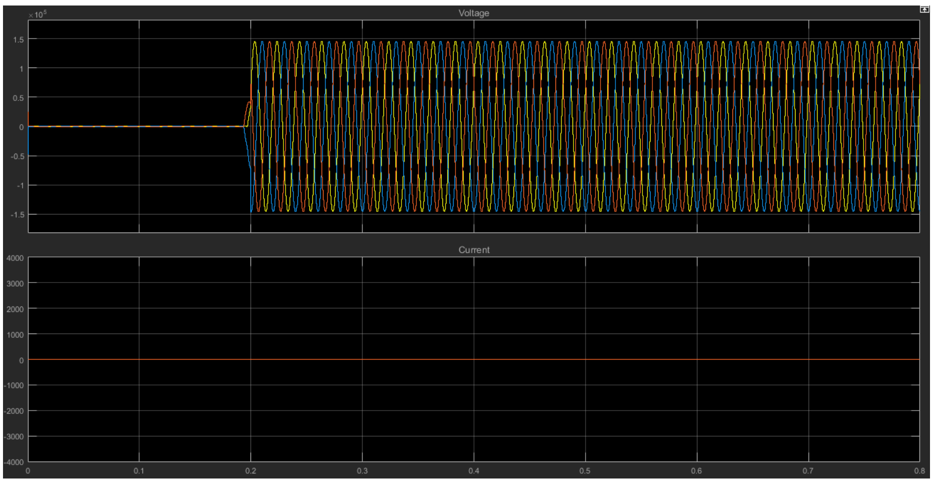

Figure 4: b) Voltage–Current Transient Response of Healthy capacitor bank switched ON for 25 MVAR capacitor bank

From the waveform above, it can be observed that for the unhealthy predictive states of the 20 MVAR and 25 MVAR capacitor banks, the Ensemble Learning model sends a logic ‘0’ signal to the control relay. In response, the control relay initially gives a signal to disconnect the 20 MVAR and 25 MVAR banks to protect the system from excessive switching transients and potential damage, resulting in a straight line in the current waveform. Subsequently, the system automatically reverts to a lower step size by engaging the 15 MVAR capacitor bank, thereby ensuring stability and maintaining healthy operation, as illustrated in Figure 4 (c).

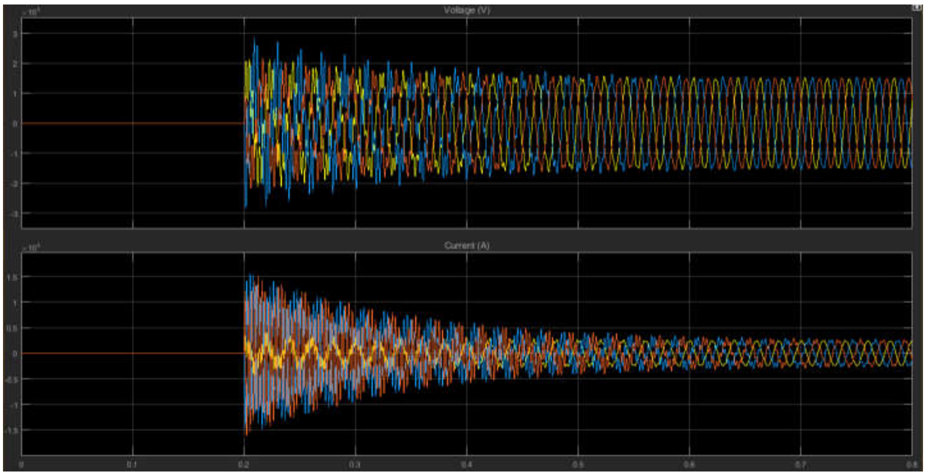

Figure 4: c) Voltage–Current Transient Response of Healthy capacitor bank switched ON for 20 MVAR and 25 MVAR capacitor bank after ELT

Case 2: Healthy Capacitor Bank Switched OFF

The voltage and current switching transients observed at Bus 6 for (a) the 20 MVAR and (b) the 25 MVAR capacitor banks are depicted in Figure 5 (a) and (b) through their respective output waveforms. In this case, the healthy capacitor bank is de-energized at t = 0.4 s.

