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RESEARCH ARTICLE

Design of Power Transformer Fault Detection of SCADA Alarm Using Fault Tree Analysis, Smooth Holtz–Winters, and L-BFGS for Smart Utility Control Centers

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ABSTRACT When a trip occurs, the utility of company-type 115/22 kV loading transformer trips out of the electrical system, cutting off power to the distribution of a company customer. The outage damage is valuable at 8.5 US$/kWh. A 12-step load transfer procedure at the utility control center takes the operator 433 seconds to complete when restoring power to a customer experiencing an outage. Problem number 1 is that many Supervisor Control and Data Acquisition (SCADA) message alarms will appear during the event, which confuses the operator and possibly leads to an incorrect analysis of the trip event details. Problem number 2 occurs in the process where the operator incorrectly predicts the MW-load data of the Loading Transformer will cause a power outage, causing the neighboring loading transformer to overload and cause damage after the operator completes the LTR process. In this study, Pyauto2, an application developed with the Python platform that connects to the utility control center's SCADA and runs automatically, is introduced Pyauto2 serves two purposes: to work as an operator to reduce person-hours in the utility company's LTR process and to analyze find accurate answers to trip events of 68 Loading Transformers installed in the electrical system in the central region of Thailand. The last purpose is to use Pyauto2 to reduce the LTR time. Pyauto2 can analyze the SCADA message alarm via fault tree analysis. To help plan the transfer load, it forecasts MW load data on the day of the loading transformer trip using two-time series forecasting techniques. Holt–Winters exponential smoothing (HWS) method is the second technique, and the triple exponential moving average (TEMA) is the first HWS method. In this study, the distorted data are filtered out via the exponential moving average (EMA) technique before being sent to TEMA and HWS for forecasting. The data gathered between 2017 and 2020 revealed distortion in the MW load data, which may be brought on using SCADA equipment or brief communication failures. Temporary outage, reduced traffic on holidays, and arrangement of the distribution grid route. In this study, the grid search method is compared with limited-memory Broyden–Fletcher–Goldfarb–Shanno (L-BFGS) to modify the alpha–gamma–beta value used in this HWS. The prediction error values of the L-BFGS calculations are lower than those of the grid search method,

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with a mean absolute error of 0.4576, a mean square error of 0.3996, and a root mean square error of 0.6084. After Pyauto2 is introduced, the average LTR time decreases from 433 s to only 64.88 s, and Pyauto2 works as a substitute for the operator and accurately diagnoses the SCADA alarm, preventing the occurrence of neighbor loading transformer supplying power overload after LTR.

INDEX TERMS Fault section diagnosis, transformer restoration, fault tree analysis, exponential moving average, Holt-Winters method, Python language.

NOMENCLATURE

KT1A	Power transformer name "KT1A".
115/22	Primary voltage/secondary voltage of power transformer.
LP1	Provincial Electricity Authority delivery point name "Circuit number 1".
P_{1A_trip}	Probability event of "KT1A" trip.
P_{HS-1A}	Probability event of breaker high-side "KT1A" operate.
$P_{HS-1A-Tag}$	Probability event of breaker high-side "KT1A" have "TAG" caution.
P_{LS-1A}	Probability event of breaker low-side "KT1A" operate.
$P_{LS-1A-Tag}$	Probability event of breaker low-side "KT1A" have "TAG" caution.
P_{51}	Probability event of feeder overcurrent relay operate.
P_{51T}	Probability event of transformer overcurrent relay operate.
P_{87}	Probability event of transformer differential operate.
P_{watt}	Probability event of real power flow at delivery point.
P_{var}	Probability event of reactive power flow at delivery point.
P_{volt}	Probability event of delivery point voltage.
$P_{current}$	Probability event of current flow through delivery point.
SLG	Single Line to Ground Fault.

I. INTRODUCTION

Restoration trip event is an essential function of the utility control center. This feature will help minimize the inconvenience brought on by power outages. The effects of power outages on Household electricity users will have difficulties in their daily routines. Industrial power consumers will impact the production process. The loading transformer is the most crucial equipment in the electrical system, supplying customers with electricity. When a loading transformer trips out of the electricity system, customers in large areas will be negatively impacted. Hence, in this study, the utility control center must be able to determine ways to minimize the time lost by customers due to power outages caused by loading transformer trips. The utility company is in charge of generating and acquiring electrical energy that will be delivered to the distribution company. The Loading Transformer 115/22 kV serves as the point of power delivery between them. Once the power is delivered, the distribution company will divide it into multiple feeders for further distribution [1]. The product is delivered by a loading transformer to the substation delivery point. In Thailand's central electrical system area, electrical issues and power outages are most common [2]. When utility control centers attempt to shorten the average outage duration, customers experience power outages [3], [4], [5]. The industrial customer group's unplanned outage cost is shown to be 8.5 US$/kWh. Flashover at the loading transformer insulation support due to a common SLG fault that causes power outages.

When the incident described above takes place, the loading transformer protection system detects the anomaly. To guard against damage, it prompts the open circuit breaker to cut the loading transformer off from the power supply. Having 6,875.55 circuit kilometers of 500, 230, and 115 kV transmission lines, Thailand's company utility currently operates a central electricity system (CKM), with 141 transformers and 56 substations, totaling 32,489 MVA. The utility control center employs the Supervisor Control and Data Acquisition (SCADA) system to monitor and restore various measured values at each substation in the electrical system when a trip event occurs [6], [7], [8], [9], [10]. This enables the center to control electrical equipment without overloading, such as the electric power flow in the transmission line and the transformer. An alarm text message on the SCADA will appear when an electrical system anomaly takes place. The utility control center presents these text message analyses to monitor and determine which device is abnormal [11]. The relationship between the Fault section, the Status Circuit Breaker, and the Status of Relay Protection at Operation creates a diagram to analyze the Fault section, and a fuzzy set is used to analyze the failure device [12]. A cause-effect network was created to analyze SCADA alarm messages [13], [14]. The casual relationships are employed to establish a substation automation system that analyzes protection relays, including lockout, bus protection, transformer differential, current, Buchholtz relays, and approaching equipment failure at substations.

In 1961, while working for Bell Laboratories and the United States Air Force Ballistics Systems, Watson established the fault tree analysis (FTA) [15]. It is a type of failure analysis through which the undesirable state of the system is investigated. To understand the causes of system failures, it performs risk analysis, determines the most efficient way to minimize risk, and determines the event rates of a safety accident or a particular system-level failure; this method is employed especially in the field of reliability and safety engineering [16]. To establish a system fault tree, boundary conditions and Boolean operators, which include "AND" Gate and "OR" Gate must be determined [17]. To simplify mathematical and programming calculations, FTA converts the system fault tree into a structure function [18]. By creating a system fault tree with event symbols, FTA can be employed to analyze five different types of faults that may occur in power transformers. By utilizing the "OR" gate and "AND" gate, a bottom event can be operated [19]. FTA analyzes the generator fault tree by employing the "IF-THEN" rule to assist in creating a system fault tree. This type of analysis leads to a rapid diagnosis and determination of accurate charging device fault location [20]. By analyzing the SCADA message alarm at the control center, FTA can differentiate between the events that involve the loading transformers. The trip is removed from the electrical system by examining the bottom event, comprising the protection relay, which includes the transformer differential relay and the overcurrent relay [21], [22]. FTA provides a method for converting the system fault tree to a structure function that can be mathematically calculated [22]. It also offers failure probabilities on fault trees and the application of Boolean algebra to resolve the complexity of modeling large scale systems. After the occurrence of a power outage due to the loading transformer, the utility control center will implement a procedure known as the load transfer procedure in order to restore the supply of electricity. It takes a significant amount of time for the initial LTR procedure to be completed, and the MW load data that are utilized in the LTR procedure can deviate from the actual data. This results in a loading transformer trip with the overload protection tie [23]. It enables the overload relay settings to be adjusted to 125% of the secondary full-load current, which is the standard setting that ensures the transformer is not damaged. Repeated instances of overloading describe the varying loading states of the transformer and how they influence the transformer's loss of life [24], [25]. Its capability to overload transformers to reduce normal life expectancy loading shows the average temperature of the equipment that affects the reduction in the transformer's lifetime. When a trip event occurs in the electrical system of the utility control center, the primary objective is to make the most efficient use of the time available to analyze the SCADA message alarm and examine in which device the fault occurred. After the root cause of the fault is found, the utility control center will restore equipment not related to the fault at the trip. Restoring the loading transformer in the case of a trip cannot be energized immediately due to concerns that damage may occur within the loading transformer while supplying fault current during the fault. Therefore, it is necessary to have the Dissolved Gas Analysis test (DGA), see the analysis results first, and consider energizing the loading transformer. The utility control center has LTR procedures to use another loading transformer to supply MW load outage to reduce the outage time required to wait for DGA. Forecasting techniques are used to determine MW load data that will occur, such as the double exponential moving average (EMA) and the triple exponential moving average (TEMA) method, which is a widely used approach in determining, for instance, local water company revenue targets for the coming year, can be utilized to carry out time series forecasting [27]. In building air conditioning systems, TEMA has also been employed as a load forecasting method [28]. Holt–Winters (HW) was initially proposed in 1960 by Peter Winters, a student of Charles Holt, and since then become the standard approach in predicting the behavior of a sequence of values over time (i.e., a time series). HW method is an exponential smoothing method that can directly analyze seasonal time series.

Over the past few years, HW has been employed in the process of forecasting various fields, which include but are not limited to the following: cloud computing that supports distributed services [29], Brazil patent deposits [30], air transportation demand [31] and total Electron Content data [32]. In this study, we will present the formula for forecasting the number of days for both the HW exponential smoothing (HWS) additive and HWS multiplicative models. The HWS method includes α, β, and γ parameters, whose values range from 0 to 1. This study also presents the grid search method for determining the values of HWS parameters via loop calculations. In this method, each iteration adds all three HWS parameters by increasing the value by 0.1, one variable at a time, and selecting the three HWS parameters that make the MAD at the lowest value [33], [34]. Trends, cycles, seasonality, and irregular events are the components of the time series dimension. Different characteristics will be exhibited by the forecast input data in comparison to the four aforementioned components [35]. HWS is a method that was developed through the exponential smoothing technique [36]. It presents four types of time-series-based predictive models: an exponential smoothing technique, an MA model, a regression model, and a neural network model. HWS forecasting techniques that do not calculate the seasonality and ARIMA model components to predict the number of tourists traveling to Zambia are presented in this study [37]. The input data for calculation in HWS is divided by window length into two data ranges, namely, the training and the test sets, to calculate forecasting [38]. HWS forecasts electricity usage a day in advance using HWS. and ARIMA methods, with dataset durations of 7, 14, 30, 90, and 180 days [39]. The genetic algorithm must be employed in MATLAB to calculate the HWS parameters. The HWS parameters α, β, and γ are utilized to determine the most appropriate value that will result in the most accurate prediction [40]. Using the solver toolbox function in Microsoft Excel, the HWS parameter values with the lowest mean square error (MSE) can be calculated. This allows for the study of the investment, installation of the PV rooftop, and utilization of the HWS for solar energy output. Using the HWS method, important data can be updated prior to employing them for calculation via the time series decomposition method [41]. Through the HWS method, the number of passengers on the Shanghai subway in the short term can be estimated [42], which allows for the extraction of various types of passenger flow. In Spain, transmission system operators can make an accurate prediction of future energy demand using the HWS method [43]. For instance, with 70 days of imported data and 48 days of forecasting, the HWS method and MAPE can be employed to predict the number of patients with coronavirus disease 2019 (COVID-19) in India [44]. Using grid search by adjusting the values of the three HWS method parameters, increasing them by 0.1 per cycle by performing 1,000 iterations and then calculating the HWS forecasts as well as the MAPE and root mean square error (RMSE) tolerances for each iteration to select the best values for all three HWS parameters from the available options [45]. When making predictions about the management of water resources, we employ the HWS multiplicative and HWS additive methods [46]. Finding the HWS parameter can be accomplished by minimizing the MAPE or RMSE using the generalized reduced gradient algorithm (nonlinear) [47], [48]. To solve the unconstrained optimization problems and adjust the HWS parameters, the limited-memory Broyden–Fletcher–Goldfarb–Shanno (L-BFGS) technique is used. The HW method is the most effective for regular trend prediction, which includes how energy consumption shifts with the seasons and how it increases annually. When calculating how to configure the hyperparameters in HW, grid search, and the L-BFGS methods are utilized. This is carried out to ensure that the prediction is as accurate as possible. Before transferring the load to another transformer, the amount of electricity consumed should be estimated by applying the HW method's exponential smoothing function.

A summary of the most important contributions of this article is as follows:

1. The LTR procedure reduces the time customers experience power outages due to the loading transformer type 115/22 kV trip.
2. An automated tool that can connect with the SCADA system at the utility control center to perform operations rather than relying on the operator to evaluate the situation is developed. The SCADA message alarm employs the FTA technique to analyze the message to identify the most accurate response in the shortest time.
3. The forecasted MW load for use in the LTR procedure. This will prevent the loading transformer from having to supply MW load, which will not resolve the power outage because of continuous overloading, resulting in the electrical system tripping out.

II. DECISION METHODS BASED ON POWER SYSTEM

A. FAULT TREE ANALYSIS

The FTA process converts a physical system into a structured logic diagram, which is also known as a fault tree, in which particular causes are shown to result in a single TOP event of interest. The event and logic symbols are employed in constructing the logic diagram. The "AND" and "OR" gates are the two fundamental symbols; the "NOT" gate is an additional symbol that is utilized less frequently. To determine the TOP events, a preliminary hazard analysis is used. The FTA comprised three steps as follows:

1. Definition of the system
2. Construction of fault trees
3. Analysis of the fault tree

1) SYSTEM DEFINITION

To conduct a meaningful analysis, FTA originates from an undesirable event statement, including a state of system failure. The three categories of fundamental system information that are required are as follows:

1. Components and failure modes: The description of the output stage of each component is influenced by the input state of the component as well as the internal operating mode of the component.
2. Components connected: identification of model the relationships and dependencies between events leading to a specific top-level undesired event. The connections are represented using logical gates, and the structure forms a tree-like diagram.
3. System boundary conditions: These conditions determine the extent to which the fault tree (map) will be drawn. The system boundary conditions include the top event, the initial conditions of events that are already occurring or not permitted, and the tree top.

2) FAULT TREE CONSTRUCTION

FTA is a graphical representation that depicts the various potential causes of a system failure or an undesirable event. For fault tree construction, a systematic analysis of the system, identification of possible failure modes, determination of causal relationships, and organization of this information in a graphic representation that is both clear and coherent are the steps necessary. Engineers can make informed decisions that will improve the design and performance of a system by using the fault tree that is produced. This tree can be employed to evaluate a system's risk, reliability, and safety.

3) FAULT TREE EVALUATION

The evaluation of the fault tree comprises two substeps: The first is the qualitative evaluation, and the second is the quantitative evaluation:

1. Qualitative FTA: This is the first step in qualitative evaluation, which determines the minimal cut, path sets, and common cause failures. The deterministic methods and the Monte Carlo simulation are two of the most important approaches in determining the minimal cut sets for fault trees.
2. Quantitative analysis and criteria: As mentioned earlier, reliability analysis is a probabilistic process; consequently, to determine a meaningful value for the system's reliability, a comprehensive quantification of the system must be performed. Since the logic of the system structure is composed of a series of opposing logics, which are also known as failure

logics, in FTA, the term ''unreliability'' is always employed in place of ''reliability.'' For quantitative analysis, the unreliability can be understood as a value that complements the reliability. The generation of the minimal cut sets is the initial step in any FTA, as discussed in the preceding section. The second step in the FTA process is determining which primary event is the most unreliable by correctly assigning probability values (data) to each primary event (component failures).

B. EXPONENTIAL SMOOTHING

Exponential smoothing is a family of forecasting methods that can handle various characteristics of time series data. There are several variants of exponential smoothing. The following are the primary categories of exponential smoothing methods:

1. The level component is the only factor that is considered in the single exponential smoothing (SES) method, which is the most fundamental form of exponential smoothing. Time series data that do not exhibit a discernible trend or seasonality are adjusted using this method.

2. Double exponential smoothing (Holt's method): This technique extends the capabilities of SES by incorporating a trend component. This allows the method to capture the direction and slope of the data. When there is no seasonality in the time series, a downward trend should be observed.

3. Triple exponential smoothing (HW method): To extend it further, a seasonality component is added to double exponential smoothing. This method is called triple exponential smoothing, which is also known as the HW method. It is a method appropriate for time series data that exhibit both trends and seasonality.

4. Additive and multiplicative seasonal exponential smoothing: The HW method can be modified to handle both additive and multiplicative seasonalities. This is referred to as the ''seasonal exponential smoothing strategy.'' Decision-making can be done by evaluating whether the magnitude of seasonal fluctuations remains relatively constant (additive) or changes proportionally with the level of the series. A decision is made on the basis of this information (multiplicative).

C. UTILITY SUBSTATION

Specifically, the electrical system of Thailand is composed of five distinct parts: 230, 115, 69, 33, and 22 kV. The voltages were controlled by the utility company. This includes power plants, transmission lines, substations, and delivery points. To fulfill its obligation to supply the distribution company with electrical energy, the utility company is responsible for either producing or purchasing electrical energy. An independent power producer, a firm small power produce (SPP firm), and an SPP non-firm will be electricity suppliers in certain regions. Substations, low-voltage transmission lines, and the distribution company are where the distribution company monitors electrical equipment. This monitoring extends from the delivery point received from the utility company to the customer power meter. The utility company substation's bus arrangements include the Breaker and a half, the double main bus single breaker with transfer bus, and the main and transfer bus. Factors including the level of flexibility required for system operation, the level of cost considerations, the ease of maintenance, and the requirements for system reliability all play a role in determining the selected bus arrangement. The selection of an arrangement must be based on electricity consumption, the number of customer delivery points, and the importance of customer load. Information on 53 substations, 68 loading transformers of type 115/22 kV, and 24 loading transformers of type 230/115 kV are all part of the utility company's inventory as of January 2021. To investigate the substation, with a pressure level of 115 kV, this study employed the main and transfer bus model. The data presented above serve as the basis for this investigation. The same substation boasts the installation of two loading transformers of the 115/22 kV type.

D. DISTRIBUTION SUBSTATION

By monitoring electrical equipment, beginning with the delivery point received from the utility company, low-voltage substations, and low-voltage transmission lines, the distribution company is responsible for receiving power from the utility company, lowering the voltage to 380 and 220 V, and then delivering it to a large number of customers, including residences, industrial plants, hospitals, and offices. Since the distribution substation will have two incomings receive power from the loading transformer and will be delivered separately to the two customer groups, it will be separated independently. Nevertheless, if one of the incoming trips loses power, the distribution company will close the circuit breaker to try the two customer groups together.

E. SCADA SYSTEM

The SCADA system is utilized in industrial control systems and other applications to monitor and control various processes, equipment, and systems [9]. A centralized computer or server is typically included in a SCADA system. This computer or server collects data from remote devices and control systems through a communication network [8]. A user interface is then used to display these data for monitoring and analysis. The user interface can also send commands back to the remote devices and control systems to carry out actions, including turning the equipment on and off and adjusting the parameters of the process. Typical applications for SCADA systems include the oil and gas industry, the water and wastewater industry, the transportation industry, the generation and distribution of electricity, and the water and wastewater industry. To guarantee dependable and secure operation, they are also utilized in the systems that make up critical infrastructure, such as power plants [7] and pipelines. SCADA systems are essential to modern industrial control and automation procedures, providing operators and decision-makers with real-time information and control capabilities. However, SCADA systems are a potential target for cyberattacks because of their widespread use and critical role [6]. Therefore, taking precautions to protect them from such attacks is necessary.

In recent years, SCADA systems have been the subject of significant research. Security is one of the numerous subjects that are covered by this research. In addition to developing new security mechanisms and technologies for SCADA systems, researchers have focused on identifying and mitigating security threats including cyberattacks and unauthorized access. Enhancing the interoperability of SCADA systems is another area of research that is being conducted. This will allow seamless and efficient communication and data exchange between various systems. Research on developing new technologies and methods for remote monitoring and control of SCADA systems has also been conducted. This research has enabled operators to access and control the systems at any time and from any location using the systems.

Furthermore, research on enhancing SCADA systems' capabilities in data management and analysis has been carried out. This has enabled improved inefficient decision-making and operations. Real-time monitoring capabilities of SCADA systems have also been enhanced through research. This has made it possible for these systems to react rapidly to shifting conditions and provide operators with timely information. The human–machine interface of SCADA systems has been the subject of research to make these systems more user-friendly and intuitive to operate and improve the overall user experience. These are some of the most important research areas in SCADA systems. Due to the constant introduction of new developments and technologies, SCADA systems are becoming increasingly sophisticated, highly secure, and efficient in their ability to control and monitor industrial processes and systems.

III. THE CONTROL CENTER OF THE POWER SYSTEM

The utilization of company's SCADA systems monitors incoming events or alarms, controls and responds to commands generated by those events, and collects, stores, and records data. In Fig. 1, the diagram that depicts the data transfers between the substation and the power system control center is constructed via three distinct data groups. The first category comprises digital inputs. It is composed of many annunciator alarms, including KT1A WINDING TEMP ALARM STATE 1, KT2A BUCHHOLT ALARM, KT1A MAJOR TROUBLE, and KT2A KWH LOSS OF PT. It represents the current status of the circuit breaker between closing or opening and the annunciator alarm. It displays the trip event and the operating protective relays when the trip occurs in the electric system. The second group is composed of analog inputs. All of the values that have been measured at the substation are transmitted to the control center of the power system [10], which includes the voltage, current, power, and tap position of the transformer. The third group includes digital outputs. It involves commands to CLOSE or OPEN circuit breakers, RAISE or LOW tap position commands of the tie transformer and loading transformer, and ON or OFF commands and protection devices including recloser relay, under frequency, relay under, and voltage relay. It also comprises all of the commands the operator provides at the power system control center. The "SINGBURI" 115 kV of the utility substation is depicted in a single-line diagram, as shown in Fig. 2, including the primary and transfer bus strategy. This particular substation is equipped with "KT1A," which is equipped with a high-side breaker known as "7012" and a low-side breaker known as "2212," to supply the "PEA#1" delivery point, and "KT2A," which is used to supply the "PEA#2" delivery point. The measured analog values, such as the voltage, MW, and Mvar of the transformer and the transmission line, are also displayed in the figure below. A red square box represents the digital values that have been measured, such as the closed status of a circuit breaker. As for the open status of the circuit breaker, a green box is used to represent the open status. Furthermore, this figure shows the equipment status after "KT2A" tripped out of the electrical system. This confirms that the transformer trips out of the electrical system, the high- and low-side circuit breakers trip, and the analog load value "KT2A" equals 0. A "TAG" is what SCADA is designed to do to prevent an operator from controlling a digital point while they are located at one of the power system control centers. An "ON–OFF" relay protection, a recloser relay, and a communication carrier for a distance relay are some examples of what can be prevented. An "OPEN–CLOSE" circuit breaker and an order should be prevented. At the transformer tap position, "RAISE–LOW" is displayed. If the device is damaged or if it is being operated by maintenance, the control center will attach a "TAG" to it. If the abnormal message alarm indicates an open circuit breaker and the circuit breaker itself has a "TAG," then there is an open circuit breaker that must be maintained. There has been no trip event that has occurred in the electrical system.

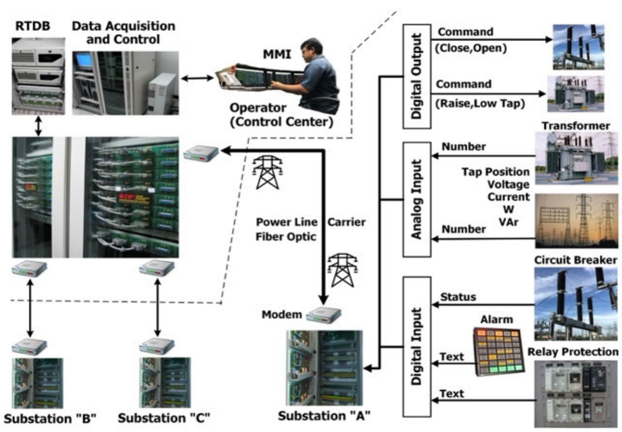

FIGURE 1. Schematic data flow at the control center.

If a trip event occurs, the SCADA system allows the control center to monitor the status of the power equipment in the electrical system and provides a solution to the problem. Fig. 3, which illustrates the "ALARM ALL" command, presents six columns. The alarm sounded at

6:31 a.m. on January 24, 2019. A trip transformer designated as "KT1A" can be found at the SATTAHIP 1 substation. By utilizing an electrical apparatus, the operator of the control center performed an analysis and interpreted the trip event. In this scenario, we assume that any abnormal occurrences, including a loss of loads, a failure in communication, or a trip in the transmission line, take place simultaneously. In such a scenario, numerous incoming alarms will occur, and the trip transformer will be displayed throughout the process. Because of this, the operator might become confused and fail to screen and investigate the factors that led to the occurrence of the events.