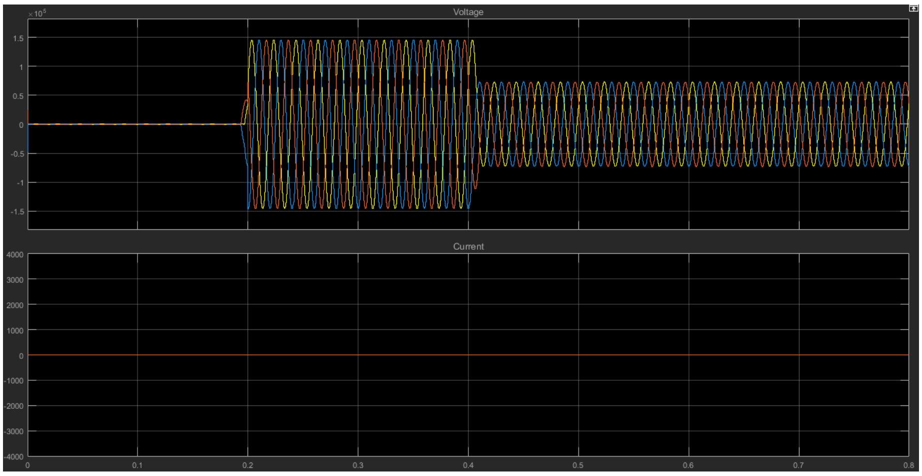

Figure 5: (a) Voltage–Current Transient Response of Healthy capacitor bank switched OFF for 20 MVAR capacitor bank

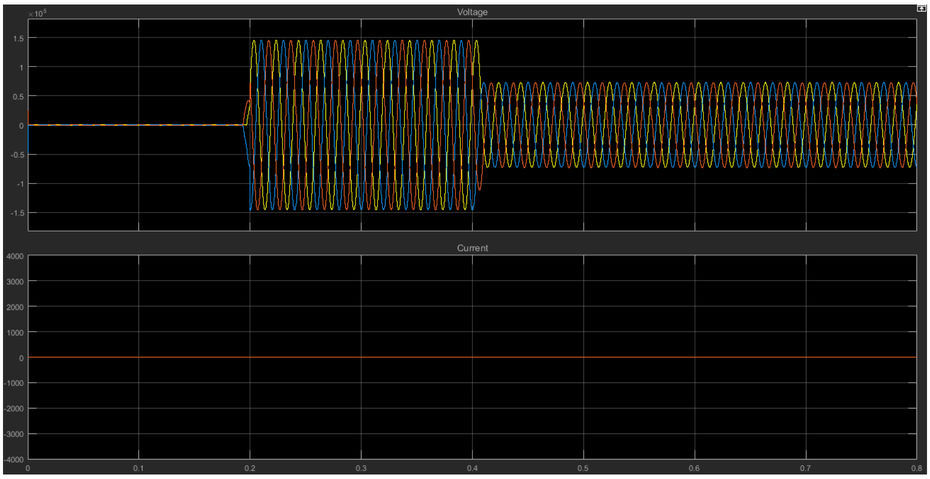

Figure 5: (b) Voltage–Current Transient Response of Healthy capacitor bank switched OFF for 25 MVAR capacitor bank

From the waveform above, it can be observed that for the unhealthy predictive states of the 20 MVAR and 25 MVAR capacitor banks, the Ensemble Learning model sends a logic ‘0’ signal to the control relay. In response, the control relay initially gives a signal to disconnect the 20 MVAR and 25 MVAR banks to protect the system from excessive switching transients and potential damage, resulting in a straight line in the current waveform. Subsequently, the system automatically reverts to a lower step size by engaging the 15 MVAR capacitor bank, thereby ensuring stability and maintaining healthy operation, as illustrated in Figure 5 (c).