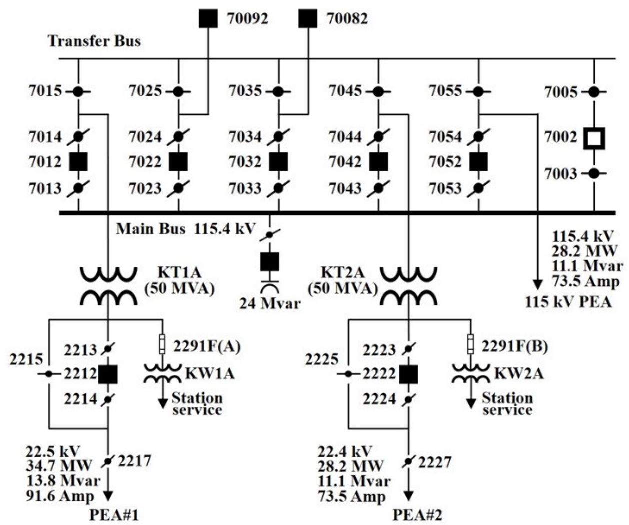

FIGURE 2. Utility substation bus arrangement of "SINGBURI" 115 kV.

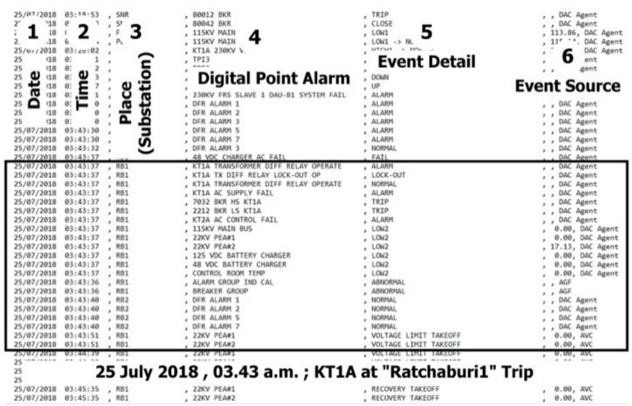

FIGURE 3. SCADA annunciator alarm when transformer "KT1A" trips.

The Man Machine Interface (MMI) console for the operator, five consoles, and four monitors are depicted in Fig. 4, which illustrates the hierarchical architecture of all operating software applications. There is a practical program called "Power Application," which collects data and displays voltage deviation, as well as the "DDT Viewer" tool. Using a "Report Generator," the digital and analog values of the data are automatically recorded at regular intervals of 30 min and saved in the CSV format. "Data Processor" is a computation result generator for analog values such as the VA value, percentage of the rated values, and current and trend graphs. Additional examples of these types of values include the VA value. "Display Converter" is a tool for converting measurement data from the remote terminal unit (RTU) of substations to be displayed on the MMI console for the operator to control. An alarm that occurs is managed by a component known as the "Alarm Processor." Furthermore, the abnormal alarm classification communicates with the RTU of each substation, sending and receiving information, updates, and scanning the alarm. Its sound pattern is distinct from a regular "DACAgent" alarm. The status circuit breakers, alarm events, and relay protection operations in substations are the sources of "DI" (digital input).

Moreover, in substations, SCADA displays on MMI consoles are created using "AI" (analog input) data, including the voltage, current, watt, and var, and "AO" (analog output), which is brought from the control room to the substation. Examples of the latter include the close–open circuit breaker and the raise–low tap position of the transformer. The SCADA power control center will sound an alarm whenever there is a problem with the power system. Among the various types of alarms, digital point-types are included. These types of alarms include information about the open circuit breaker status, active protection relay information, and alarm type. The voltage–current measurement is either higher or lower than the average amount (MW, Mvar). Owing to the numerous electrical devices connected to the modern electrical system, alarms are frequently triggered from various pieces of equipment, and sometimes, they are triggered simultaneously. In addition to processing digital and analog point alarms, the SCADA application "Alarm Processor" helps filter and display alarms. It displays significant alarms as text with color and sound that are distinct from those of other alarms.

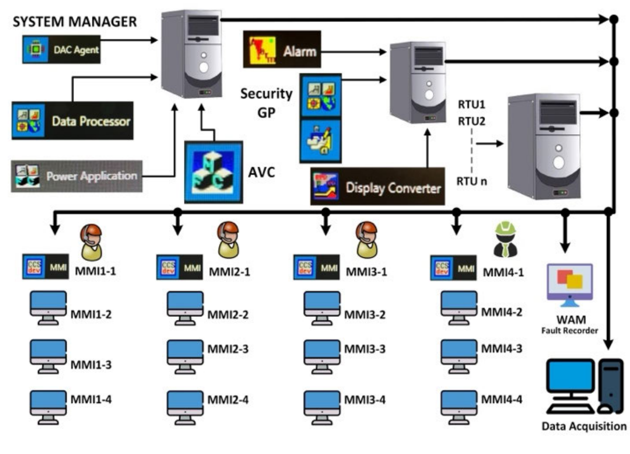

FIGURE 4. SCADA application and MMI console.

IV. LOADING TRANSFORMER PROTECTION RELAY

Detecting fault events in electrical equipment necessitates the use of measurement quantities including currents and voltages. The current transformer measures current, and the potential transformer measures voltage. The protection relay is responsible for obtaining and treating these two measurements accordingly. Fig. 5 shows a portion of the Bay loading transformer depicted in Fig. 2. The current transformer, potential transformer, and relay at the installation location are all displayed on this screen. A 115/22 kV loading transformer with the designation "KT2A" has circuit breakers with the designations "E" and "F" on the high and low sides, respectively. It is the 22 kV voltage level referred to as the delivery point, and it is the 115 kV voltage level connected to the main grid. From here, the distribution company receives power. A protection system primarily operates quickly while isolating only the defective equipment from the rest of the electrical system. Put another way, the information about the electrical system that surrounds the electrical equipment that must be protected is measured by the current and potential transformers. The data from the measurements are then sent to the relay to be processed from there. For instance, assume that the prerequisites for the occurrence of a fault, such as a relatively high electric current, are met. In comparison to the norm, the direction of the electric current is different. The relay will determine whether there is a problem with the electrical equipment and if a low voltage occurs. The relay will send a command to open the circuit breaker to separate the malfunctioning electrical equipment from the rest of the electrical system.

The electrical power system control center cannot be immediately energized if the loading transformer trips out of the electrical system. To verify the equipment's zone of differential relay (87k1) flashover traces, it is necessary to wait for the maintenance unit to perform an inspection initially. The insulator that supports the apparatus deteriorates. Oil stains can make their way into the transformer, or the oil in the transformer might require inspection by someone from DGA. If the loading transformer trips, the electrical power system control center must devise a load transfer plan rather than a restoration transformer back plan. This is to shorten the amount of time that power is out. A wide variety of protection devices can detect various faults, and these devices are used for loading transformers. As shown in an illustration, the "87k1" transformer differential relay can determine irregularities in how electricity is transmitted through a transformer. If the "51T" overcurrent high-side relay detects abnormalities in the magnitude of the high current flowing through it, it will alert the user. The Buchholz relay, pressure relay, and oil flow relay that make up the "86 × 1" transformer self-protection relay are responsible for detecting any issues or faults within the transformer.

V. LOAD TRANSFER PROCEDURE

The utility company and the distribution company are responsible for controlling the electrical equipment shown in Fig. 6. The utility company supervises and controls the device that is located above the blue dotted line. Conversely, the distribution company is in charge of the electrical equipment below

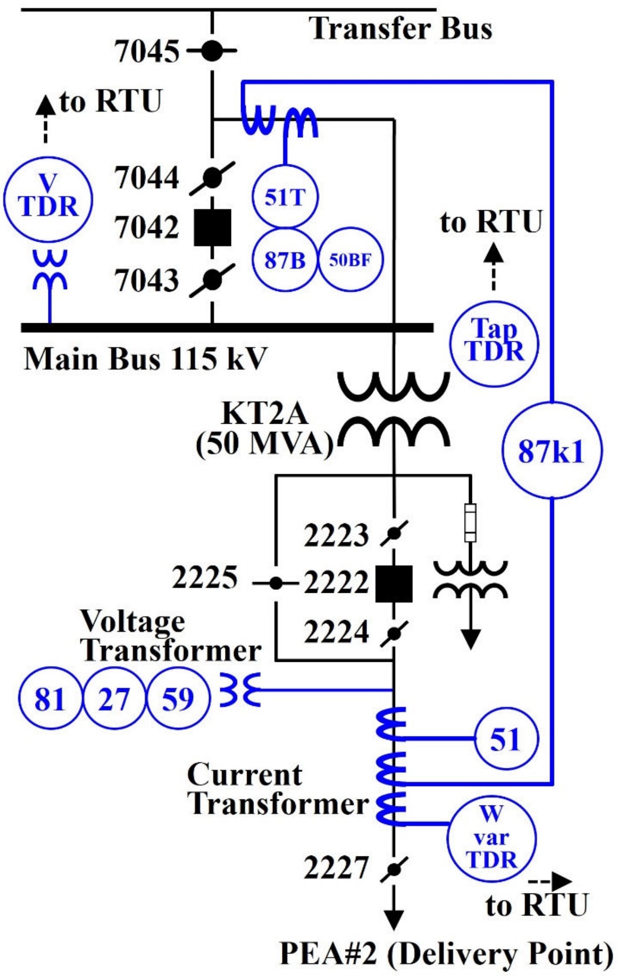

FIGURE 5. Overall protection of the transformer in the main and transfer bus arrangements.

the blue dotted edge. The utility company utilizes the "main and transfer" bus arrangement pattern. The 115/22 kV loading transformers in this substation are designated as "KT1A" and "KT2A," and each has a capacity of 50 MVA. The square symbol represents a circuit breaker. The black square represents the status of the closed square. In contrast, the white square highlights the open status. Sixty-eight delivery points are supplied to the distribution company by 33 substations in the central region of Thailand. These are referred to as the "main and transfer" distribution system. Two feeders are supplied by "KT1A," which are made up of loads with four load points, that is, LP1, LP2, LP3, and LP4. Alternatively, three feeders are supplied by "KT2A," which are composed of four load points, namely, LP5, LP6, LP7, and LP8. That "KT1A" will not be connected with "KT2A" in the electrical system of distribution companies is the result of the agreement, which stipulates that "BVB-01" will always be in an open status. The process of load transfer for the "KT2A" trip will begin only after the distribution control center receives the notification of the "KT2A" trip confirmation event from the utility control center and information regarding the trip event, which includes the date and time of the event. The operator verifies that circuit breakers "7042" and "2222" are open, determines the type of protection relay that is functional, and obtains information about the MW load of "KT1A" and "KT2A."

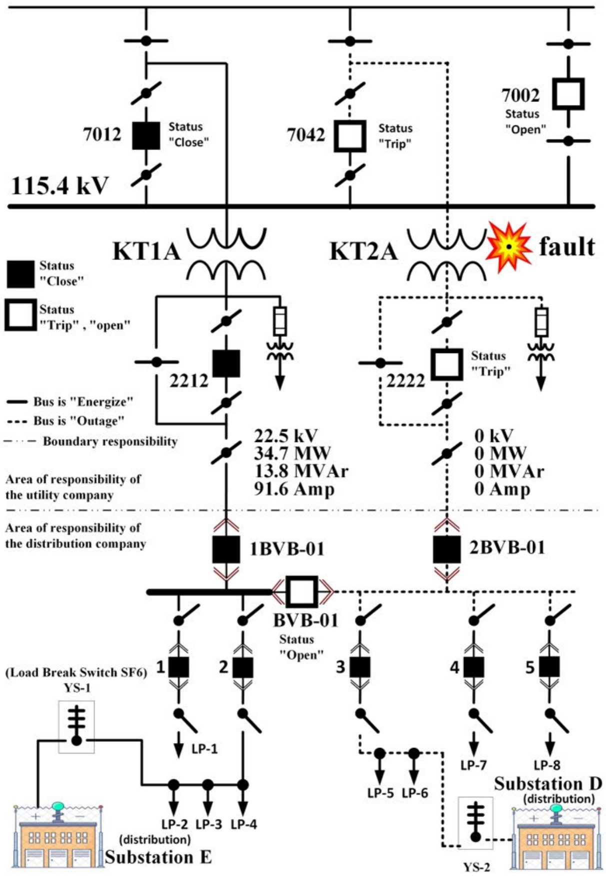

FIGURE 6. Single-line diagram when "KT2A" trips.