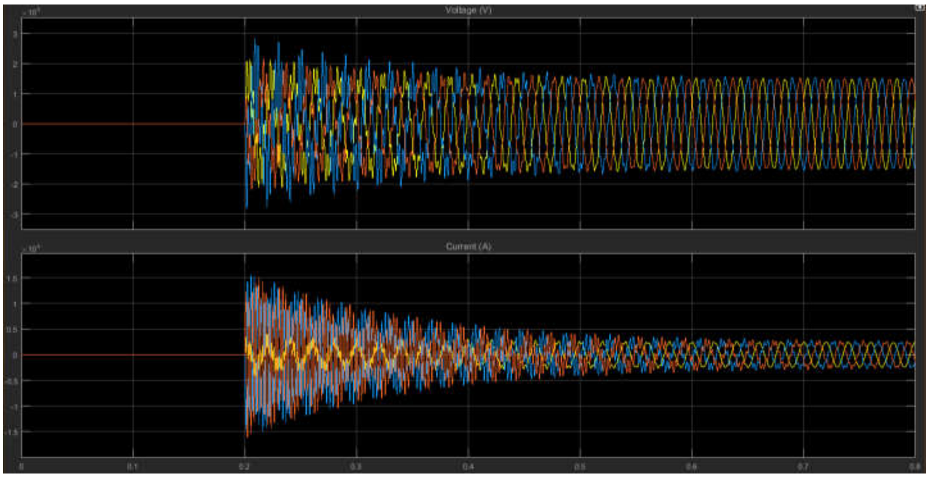

Figure 5.10: c) Voltage–Current Transient Response of Healthy capacitor bank switched OFF for 20 MVAR and 25 MVAR capacitor bank after ELT

Case 3: Capacitor bank breaker switching OFF in case of fault in capacitor bank

The voltage and current switching transients at Bus 6 for (a) the 20 MVAR and (b) the 25 MVAR capacitor banks are illustrated in Figure 6 (a) and (b) through the corresponding output waveforms. In this scenario, the healthy capacitor bank is switched ON at t = 0.001 s, immediately followed by the occurrence of a fault at the same instant.

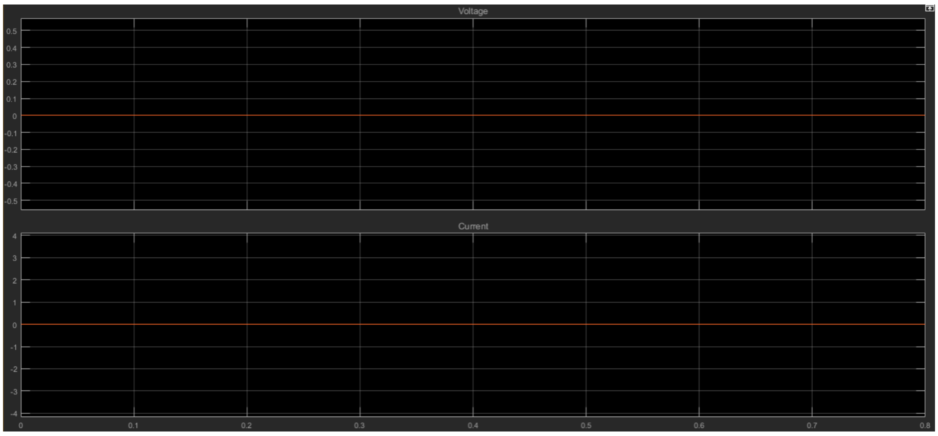

Figure 6: a) Voltage–Current Transient Response of Healthy Capacitor bank breaker switching OFF in case of fault in capacitor bank for 20 MVAR capacitor bank