In the first method, which is referred to as "moving the load within the same substation," the distribution company has two options. Carrying out this method will take approximately 3 min. To deliver the LP5-LP8 load, the distribution control center will open "2BVB-01" and then close "BVB-01." At this point, the power will be turned off to pick up from "KT1A." The second method involves moving the load to a location that is not the source of the substation operation. When moving in this direction, the maintenance team must drive the vehicle to the switching load break switch, which causes the process to take longer than when moving in the first direction. Given the distance between the location and the power source, bringing the power from another location takes approximately half an hour. This method is only employed when the combined load of "KT1A" and "KT2A" before the trip is greater than 50 million volts of air. The overload will cause damage to the "KT1A" if the load is moved using the first method, which is the most common method. The "YS-2" load break switch will be closed once the distribution company has determined the source of the trip and the amount of power being consumed. The load is recommended to be moved from LP5–LP8 to Substation "D" instead. The load is transferred from one location to another within the same substation. The "KT1A" loading transformer risks experiencing an overload trip because of this, but it is possible to provide a fast service. Fig. 7 shows the traditional loading transformer restoration procedure case. The procedure has 14 steps, starting when the loading transformer trips out of the electrical system and ending when the distribution control center switches and transfers the outage customer to receive MW load from the neighboring loading transformer. This step is referred to as the LTR, which is carried out by the utility control center, responsible for Steps A1–A12 functions. The distribution control center is responsible for the functions of Steps A13–A14.

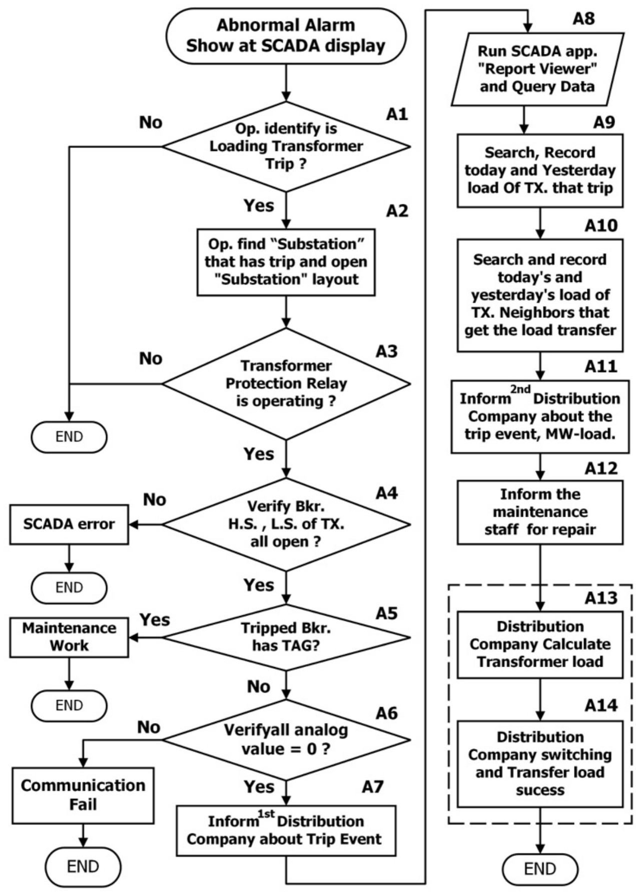

FIGURE 7. Traditional loading transformer restoration procedure flowchart.

During the period beginning on January 1, 2018, and ending on December 31, 2018, the utility control center has recorded nine instances of loading transformer event statistics, as indicated in Table 1. LTR is composed of 12 steps and takes an average of 433 s. When the utility control center is in operation, the SCADA system frequently displays the text of the message alarm. In the case of the capacitor bank, shunt reactor, transmission line, bus, tie transformer, loading transformer, BESS, and SVC, for instance, the alarm text notifies the voltage level that the delivery point is either higher or lower than the MW Mvar control threshold. This occurs in electrical devices near the rated or message alarm text. This is a result of electrical equipment-producing trips. The SCADA receives a wide variety of alarm texts every time.

This study focuses solely on the 115/22 kV loading transformer event during its investigation. "A1" is the operator's procedure when the alarm messages appear on the SCADA in the control center. This procedure involves the operator reading the alarm message text row by row and then analyzing what causes the loading transformer trip event following the reading. When the operator is in "A2," they will first examine the text of the alarm message, then determine the substation's location, and finally examine the layout of the substation. The A3–A6 procedure is a procedure for confirming that the loading transformer trip is actually out of the electrical system. "A3" is when the operator opens the SCADA alarm message summary page to view the text line by line. While the event occurred, the protection relay worked and checked if the protection relay that operated as the protection relay of the loading transformer caused the trip event. "A4" opens the substation layout to inspect the high-side status and the loading transformer's low-side circuit breaker. "A5" checks for every circuit breaker in "A4" without TAG, whereas "A6" checks for the analog value of the loading transformer consisting of MW, Mvar, current, and voltage. All values must be equal to 0. After confirming the data in steps "A3"–"A6," the conditions have been completed, indicating that the loading transformer is tripping out of the electrical system. Next, the "A7" step will be the first one to inform the distribution control center about the preliminary trip event. The data that will be sent to the distribution control center will include the date that the event known as the loading transformer occurred, the name of the substation, and the protection relay that is currently operating. A SCADA application called "Report Viewer" is opened when the "A8" operator is activated. This application is utilized to view analog data in reverse. A time limit of 30 min has been included. The operator first opens the substation layout and records the MW load data, the period before the event of the loading transformer, the trip, and the period yesterday. Finally, the operator orders the Query Application, which takes approximately 25 s to query. This is the procedure known as "A9."

The MW load data of the neighbor loading transformer from yesterday and the time period before the trip's occurrence is recorded by the section labeled "A10." At the distribution control center, which contains data comprising the MW load of the loading transformer that trips out of the electrical system and the neighbor loading transformer that supplies the transfer load, the procedure known as "A11" informs the distribution control center about the trip event information. The operator opens the line application, enters the trip event detail information, and then sends it to Maintenance Term Contact to fix it as quickly as possible. This is the procedure known as "A12." In procedure "A13" of operation following the receipt of MW load data, the distribution control center will calculate the impact of transformer overloading and plot out the process of load movement. The distribution control center has two options for accomplishing this task: The first one is to move the load within the same substation, and the second one is to move the load between substations by switching the load break switch. Both of these options are available to the distribution facility. The switching and transfer load was completed in "A14." The LTR process was found to have three limitations, as described in this study: It takes a significant amount of time for the utility control center operators to monitor and analyze the text of the message alarm, execute query data at the "Report Viewer," search for and record MW load data, and comply with the requirements of "LTR."

As a result of the large number of message alarms that are displayed, the operators are accustomed to monitoring SCADA alarms, which have the potential to be incorrect. The utility control center uses MW load data from before the trip event and yesterday to calculate the MW load that will be transferred to the neighbor loading transformer. The data used in this calculation must be highly accurate.

TABLE 1. Time used in the conventional procedure of 115/22 kV transformer load transfer.

Step	Details of procedures	Time (s)
A1	The operator identifies the SCADA message alarm as a loading transformer trip event.	32
A2	The operator analyzes the SCADA alarm message text again and then answers which substation the trip incident occurred at. Then click to see the substation layout.	19
A3	Confirm that the transformer protection relay is operating.	32
A4	Verify that the transformer's high- and low-side circuit breakers are all open.	24
A5	Verify that the transformer's high-side and low-side circuit breakers have entered no "TAG" Switching value.	15
A6	Verify that V, Amp, MW, and Mvar on the low side of the loading transformer are all equal to zero.	22
A7	1st, inform the Distribution control center of the preliminary trip event with the date of occurrence of the event named loading transformer, substation, and the protection relay at work.	42
A8	The operator opens a SCADA application called "Report Viewer" and query data.	48
A9	Open Query Data to search and record the MW load data, the period before the event of the loading transformer, the trip, and the period yesterday.	53
A10	Open Query Data to search and record the MW load data of the neighboring loading transformer from yesterday and the period before the trip's occurrence.	55
A11	2nd, Inform the MW load of the loading transformer that trips out of the electrical system and the MW load of the neighbor loading transformer.	51
A12	Inform maintenance staff about trip event.	40
A13	Distribution control center calculates transformer load.	-
A14	Distribution control center switching and transfer load.	-

VI. FAULT TREE ANALYSIS

The modern electrical system comprises an ever-increasing number of apparatuses, such as transmission lines. To accommodate the increasing load, a new substation will be established besides adding a transformer. More electrical equipment will be connected to the electrical system, which will increase the frequency of abnormal alarms during events that involve high–low analog voltage at the main bus and high voltage values at distribution points. For instance, a transmission line or tie transformer operates at 115 or 22 kV of power flow. The daily load curve changes at various points throughout the day, impacting the analog values. This occurs when a maintenance circuit breaker or protection system is in operation during the period. It transfers from the control center's close–open capacitor bank connectivity to the power system for abnormal digital alarms, trips out of the system, or appears in other equipment. It also appears in varying power system equipment. Assume that >25 messages appear on SCADA display devices simultaneously and that abnormal alarms occur frequently. If this is the case, the operator at the control center will examine the abnormal text alarm to identify the component of the electrical system that makes the trip, requiring a significant amount of time to diagnose complicated problems. Moreover, the operator may incorrectly diagnose the occurrence. The decision tree technique is the foundation for the FTA, which describes the cause and impact of an event. It will be organized as a tree, with a root node that represents the top-layer decision node. These branches contain the decision node or the significant cause and leaves that contain the event being considered. To determine whether the outcomes are true or not, the FTA requires the true and false subevent inputs and then analyzes them. In the present study, FTA was utilized to analyze abnormal alarms. It refers to the root node, which is the event that causes the loading transformer to trip out of the system. Conversely, the leaf node is for the 1, 2, 3, and 4 instances of the loading transformer that occur for the decision node. It is possible to combine leaf node events by utilizing the "AND" and the "OR" gate conditions. The event or leaf node is represented by the green circle at the bottom of the diagram, while the leading cause, also known as the root node, is represented by the red square at the top of the diagram.

Fig. 8 illustrates the abnormal alarm that is included in the electrical system. "AND," "OR," and "NOT" are examples of logic gates that are utilized by a decision node to connect many events. Considering that it analyzes and comprehends images, FTA is a user-generated model that is easy to construct. There are a significant number of events, associated events, and FTAs that can be utilized for root cause analysis. Given that the loading transformer trips are not mutually independent, the FTA 1 figure illustrates the investigation of the Trip 1 loading transformer event. This means that a single trip of a loading transformer will not cause other loading transformers to trip. There is only 1 the loading transformer in existence. This study examines an electrical system with 68 loading transformers installed in central Thailand. To evaluate each loading transformer connected to the power supply of the electrical system, the authors developed 68 FTAs. Three primary cause groups are provided to facilitate the process of designing systems that incorporate experiences. The initial sequence of occurrences is associated with the status of the circuit breaker tag on the loading transformer, which can be described as "Close" or "Open" and "On" or "Off." This event is performed to maintain the circuit breakers. Group 2 includes both the event check that is employed to identify the analog value of the loading transformer and the protection relay event that causes the loading transformer to trip. This group comprises the event caused by the protection relay. Several types of flow fall under this category, which includes wattage flow, var flow, current flow, and delivery point voltage. Event A's probability of occurring is abbreviated as P(A). There are two possible outcomes for each of the events described in this study: "0" indicates that Event A does not occur, and "1" indicates that Event A transpires. The joining event uses logic gates as operators despite FTAs comprising branches and multiple events. For instance, for Event C to occur, both Events A and B must take place. Specifically, the "AND" gate is employed in this scenario, as depicted in (1). To carry out event operations, this study uses the "OR" logic gate, represented in (2). There are several types of transformer protection relays, including the "51T" overcurrent high-side relay, the "87k1" transformer differential relay, the "86 × 1" transformer self-protection, and the "51" low-side overcurrent relay protection. With a "NOT" gate function, (3) generates an event associated with the "TAG" symbol of all loading transformer circuit breakers. Equation (4) shows all events of the loading transformer trip "KT1A" or P(1A_Trip). A "KT1A" trip out of the system occurs if the result of calculating the events in (4) makes the result P(1A_Trip) equal to 1. This program employs Python to convert the abnormal alarms generated by the SCADA system into Event P(A) and then transmit this information to the FTA to analyze the trip event.

$$P_{(A\ and\ B)} = P_{(A\cap B)} = P_{(A)} * P_{(B)} \tag{1}$$

$$P_{(A\ or\ B)} = P_{(A\cup B)} = P_{(A)} + P_{(B)} \tag{2}$$

$$P_{(Not\ A)} = \bar{P}_{(A)} = 1 - P_{(A)} \tag{3}$$

$$\begin{aligned} P_{(1A\_Trip)} = &\left\{P_{(HS)} * \bar{P}_{(HStag)} * P_{(LS)} * \bar{P}_{(LStag)}\right\} \\ &* \left\{P_{(51T)} + P_{(87k1)} + P_{(86x1)} + P_{(51)}\right\} \\ &* \left\{P_{(Voltage)} + P_{(current)} + P_{(Watt)} + P_{(Var)}\right\} \end{aligned} \tag{4}$$

where $P_{(i)} \in [0, 1]$ is the probability of occurrence of the i_{th} SCADA event.

VII. TIME SERIES FORECASTING METHODS

Time series forecasting methods make predictions about the load data associated with the loading transformer triggered by the electrical system. The essential step is to utilize this load information in the planning process for assigning electricity consumers who experienced a power outage to another loading transformer. Assume that the predicted load data are lower than the actual load data. In this case, the loading transformer will have to be transferred to the other loading transformer

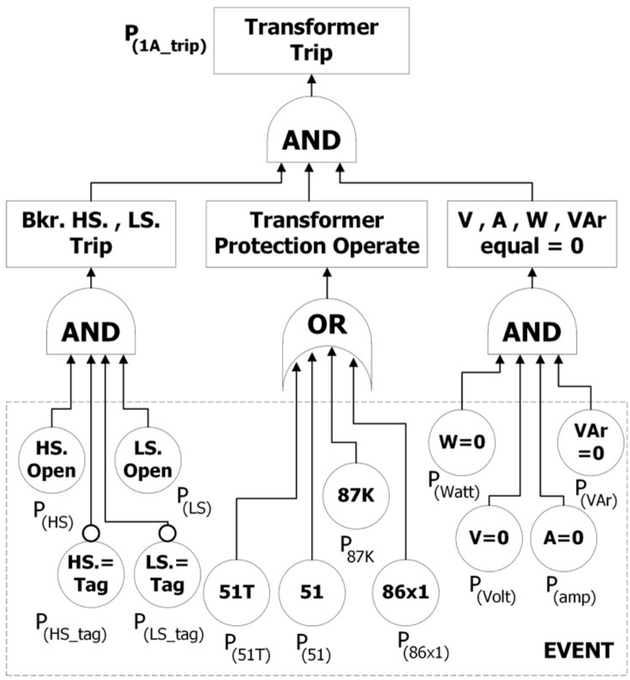

FIGURE 8. Fault tree analysis of "RATCHABURI 1" KT1A trip.

with a higher supply, which will cause overload problems and trip from the power system. Moreover, assume that the load data are predicted to be higher than what occurs. In this scenario, the distribution company will require additional time to switch equipment to transfer the load to a loading transformer located at another distribution substation, which results in an extended power outage. When using load data from the previous day, planning of transfer, and transferring the load, the load data may be inaccurate owing to the weather conditions, modifications made to the distribution grid for maintenance, or the movement of the load from one location to another. The production capacity of smaller solar power plants connected to the distribution grid remains unclear. Owing to these factors, the load data from the day before is not accurate when compared to the data of the current day.

The time series forecast method was selected to predict the load data in this study to eliminate fluctuations due to the external factors mentioned earlier. The most recent data points are given greater weight and significance by an EMA, which is a type of MA that differs from an MA in terms of weight and importance. An exponentially weighted MA responds more strongly to recent changes in data than a simple MA (SMA), which gives the same amount of weight to every observation taken during the period. One of the most important distinctions between an EMA and an SMA is the degree to which each one is sensitive to variations in the data used in its calculation. The EMA emphasizes recent prices more, whereas the SMA gives equal weight to all values. The two averages are comparable because technical traders frequently use them to smooth out price fluctuations and interpret them in a relatively similar manner. Considering that they give more weight to recent data than to older data, EMAs are more responsive to recent changes in data than SMAs. The TEMA, an advanced version of the EMA, is designed to reduce lag and provide a more responsive MA. An EMA already gives more weight to recent prices, but the TEMA applies the triple smoothing technique, which takes this concept even further.

Compared to traditional MAs, the TEMA provides trend information that is smoother, more accurate, and more reliable. It incorporates multiple levels of smoothing to get rid of the lag that is associated with MAs that are more straightforward. Users frequently utilize TEMA to recognize trends, patterns of reversal, and possible entry or exit points within the data. This study utilizes two prediction methods: the triple EMA method [27], [28] and the HWS method. The HWS method is a powerful technique that manages several components of time series data (level, trend, and seasonality) and adapts to various situations that require prediction. The HWS has also produced excellent results with low forecasting errors, especially when seasonality is present. When time series data is complex with trends and seasonality, The HWS produces more accurate forecasts than simpler methods. Multiple components help it capture data patterns and variances. The Holt-Winters technique is a common trend- and seasonality-capturing forecasting algorithm.

There are two types of recurring behavior for data on power consumption: a daily recurrence, which includes an increase in electricity use between 05:00 a.m. and 06:00 a.m., 08:00 a.m. and 12:00 a.m., 01:00 p.m. and 04:00 p.m., and 06:00 p.m. and 08:00 p.m., and a decrease in power use between 08:00 a.m. and 04:00 a.m. In general, Thailand is divided into three distinct seasons, which begin at the beginning of each year. Winter is the 4^{th} month with the lowest electricity usage and then transitioning to summer, which starts in April, with the highest electricity usage. Afterward, the rainy season arrives, which has lower electricity usage. To enable the operator to make use of the control of the electrical system, analog values such as active power (W), reactive power (var), current (A), voltage (V), and tap position will be transmitted to the SCADA system and displayed on a monitor located at the power system control center. These files will be stored in CSV format once SCADA has shown them. Between 00:00 and 23:30, the information is saved in a single file, updated every 30 min. The operator control center can view historical data of the mw load data by opening the personal computer and then opening the shared folder of the SCADA enterprise: Select the folder year, choose the folder month, and then select the date to view the file CSV format. On January 1, 2018, the control center had 59 substations and 8,860 analog values that needed monitoring and controlling. The SCADA system will record any 30-min interval beginning at 00:00 a.m., 00:30 a.m., 01:00 a.m., …, 11:00 p.m., and 11:30 p.m. for a total of 48 times. A CSV file that contains all analog values and has a dimensional size of [8,860*336] in [Row*Column] is stored by SCADA on a daily basis.

The process of calculating TEMA will start with (5). The choices made in this study for smooth = 2 and period = 7 resulted in an alpha value of 0.25 for smoothing factors, which has a value between 0 and 1. The selection of smoothing factor value the most recent data are given a higher weight when the smoothing factor value is 0.1, and applying a smoothing factor between 0.2 and 0.3 will produce a result that strikes a balance between smoothness and responsiveness. As with a straightforward MA, a smoothing factor 0.5 assigns the same weight to every data point. An EMA that is smooth and less responsive to recent changes is indicated by a smoothing factor greater than 0.5. This indicates that older data are weighted more than more recent data. The calculation process makes use of Equations 18–20, where the values are the outcomes of the calculation that was performed using Equations 6–8. These values are referred to as the linear, exponential smoothing value, the double exponential smoothing value, and the triple exponential smoothing value of the time series, respectively, in period T. The parameters are referred to by their names, and they are the smoothing model parameters of the TEMA method that are calculated using Equations 9–11. The value is the forecast interval, which in this study provides a forecast of 48 values or data every half hour for 1 day. It is the value that is anticipated at the point in time from the time series (12).

$$\alpha = \frac{smooth}{1+k} \tag{5}$$

$$S_t^{(1)} = (\alpha * Y_t) + (1-\alpha) * S_{t-1}^{(1)} \tag{6}$$

$$S_t^{(2)} = (\alpha * S_t^{(1)}) + (1-\alpha) * S_{t-1}^{(2)} \tag{7}$$

$$S_t^{(3)} = (\alpha * S_t^{(2)}) + (1-\alpha) * S_{t-1}^{(3)} \tag{8}$$

$$a_t = 3S_t^{(1)} - 3S_t^{(2)} + S_t^{(3)} \tag{9}$$

$$b_t = \frac{\alpha}{2(1-\alpha)^2}\left[\begin{array}{l}(6-5\alpha)S_t^{(1)} - (10-8\alpha)S_t^{(2)} \\ +(4-3\alpha)S_t^{(3)}\end{array}\right] \tag{10}$$

$$c_t = \frac{\alpha^2}{(1-\alpha)^2}(S_t^{(1)} - 2S_t^{(2)} + S_t^{(3)}) \tag{11}$$

$$F_{t+m} = a_t + b_t m + \frac{1}{2}c_t m^2 \tag{12}$$

Alpha (α), beta (β), and gamma (γ) are the three HWS parameters that are utilized in the HWS approach. These parameters, also referred to as the smoothing components, have values ranging from 0 to 1 and illustrate the behavior of the data. An initial calculation of the internal values of level (L_s), trend (b_s), and seasonality is performed by HWS using Equations 13–15. Following this, the subsequent calculation is performed using Equations 16–18. MW load forecasting can be quantified using Equation 19 because Thailand's electricity demand forecast data ''pdp2018'' and the level component of information on central Thailand's electricity use made it possible for this study to make use of the HW additive model. Four different kinds of errors are employed to evaluate the performance of the models that are being tested. A well-known method for determining the disparity between what a model or estimator predicts and what occurs is the measurement of MSE is depicted in (20). The fields of statistics and machine learning make use of it. To evaluate how accurate a prediction or estimate method is, MSE is designed to measure its effectiveness. When the MSE is low, the model or estimate is more effective in making predictions. In the context of time series forecasting and regression, the mean absolute error (MAE) shown in (21), as well as the MAPE, are utilized to evaluate the accuracy of predictions. The difference between the values that were expected and those that were observed is quantified in slightly different ways by each of them. MAE is the measure of the average absolute difference between predicted and observed values. RMSE is typically called the ''root mean square'' shown in (22) because it computes the square root of the average of the squared differences between the expected values and those observed. Squared errors can be quickly identified using the square root after the converted data units.

$$L_s = \frac{1}{s}\sum_{i=1}^{s} y_i \tag{13}$$

$$b_s = \frac{1}{s}\left(\frac{y_{s+1}-y_1}{s} + \frac{y_{s+2}-y_2}{s} + \ldots + \frac{y_{s+s}-y_s}{s}\right) \tag{14}$$

$$S_1 = y_1 - L_S \tag{15}$$

$$L_t = \alpha^*(y_t - S_{t-s}) + (1-\alpha)^*(L_{t-1} + b_{t-1}) \tag{16}$$

$$b_t = \beta^*(L_t - L_{t-1}) + (1-\beta)^* b_{t-1} \tag{17}$$

$$S_t = \gamma^*(y_t - L_t) + (1-\gamma)^* S_{t-s} \tag{18}$$

$$F_{t+m} = L_t + mb_t + S_t \tag{19}$$

$$MSE = \frac{1}{T}\sum_{i=1}^{T}(F_i - Y_i)^2 \tag{20}$$

$$MAE = \frac{1}{T}\sum_{i=1}^{T}|F_i - Y_i| \tag{21}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{T}(F_i - Y_i)^2}{T}} \tag{22}$$

where

Y_i is the measurement load data
F_i is the forecast load data
s is the length of the seasonal cycle = 48
T is the length of the test set = 48 points/day * 7 days = 336

Fig. 9 depicts the imported data and the prediction data generated via the HWS method. Moreover, the import data utilized in the forecast is represented by the blue line on the graph. The following two categories can be used to classify these data: 365 days are referred to as the training set for the first set, and 7 days are referred to as the test set for the second set. The date of the trip event is relevant. One can observe it on the dotted line, located in the area where the orange line displays the proposed data. A full-day alpha, gamma, and beta are the three HWS parameters. The values fall within the range of 0 to 1. Within this study, the datasets for each HWS parameter are defined. There are 10 numbers involved: $\alpha = 0.1, 0.2\ldots, 1.0$, $\beta = 0.1, 0.2\ldots, 1.0$, and $\gamma = 0.1, 0.2\ldots, 1.0$. All of these numbers represent individuals as part of the sorting process according to Table 2; an iteration of setting the value of the HWS parameter is performed. When the results of the calculations for MAE, MSE, and RMSE are the lowest, the HWS parameter value that produces the best forecast result within a total of 1,000 iterations is determined. This is performed to ensure that the results are accurate. Data on the MW load of the loading transformer "KT1A" are displayed in the top graph of Fig. 10, covering 372 days before the trip date. With a Windows time of 30 min, these data are available. As shown in the graph below, the MAE calculation result of the 1,000 iterations with different HWS parameter values was found at Iteration No. 800. The values of α, γ, and β were found to be 0.9, 0.1, and 0.1, respectively, which resulted in a minimum MAE value of 0.306511.