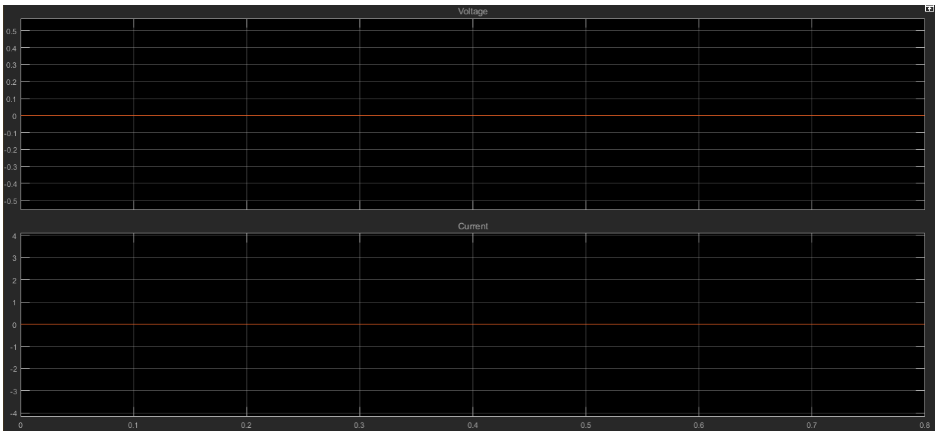

Figure 6: b) Voltage–Current Transient Response of Healthy Capacitor bank breaker switching OFF in case of fault in capacitor bank for 25 MVAR capacitor bank

From the waveform above, it can be observed that for the unhealthy predictive states of the 20 MVAR and 25 MVAR capacitor banks, the Ensemble Learning model sends a logic '0' signal to the control relay. In response, the control relay initially gives a signal to disconnect the 20 MVAR and 25 MVAR banks to protect the system from excessive switching transients and potential damage, resulting in a straight line in the voltage and current waveform. Subsequently, the system automatically reverts to a lower step size by engaging the 15 MVAR capacitor bank, thereby ensuring stability and maintaining healthy operation, as illustrated in Figure 6 (c).

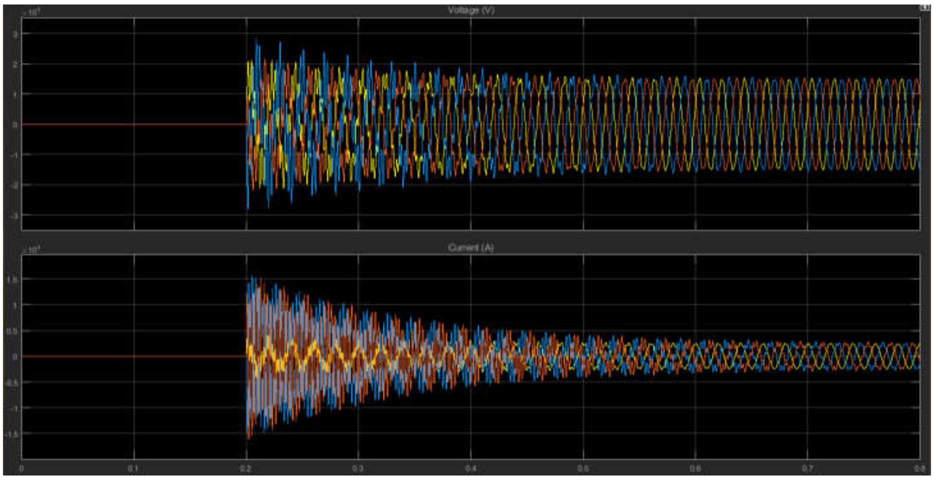

Figure 6: c) Voltage–Current Transient Response of Healthy Capacitor bank breaker switching OFF in case of fault in capacitor bank for 20 MVAR and 25 MVAR capacitor bank after ELT

Case 4: Capacitor bank breaker switching OFF in case of fault on 132 KV Bus or very near to Bus

The voltage and current switching transients for the 20 MVAR and 25 MVAR capacitor banks, recorded at Bus 3 and Bus 6, are shown in Figure 7 (a), (b), (c), and (d) through their respective output waveforms. In this case, the healthy capacitor bank is energized at t = 0.2 s, followed by the occurrence of a bus fault at t = 0.5 s.

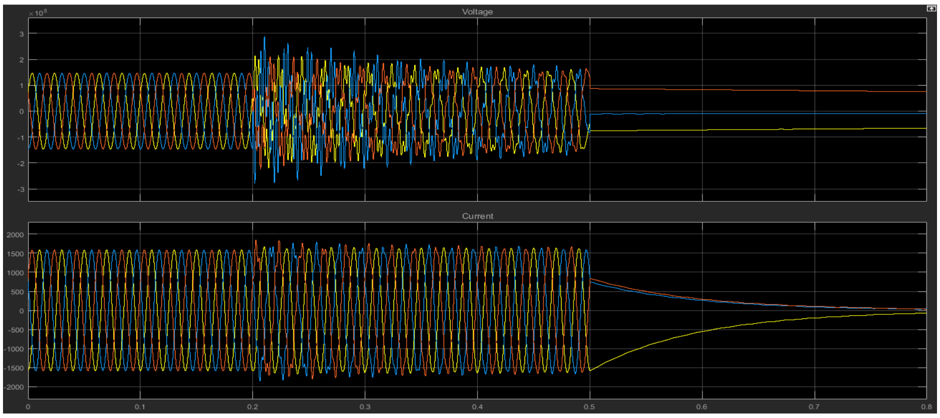

Figure 7: a) Voltage–Current Transient Response of Capacitor bank breaker switching OFF in case of fault on 132 KV Bus for 20 MVAR capacitor bank at bus 3

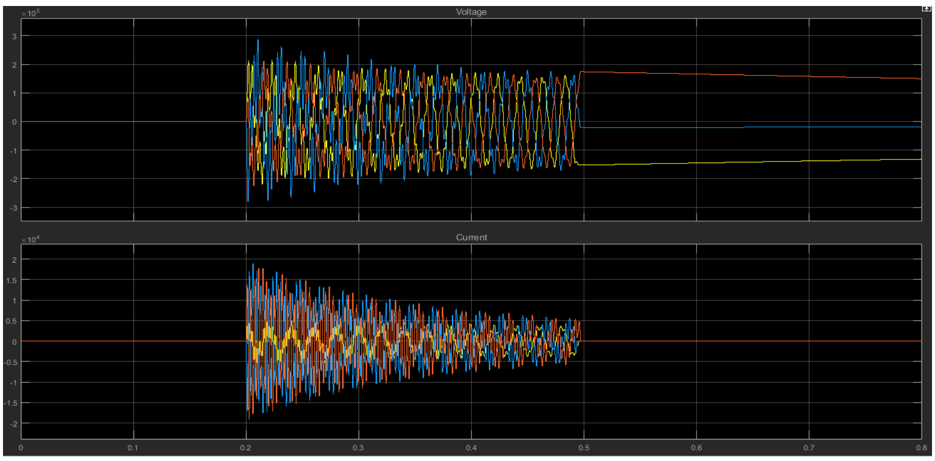

Figure 7: b) Voltage–Current Transient Response of Capacitor bank breaker switching OFF in case of fault on 132 KV Bus for 20 MVAR capacitor bank at bus 6