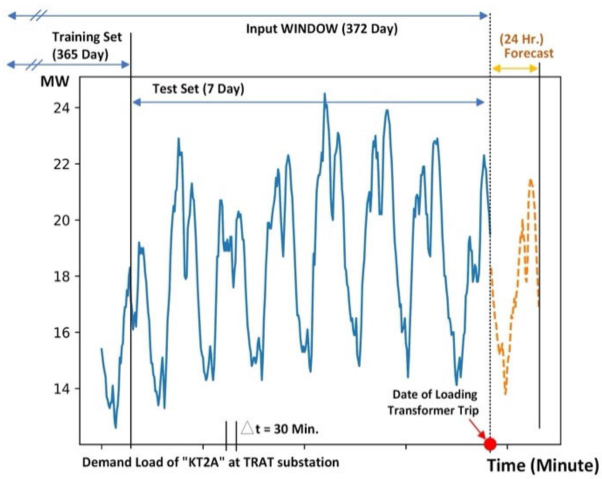

FIGURE 9. Training and test sets and forecasting of "KT2A."

TABLE 2. Settings for the holt–winters model parameters.

State setting	α	β	γ
1	0.1	0.1	0.1
2	0.1	0.1	0.2
…	…	…	…
…	…	…	…
999	1.0	1.0	0.9
1,000	1.0	1.0	1.0

Table 3 and Fig. 11 illustrate the application developed for this study, referred to as "Pyauto1." It consists of 17 steps. Using the Automate tool to replace the operator's work at the utility control center was the goal of this application, which was developed to solve the LTR problem of reducing the

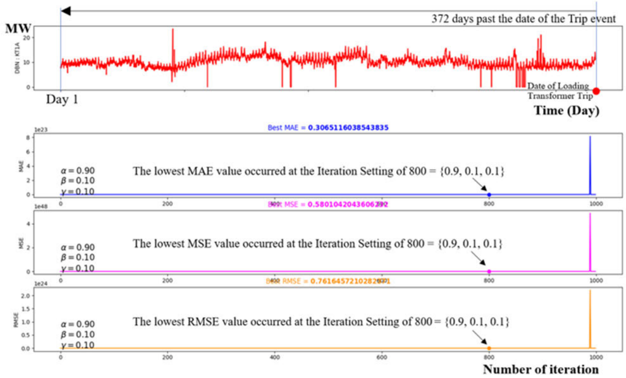

FIGURE 10. MAE, MSE, and RMSE results using the grid search method.

amount of time spent in "LTR," locate the actual MW load information without causing it to be distorted, and accomplish this goal. Pyauto1 will use the FTA technique to analyze to confirm that the loading transformer trip occurred from the electrical system. It will automatically retrieve the data from the SCADA message alarm every 60 s, then convert each line of the message alarm to P(x) and calculate the P(1A_Trip) and P(2A_Trip) of every loading transformer. If any P(1A_Trip) or P(2A_Trip) value is found to be equal to 1, it means that a trip event has occurred in the electrical system. The next step is Pyauto1 forecasting of MW load using two methods. The first method is called TEMA. Calculate the forecasting value of the MW load of the loading transformer at trip, denoted by F(TEMA, TX_trip). Then calculate the forecasting value of the MW load of the neighboring loading transformer, denoted by F(TEMA, TX_LTR). Pyauto1 then calculates the sum of F(TEMA, TX_trip) and F(TEMA, TX_LTR) to be F(TEMA, TX_trip+TX_LTR). The HMS additive method is the second approach used to calculate by using grid search to adjust the three HWS parameters to produce forecast results that are as close to reality as possible. The HMS additive method calculates F(HWS, TX_trip) and F(HWS, TX_LTR) to be F(HWS, TX_trip+TX_LTR). The loading transformer trip between March 2021 and November 2021 is presented in Table 4. The findings show that the processing time for certain events could take up to 190.1 s.

VIII. ABNORMAL ELECTRIC LOAD CURVE PROBLEM AT A DELIVERY POINT IN THAILAND

In this study, the subject was found to be interesting after the authors collected the active power or MW load data of the 115/22 kV loading transformer, which had 68 installations in substations in central Thailand. The Matplotlib Library, a Python program, was used to generate a 365-day plot graph by using data from the year 2020. Compared with the standard graph, the graph revealed that specific data must be adjusted. Several pieces of information, for instance, were abruptly reduced to 0. Eventually, the data went back to its initial value, or the MW data went from being excessively high to extremely low in a short amount of time, and then,

TABLE 3. Flow chart of the pyauto1 application.

Step B1:	Pyauto1 starts a connection via the SCADA enterprise and collects the SCADA text message.
Step B2:	Pyauto1 loads 68 fault tree analysis equations.
Step B3:	Convert the SCADA message alarm row by row to P(A) and calculate P(1A_Trip)
Step B4:	Check 68 FTA if the FTA equation is equal to 1, which means that the loading transformer trip is out of the electrical system.
Step B5:	Record the date and time of the event, the name of the substation where the event occurred, the name of the loading transformer that trips out of the electrical system, and the name of the neighbor loading transformer unit that must supply the transfer load.
Step B6:	Pyauto1 will connect to the SCADA enterprise to retrieve the MW CSV format 372 days past the date of the trip event. Calculate $S_t^{(1)}$, $S_t^{(2)}$, and $S_t^{(3)}$.
Step B7:	Calculate the loading transformer's MW forecast with the TEMA method by calculating the values of F(TEMA, TX_trip), F(TEMA, TX_LTR), and F(TEMA, TX_trip+TX_LTR).
Step B8:	Configure all three HWS parameter members, and create a state setting table.
Step B9:	Pyauto1 pulls data from the list data Python done earlier in Step 6. Pyauto1 uses the HWS parameter values of each state from step 8 to calculate the values $\{L_1, b_1, S_1\}$.
Step B10:	Use the HWS method to calculate the F(HWS) value with Equation 12, resulting in two sets of MW load forecast values.
Step B11:	Calculate MAE, MSE, and RMSE values.
Step B12:	Check if the state setting is the final state. If not, go to Step 13.
Step B13:	Update the three HWS parameters taken from the state setting table. Do Steps 9, 10, 11, 12, and 13 until all states are complete.
Step B14:	Find and record the three HWS parameters that produce the lowest MAE, MSE, and RMSE.
Step B15:	Calculate the loading transformer's MW forecast with the HWS method by calculating the values F(HWS, TX_trip), F(HWS, TX_LTR), and F(HWS, TX_trip+TX_LTR).
Step B16:	Pyauto1 brings the information from Steps 7 and 15 together to create a graph using the Python Matplotlib Library.
Step B17:	Pyauto1 sends information in Step 16 to the line application and sends the information to the mobile phone.

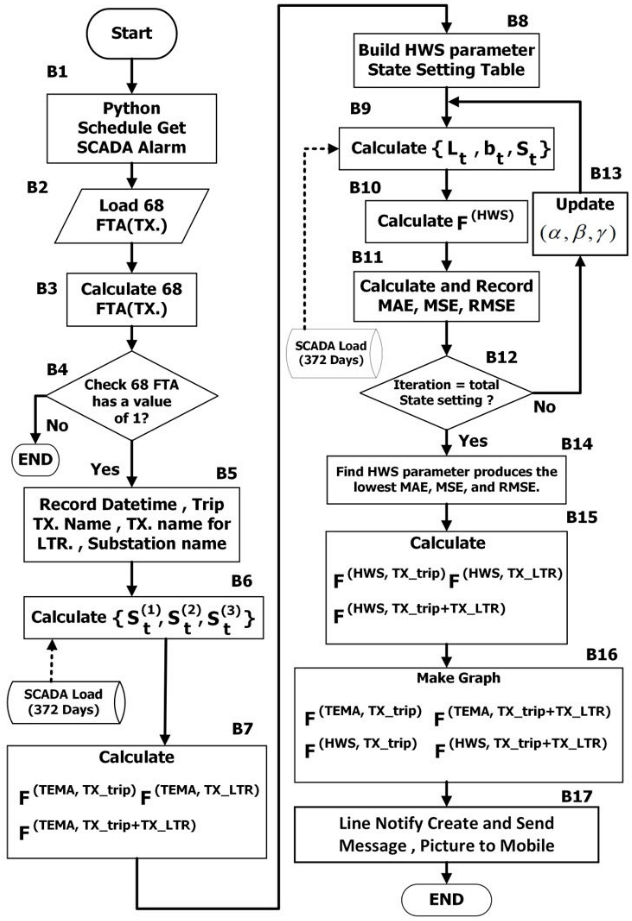

FIGURE 11. Flowchart of PyAuto1 using TEMA and HWS with grid search technique.

TABLE 4. Time used of hws grid search technique in Pyauto1.

No.	Trip event date time	TX. name-substation	MAE	MSE	RMSE
1	Mar 13, 2021; 11.43 a.m. $\alpha = 0.9, \beta = 0.1, \gamma = 0.1$ Process Time = 172.9 s	KT2A-CB	2.9713	1.0740	5.0364
2	Apr 18, 2021; 08.57 p.m. $\alpha = 1.0, \beta = 0.1, \gamma = 0.1$ Process Time = 145.1 s	KT1A-CBD	1.5854	2.6475	4.2835
3	May 07, 2021; 00.41 a.m. $\alpha = 0.7, \beta = 0.1, \gamma = 0.1$ Process Time = 157.4 s	KT1A-CB	2.8699	1.7641	3.8741
4	June 30, 2021; 02.06 a.m. $\alpha = 0.9, \beta = 0.1, \gamma = 0.1$ Process Time = 205.0 s	KT1A-DBN	2.0203	1.8866	4.3406
5	Oct 2, 2021; 00.06 a.m. $\alpha = 0.6, \beta = 0.1, \gamma = 0.1$ Process Time = 164.6 s	KT1A-SR1	3.4072	4.5410	5.7355
6	Nov 24, 2021; 06.14 p.m. $\alpha = 1.0, \beta = 0.1, \gamma = 0.1$ Process Time = 190.1 s	KT1A-LB1	2.2528	2.7914	3.6472

it went back to its initial value. Both forecasting methods TEMA and HWS, when imported, will result in inaccurate forecasting results if unusual data are used in the forecasting process. Consequently, they brought about high values for MSE, MAE, and RMSE.

The temporal abnormality pattern of MW data can be classified into four different patterns, as shown in Fig. 12, based on the data collection results. A specific time period was found to have a value of 0, according to Pattern 1, which was discovered. Afterward, the data returned to normal as more time passed. There is a momentary failure in the communication system that connects the substation to the control center, or SCADA equipment, such as the MPU and analog card is temporarily down. In some instances, maintenance work is performed on the substation's communication system. On certain days of the year, which occurred at different times throughout the year, Pattern 2 discovered that the MW data decreased and had values lower than usual for more than 24 h in a row. There is a significant difference between the pattern of the graph and the regular pattern of data collected in the past. The number of behaviors that fall under Pattern 2 is <20% of the normal range, but it is not equal to 0. It is discovered during special holidays in Thailand, such as the Songkran Festival or significant religious ceremonies, which will be holidays for 3–5 days in a row, causing businesses that use electricity to stop the production process in factories located in various industrial estates. According to Pattern 3, the MW data either decreased or increased, which was a departure from the initially collected data. When the distribution company changes the route configuration of the transmission line to perform maintenance on electrical equipment or when there is a trip incident and equipment is damaged, it typically takes place between 8:00 a.m. and 4:00 p.m. most of the time. Alterations are made to the MW load of the two loading transformers due to the distribution company's transfer of customers who receive electricity from the loading transformer to another transformer. Pattern 4 is the final pattern, comprising MW data that are either extremely high or extremely low at a specific time. Later on, things went back to how they were before. Interruptions or data packet losses, instrumentation errors, electrical noise, and other problems can be due to communication failures, which are links between the substation and the SCADA system. Using TEMA and HWS techniques to send data Patterns 1 and 4 as initial data for forecasting, the forecast results will be different from reality because the data patterns contain information irrelevant to the forecast's purpose. Consequently, the first step in the forecasting process is to employ the following steps of the EMA forecasting technique. Afterward, the study will explain how to filter and separate the data in Patterns 1 and 4 from the dataset.