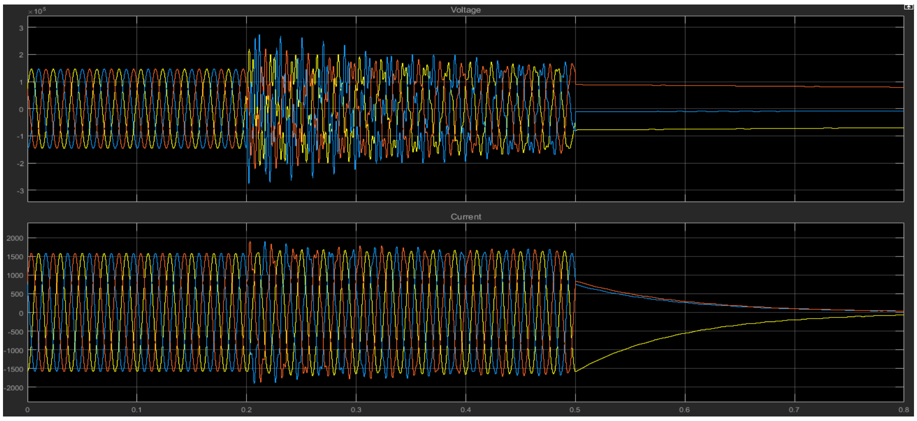

Figure 7: c) Voltage–Current Transient Response of Capacitor bank breaker switching OFF in case of fault on 132 KV Bus for 25 MVAR capacitor bank at bus 3

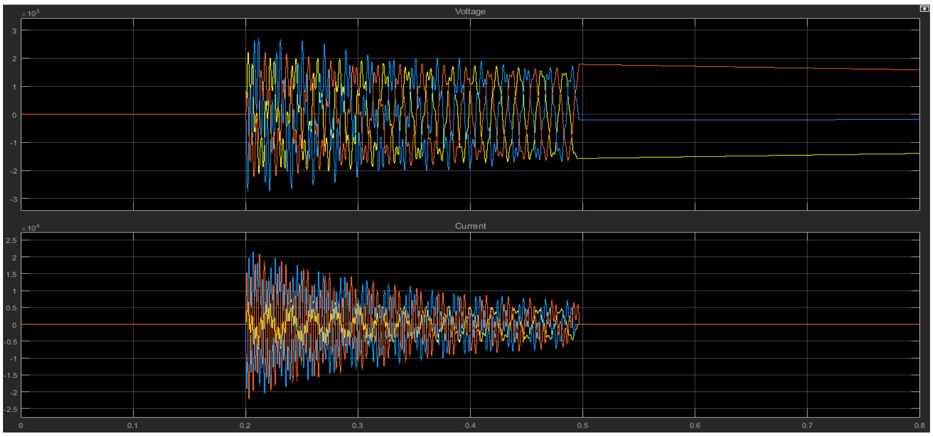

Figure 7: d) Voltage–Current Transient Response of Capacitor bank breaker switching OFF in case of fault on 132 KV Bus for 25 MVAR capacitor bank at bus 6

From the waveform above, it is observed that during the unhealthy predictive states of the 20 MVAR and 25 MVAR capacitor banks, when breaker switching occurs in response to a fault on the 132 kV bus, the Ensemble Learning model outputs a logic ‘0’ signal to both control relays. Consequently, both control relays give a signal to disconnect the capacitor banks and the bus system at bus 6 and bus 3, respectively to protect the system from excessive switching transients and potential damage, which results in a straight line in both the voltage and current waveforms. Thereafter, the system automatically initiates a complete shutdown, as illustrated in Figure 7 (e)(f).

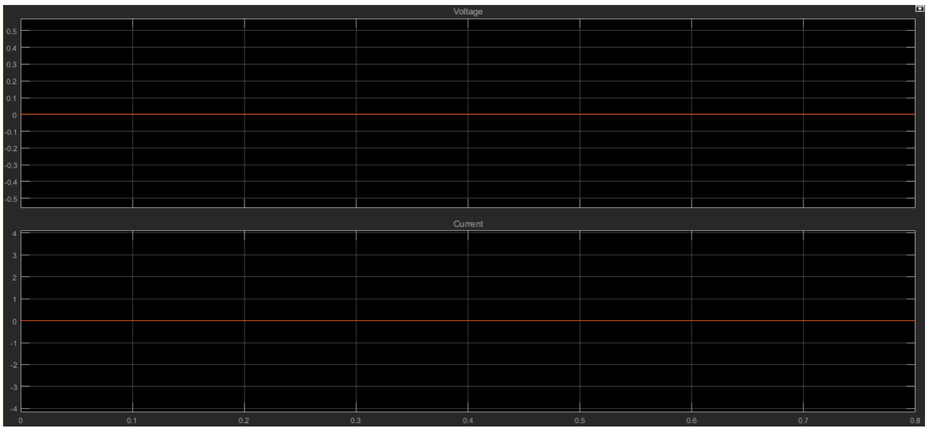

Figure 7: e) Voltage–Current Transient Response of Capacitor bank breaker switching OFF in case of fault on 132 KV Bus for 25 MVAR capacitor bank at bus 3 applying ELT