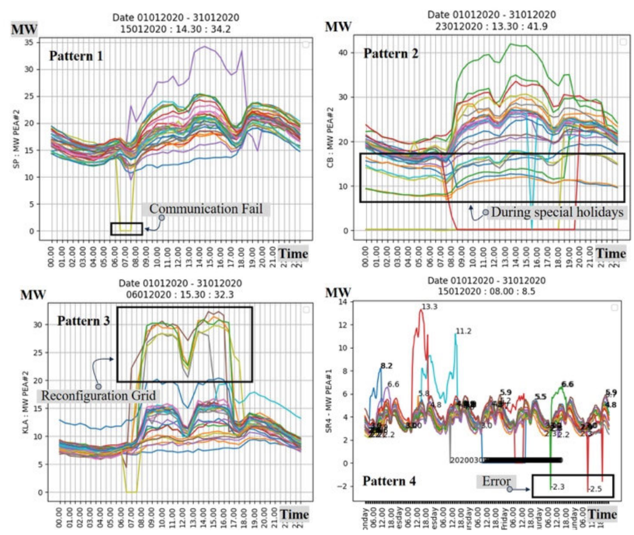

FIGURE 12. Four patterns of load data distortion in transformers.

Table 5 presents the algorithm for filtering and removing distorted data developed for this study. This algorithm filters and removes distorted data before sending good data to TEMA and HWS to calculate forecast values. This algorithm has six steps, beginning with step "C1," which will retrieve MW load data from SCADA enterprise for the past 365 days. Next, step "C2" will calculate the forecast value of MW load for 1 day, which has 48-time values from 00.00 a.m. to 11.30 p.m., using the EMA with an α value of 0.25. Finally, step "C3" will calculate the forecast value of the MW load for the next day. An upper line with a value of 130% of the EMA and a lower line with 30% of the EMA are created by step "C3" by utilizing the results of step "C2" regarding the EMA. After the addition of the upper line, a solid blue line, and the lower line, a solid orange line, the data for the loading transformer's 2-MW load is plotted together with the data for the MW load. Fig. 13 illustrates this phenomenon. It was found that the MW load data graph of any day could be considered distorted if the values were either higher than the upper line or lower than the lower line. The MW load data that are more significant than 130% or less than 30% is recorded in step "C4," which searches the data imported in step "C1" by recording the dates. A step labeled "C5" will delete days that contain distorted data and import data for other days to replace them in an amount equal to the number of deleted days. Following the recalculation of the EMA in step "C6," the steps "C3," "C4," and "C5" are repeated in the same order until the input data does not contain any distorted MW load values.

TABLE 5. Procedure: Filter abnormality curve pattern algorithm.

Step C1:	Create data for screening by importing the dataset of MW data of the loading transformer. This amount of data 17,520 points is historical data 365 days from the date of the trip event, recording the date of the first day of data imported. and the date of the last data imported.
Step C2:	Calculate the predictive value using $\alpha = 0.25$
Step C3:	Take the forecast results with EMA to create upper and lower lines. This study chooses the calculation method, which is the upper line value, which equals 130% of the EMA, and the lower line value, which equals 30% of the EMA for the number 130%, and 30% is a numerical threshold derived from the operator's work experience at the control center.
Step C4:	Take the upper and lower lines to check the 365-day dataset imported in Step C1. If MW data are found at any time with a value greater than the upper line or less than the lower line, record the date when the data were found.
Step C5:	Delete the date when the MW data were more significant than the upper line or less than the lower line, and then, import additional historical data equal to data in the cut-off date.
Step C6:	Go back, and do Step C2; repeat until no MW data with a value greater than or less than the upper line are found on any day; then, the screening process ends.

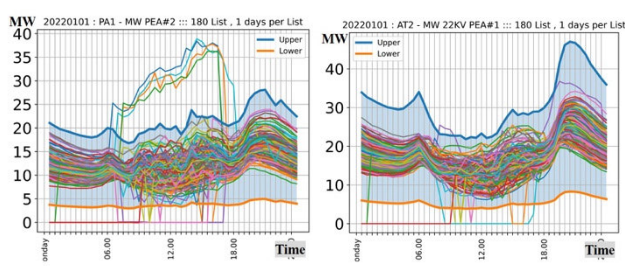

FIGURE 13. MW load of the loading transformer with the addition of the upper line and the lower line by the EMA method.

IX. LIMITED-MEMORY BFGS ALGORITHM

An alternative to the BFGS algorithm, the L-BFGS algorithm is a method that approaches the purpose of high

TABLE 6. Time used in the load transfer procedure when using python automate version 2.

No.	Trip event date time	TX. Name-substation	MAE	MSE	RMSE
1	Mar 13, 2021; 11.43 a.m. $\alpha = 0.94718$, $\beta = 6.574\text{e-}9$, $\gamma = 0.00528$ Process Time = 68.4 s	KT2A-CB	0.4277	0.3513	0.5921
2	Apr 18, 2021; 08.57 p.m. $\alpha = 0.75559$, $\beta = 8.005\text{e-}08$, $\gamma = 0.00347$ Process Time = 41.2 s	KT1A-CBD	0.5843	0.6403	0.8002
3	May 07, 2021; 00.41 a.m. $\alpha = 0.81450$, $\beta = 3.230\text{e-}7$, $\gamma = 0.00316$ Process Time = 60.8 s	KT1A-CB	0.5095	0.4297	0.6555
4	June 30, 2021; 02.06 a.m. $\alpha = 0.91019$, $\beta = 9.889\text{e-}8$, $\gamma = 0.00633$ Process Time = 83.0 s	KT1A-DBN	0.4424	0.3500	0.5916
5	Oct 2, 2021; 00.06 a.m. $\alpha = 0.92568$, $\beta = 7.119\text{e-}09$, $\gamma = 0.07431$ Process Time = 48.7 s	KT1A-SR1	0.3047	0.1915	0.4377
6	Nov 24, 2021; 06.14 p.m. $\alpha = 0.92610$, $\beta = 2.617\text{e-}09$, $\gamma = 0.00738$ Process Time = 66.2 s	KT1A-LB1	0.3871	0.2613	0.5141
7	July 26, 2023; 03.55 a.m. $\alpha = 0.87887$, $\beta = 2.025\text{e-}08$, $\gamma = 0.02191$ Process Time = 63.1 s	KT2A-LB1	0.6613	0.7886	0.8283
8	Oct 21, 2023; 09.17 p.m. $\alpha = 0.73517$, $\beta = 2.462\text{e-}06$, $\gamma = 5.419\text{e-}07$ Process Time = 74.0 s	KT1A-AY1	0.4650	0.3941	0.6210

memory requirements when considering large-scale optimization problems. Although it does not explicitly store the inverse Hessian matrix, the L-BFGS algorithm uses a limited-memory approach to approximate it. Within the context of the L-BFGS algorithm, the inverse Hessian matrix is a matrix that represents the second-order partial derivatives of a function. This matrix is utilized to determine the curvature of the function at a specific point. An approximation of the inverse Hessian matrix is constructed by making use of a restricted amount of memory and basing it on the gradients and steps that have been taken by the algorithm in the past. A small amount of memory is utilized to make an approximation of the inverse Hessian matrix by using the gradients and steps that have been taken by the algorithm in the past. In the subsequent iteration of the algorithm, the search direction computed by the inverse Hessian matrix is utilized to locate the minimum of the function (the minimum). To find the three HWS parameter values that result in the lowest RMSE, this study has used the L-BFGS algorithm rather than the grid search method to solve the problem identified. The calculation steps begin with initializing an estimate of the inverse Hessian matrix (23), typically the identity matrix. Next, the computation of the gradient of the objective function (24) at the current state is performed. An algorithm known as the line search algorithm (25) determines the appropriate step size toward the negative gradient. Bring the current state up to date by (26). To determine the difference between the old and new gradients, perform the calculation (27). To update the inverse Hessian estimate, use the formula (28) derived from the secant equation. This formula involves a low-rank update that uses the gradient difference and the step. Until convergence or a criterion is reached, continue moving forward with proceedings.

$$H_0 = I \tag{23}$$

$$g_k = \nabla f(x_k) \tag{24}$$

$$\alpha_k = \arg\min_{\alpha>0} f(x_k - \alpha g_k) \tag{25}$$

$$x_{k+1} = x_k - \alpha_k g_k \tag{26}$$

$$\begin{aligned} g_{k+1} &= \nabla f(x_{k+1}) \\ s_k &= x_{k+1} - x_k \\ y_k &= g_{k+1} - g_k \end{aligned} \tag{27}$$

$$\begin{aligned} H_{k+1} &= (I - p_k s_k y_k^T) H_k (I - p_k y_k s_k^T) + p_k s_k s_k^T \\ p_k &= \frac{1}{y_k^T s_k} \end{aligned} \tag{28}$$

X. PYTHON AND LINE API APPLICATION

Python is an open-source software that includes text cutting, arranging, connecting, and conditioning. It is a programming language that combines remarkable power with clear syntax. As it is free, a significant number of unique Python libraries have been developed. Using the Python programming language, this study uses the Matplotlib plotting library. You can use it to create graphs and plots in two dimensions. It is used with NumPy arrays to facilitate matrix operations and complicated mathematical calculations. We also use the line-bot-SDK library to send messages through the line application on a mobile phone. Python's speedy processing is another language advantage, making it an ideal choice for analyzing incoming alarms with multiple co-occurrences.

Currently, the control center of the utility company is responsible for monitoring 56 substations, which have 9,538 analog point values and 80,249 digital points. The Line application is a program that is available for free. It is utilized by utility companies as an alternative to SMS because it is more cost-effective than SMS. Graphics, still images, and moving pictures can all be transmitted using this device. Like social media, but more like social networks, it is a form of online communication. It is a mobile application that can be downloaded on various smartphone devices, including Android and iOS phones. It can also be downloaded on desktop computers, laptops, and tablets that run Microsoft's Windows and Mac OS operating systems. Users can communicate with one another through the use of text messages. Utilizing the application program interface, the Line Notify service allows the application developer to send notifications to personal accounts or groups from the service itself or any devices connected to the internet (API). Support for the Thai alphabet, the ability to send messages to many recipients, and accessibility are all advantages of Line Notify. Line Notify is similar to SMS notifications on mobile phones in that it is not expensive. We employed the Line Application on the Python platform to keep the maintenance staff and distribution company control centers informed about trip events.

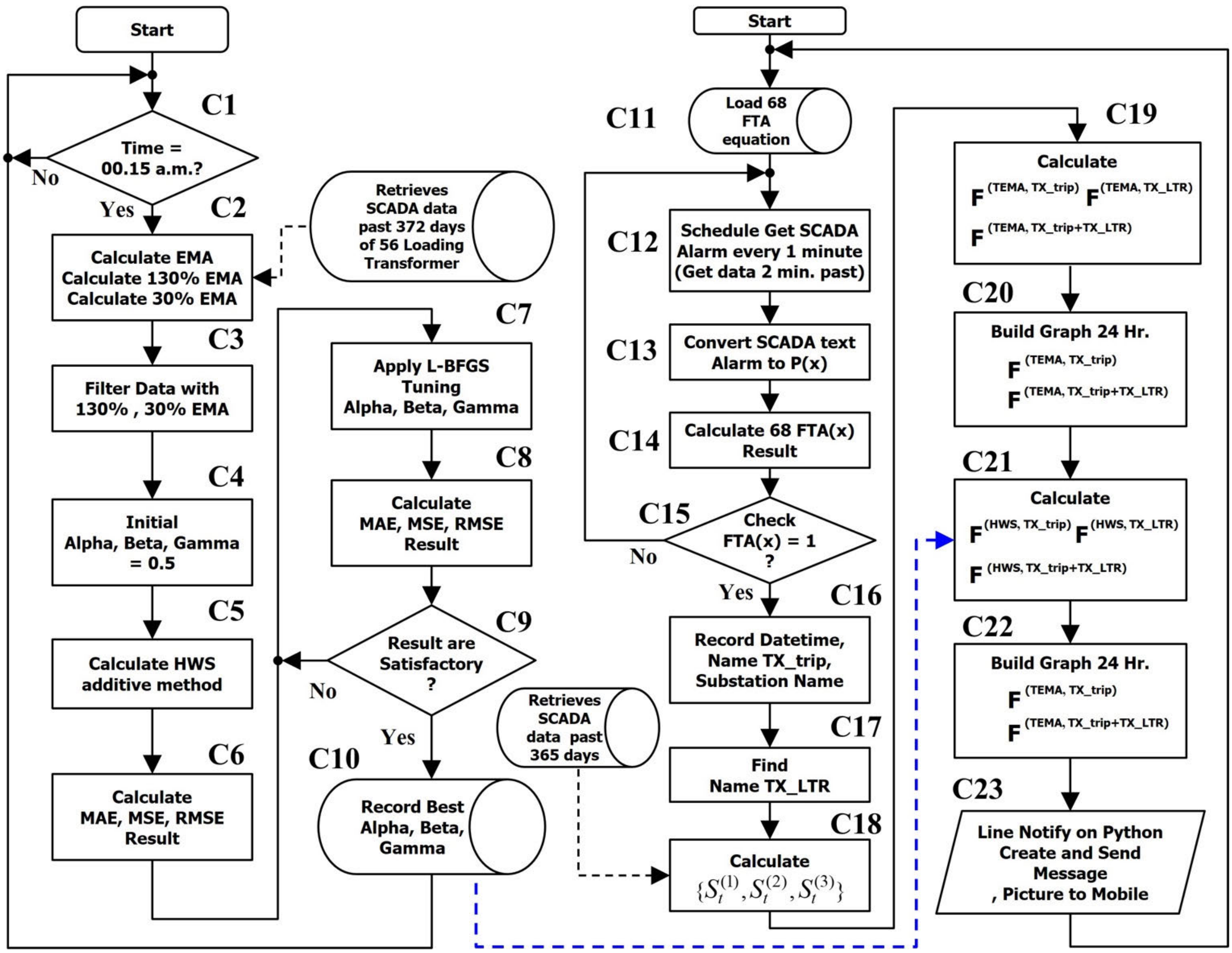

FIGURE 14. Flowchart of Pyauto2.