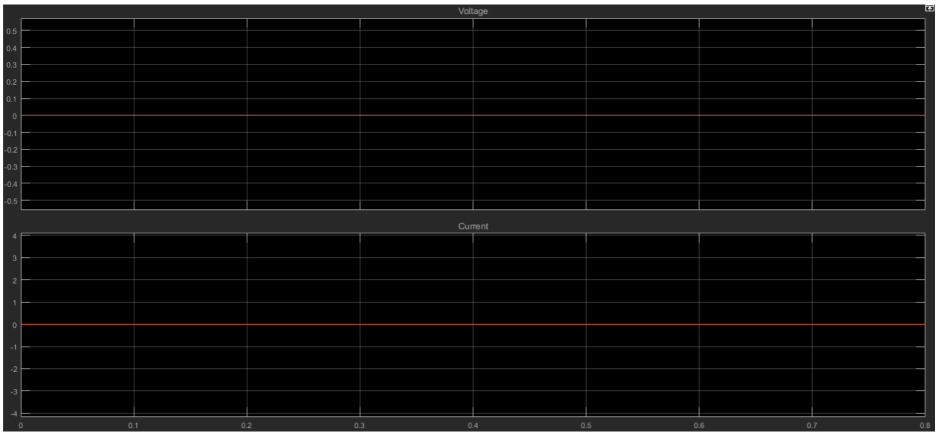

Figure 7: f) Voltage–Current Transient Response of Capacitor bank breaker switching OFF in case of fault on 132 KV Bus for 25 MVAR capacitor bank at bus 6 after applying ELT

The predictive results and corresponding interpretations are systematically documented in Tables 2 and 3, which present the circuit breaker status across different capacitor bank ratings.

Table 2: Capacitor bank switching circuit breaker status for 5MVAR, 10 MVAR, and 15 MVAR Capacitor Banks

Switching Operations	Capacitor Bank Circuit Breaker Status (Exclusive switching)	Ensemble Learning Model Prediction		Capacitor Bank Circuit Breaker Status (with due application of Ensemble Learning)
		Ensemble Bagging (Control Signal Output)	Ensemble Boosting (Control Signal Output)	
Healthy capacitor bank switched ON	Healthy	1	1	Healthy
Healthy capacitor bank switched OFF	Healthy	1	1	Healthy
Capacitor bank breaker switching OFF in case of fault in capacitor bank	Healthy	1	1	Healthy
Capacitor bank breaker switching OFF in case fault on 132 KV Bus or very near to Bus	Healthy	1	1	Healthy

Table 2 focuses on 5 MVAR, 10 MVAR, and 15 MVAR capacitor banks, where the ensemble-XAI model confirms that the circuit breaker generally operates under healthy switching conditions, as observed in exclusive switching configurations. The table summarizes the circuit breaker status of the capacitor bank under different switching operations and compares results before and after the application of Ensemble Learning techniques.

Table 3: Capacitor Bank Switching Circuit Breaker Status for 20 MVAR, 25 MVAR, and Higher Capacitor Banks

Switching Operations	Capacitor Bank Circuit Breaker Status (Exclusive	Ensemble Learning Model Prediction		Capacitor Bank Circuit Breaker Status (with due application of
		Ensemble	Ensemble	

	switching)	Bagging (Control Signal Output)	Boosting (Control Signal Output)	Ensemble Learning)
Healthy capacitor bank switched ON	Unhealthy	1	1	Healthy
Healthy capacitor bank switched OFF	Unhealthy	1	1	Healthy
Capacitor bank breaker switching OFF in case of fault in capacitor bank	Unhealthy	1	1	Healthy
Capacitor bank breaker switching OFF in case fault on 132 KV Bus or very near to Bus	Unhealthy	1	1	Healthy

Table 3, in contrast, highlights the switching response for 20 MVAR, 25 MVAR capacitor banks and above, where the ensemble learning framework identifies significant transient stresses leading to unhealthy breaker conditions.

From the above table, it is evident that the application of Ensemble Learning Techniques enables the capacitor bank circuit breaker status to transition from unhealthy to healthy operation. In particular, the 20 MVAR and 25 MVAR capacitor banks, which previously exhibited unhealthy behavior under exclusive switching conditions, has shown outstanding improvement when the proposed AI-based mitigation strategy is applied. The corresponding waveforms of different switching operations, after implementing the ELT approach, demonstrate stabilized transient responses, thereby validating the effectiveness of the method. These improved waveforms for the 20 MVAR and 25 MVAR capacitor banks are illustrated below. For the simulation of 20 MVAR and 25 MVAR capacitor bank operations, four-step and five-step arrangements of 5 MVAR capacitor units are employed, respectively. Each section is switched on sequentially with a 0.2 s delay between operations to lessen transient disturbances. To emphasize the effectiveness of the proposed mitigation approach, the transient magnitudes for the 20 MVAR capacitor bank, both before and after the application of ELT, are summarized in Table 4.

Table 4: Capacitor bank switching breaker transient magnitudes in Basic Modelling for a 20 MVAR capacitor bank before and after applying ELT

Switching Operations	Switching Transients	Magnitude of Switching Transients for 20 MVAR	
		Before ELT	After ELT
Healthy capacitor bank switched ON	Inrush Current (KA)	19	15.7
	Outrush Current (KA)	-	-
	Transient Frequency (KHz)	5	4
	Peak Re-striking Voltage (KV)	290	283
Healthy capacitor bank switched OFF	Inrush Current (KA)	-	-
	Outrush Current (KA)	-	-
	Transient Frequency (KHz)	5	4
	Peak Re-striking Voltage (KV)	290	283

Capacitor bank breaker switching OFF in case of fault in capacitor bank	Inrush Current (KA)	-	-
	Outrush Current (KA)	21	17
	Transient Frequency (KHz)	5	4
	Peak Re-striking Voltage (KV)	272	245
Capacitor bank breaker switching OFF in case fault on 132 KV Bus or very near to Bus	Inrush Current (KA)	-	-
	Outrush Current (Fault Current) (KA)	1760	0
	Transient Frequency (KHz)	5	0
	Peak Re-striking Voltage (KV)	290	0

Overall, the above table highlights how ELT significantly enhances system protection by eliminating switching transients that otherwise pose severe risks to circuit breakers and capacitor banks, thereby ensuring healthier and more reliable operation of the 132/11 kV substation system.

7. CONCLUSION

The proposed intelligent ensemble learning framework successfully mitigates switching transients associated with capacitor bank operations in EHV substations. By integrating bagging and boosting algorithms, the model efficiently analyzes transient waveform data, classifies system conditions as healthy or unhealthy, and predicts optimal switching actions to minimize transient severity. Simulation results from the 132/11 kV substation model demonstrate that the approach significantly reduces peak inrush and outrush currents, suppresses restriking voltages, and enhances both voltage stability and power factor. Furthermore, the framework extends circuit breaker lifespan by reducing stress during capacitor bank switching, offering a reliable and cost-effective solution adaptable to varying substation capacities.

Future research can expand this work by integrating real-time data acquisition and adaptive learning mechanisms to enable online monitoring and automatic control in live substations. The ensemble learning framework can be enhanced through hybrid integration with deep learning models for improved prediction accuracy and robustness under dynamic operating conditions. Additionally, the incorporation of Explainable AI (XAI) techniques can provide greater transparency and interpretability for operator decision-making

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