XI. PROCESS OF THE PROPOSED METHOD

Fig. 14 shows the flowchart of Pyauto2, an application developed from Pyauto1. It was designed to improve forecasting results, increase response efficiency, and decrease the amount of time the application takes to work. This was accomplished via the L-BFGS method in the HWS technique. The L-BFGS system used the Update 3 HWS parameter method rather than the grid search approach. When a trip occurs, Pyauto2 calculates the best three HWS parameters that have been prepared rather than performing every new calculation. This helps reduce the amount of time spent on the application. Two distinct sections comprise Pyauto2: The first consists of steps C1–C10. This section is executed once a day. In this section, the best three HWS parameter values are calculated and prepared for use in the subsequent section. Steps C11–C23 will determine whether a trip event has occurred, compute the forecast, and transmit the results to the mobile phone. The working time in Part 1 will be initiated by Pyauto2 at 00:15 in the morning. Data will be documented between the hours of 00:00 and 00:12 a.m. to avoid any potential overlap with SCADA operations. These operations will record the electrical system equipment of the previous 24 h of that day in the file CSV format database. Pyauto2 will establish a connection to SCADA enterprise as soon as 00:15 a.m. The MW load values for the past 372 days must be determined. To filter the input data, the EMA values in Step C2 must be calculated.

This study includes the definitions of smooth = 2 and period = 7. To calculate the 24-h MW load forecast, the EMA method must be used. Then, the results from the EMA must be employed to create the upper line, which will be 130% of the EMA, and the lower line, which will be 30% of the EMA. The upper and lower lines must be considered to check and filter the MW load value for 372 days. The data on days when the MW load value is greater than the upper line and less than the lower line must be eliminated. This applies to days where the upper line is higher than the lower line. In C4, the initial value of three HWS parameters, which include α, β, and γ, should be set to 0.5.

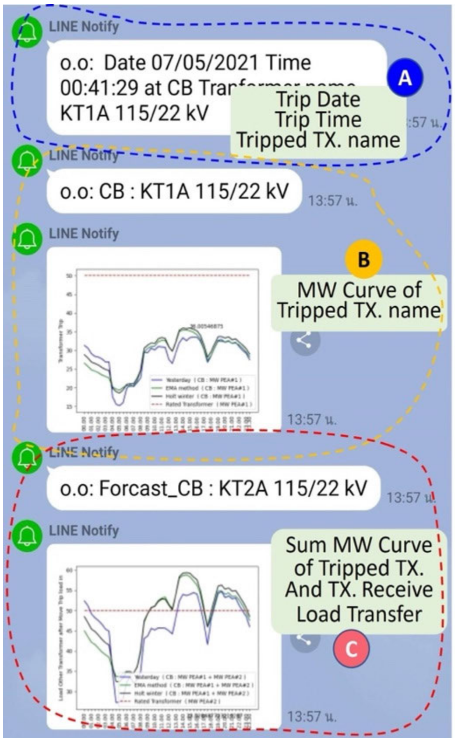

FIGURE 15. Pyauto2 results displayed on mobile.

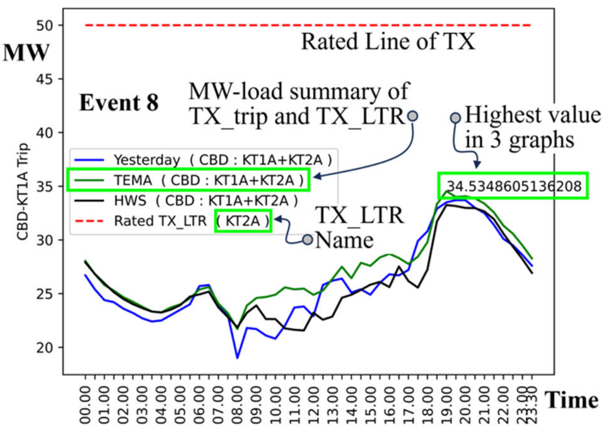

FIGURE 16. Group B data show the MW load curve of the TX_trip.

Afterward, the calculation process must be started using the additive Holt–Winter method, with the training set equal to 365 days and the test set equal to 7 days. Calculating the MAE, MSE, and RME tolerances for the given values. Pyauto2 will then utilize the L-BFGS technique in Step C7 to update three HWS parameters to generate the MAE, MSE, and RMSE values that are the lowest possible. If the three HWS parameters become suitable, it will cease updating the three HWS parameters. When steps C2–C10 are completed until the 68 loading transformer, the process is considered to have begun in Part 1. Pyauto2 Part 2 is an application that constantly conducts checks to identify any abnormal occurrences that may be occurring in electrical systems. This begins with

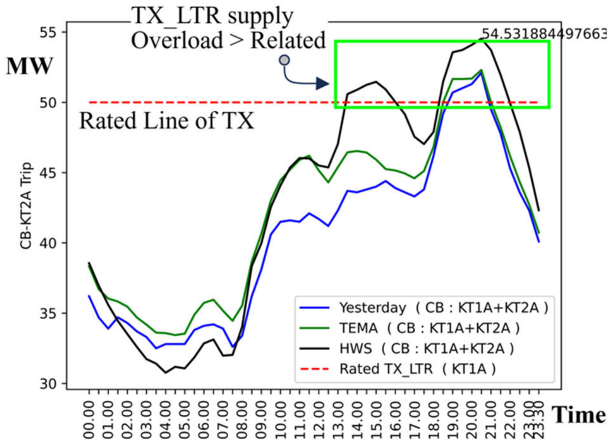

FIGURE 17. Results of group C data of event 1.

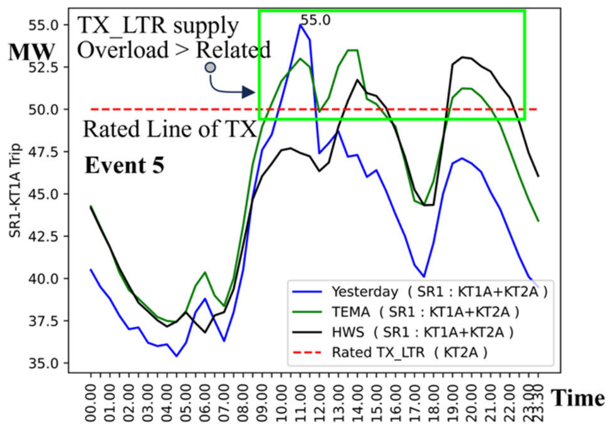

FIGURE 18. Results of group C data of event 5.

procedure C11, an FTA equation of 68 equations explicitly created to analyze the loading transformer trip. Step C12: The working time that will be used to retrieve the message text alarm from SCADA at a rate of once every minute is determined. Each retrieval time will retrieve approximately 10 to 25 lines that will then be repeated. In the 13^{th} step, the application will convert each line of message text alarm into P(x1), P(x2), …, P(xn) and then use these values to calculate the P(x). Confirming the results of the calculation for 68 equations of P(x). If any P(x) has a value equal to 1, this indicates that the loading transformer event designated as "x" has been tripped out of the electrical system. If Pyauto2 Part 2 employs the FTA technique to check the message text alarm and determines that a trip event has occurred, it will record information such as the date and time, the name of the substation where the event took place, and the name "TX_trip." Pyauto2 searches for "TX_LTR" within the knowledge base during Step C17. By considering the circumstances that arise when a loading one transformer trips, loading transformers that can supply power to replace the load in the event of a power outage are determined.

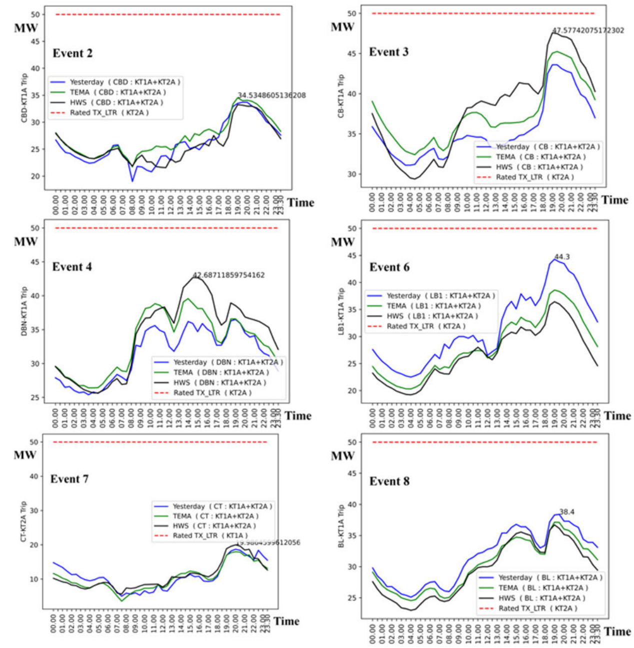

FIGURE 19. Displays group "C" data results for events in which TX_LTR does not supply overload.

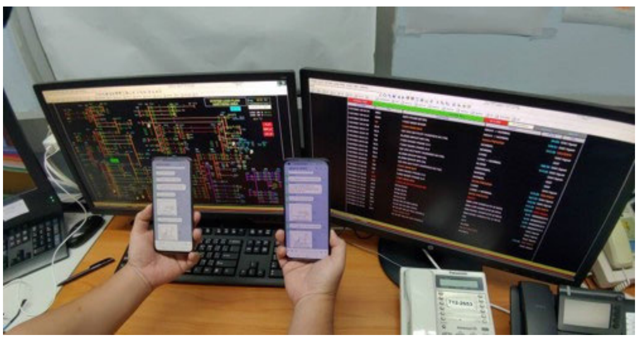

FIGURE 20. Display on the operator's mobile phone.

Pyauto2 uses the TEMA method to compute the MW load forecast. These calculations begin with the calculation and then estimate the MW load values of the two load transformers, namely, F(TEMA, TX_trip) and F(TEMA, TX_LTR). The next step is to compute the value F(TEMA, TX_trip+TX_LTR), which is derived from the sum of F(TEMA, TX_trip) and F(TEMA, TX_LTR). The value F(TEMA, TX_trip+TX_LTR) represents the MW load value of the loading transformer "TX LTR" responsible for supplying the power outage rather than the loading transformer tripping. To generate a 24-h MW load forecast, Step C20 makes use of the TEMA method. Using the HWS method, the forecast is created in Step C21. This is accomplished by calculating the three HWS parameters earlier in the step. This calculation uses Section C10, which significantly reduces the time required. HWS first computes the values F(HWS, TX_trip) and F(HWS, TX_LTR), and then, it computes the values F(HWS, TX_trip+TX_LTR), and finally, it generates a graph showing the results. The final step, part 2, of Pyauto2 is to send 24-hour MW load forecast graph data on the day of the Loading Transformer trip event. This data consists of Graph1, which is the MW load of "TX-trip," and Graph2, which is the MW load, the sum of "TX_trip" and "TX_LTR," sending information with Line Notify to the Mobile Phone of the operator, the Distribution Company, and the Maintenance Term.

XII. RESULTS AND DISCUSSION

Suppose the loading transformer trips event takes place on a particular day. In that case, the results of Application Pyauto2 are the 24-h MW load forecasting graph of the loading transformer associated with the LTR procedure. After the trip event was identified, the results of Pyauto2 are displayed in Fig. 15. Each of the three data groups, namely, groups A, B, and C, can be applied to the display comprising one message and two images. Group A will display information regarding the trip event, including the name of the "TX_trip" that occurred during the trip, the name of the substation that was created as a result of the trip, and the date that the event took place. MW load graph data of the "TX_trip" is included in Group B shown in Fig. 16. A graph of the data obtained from the sum of the MW load between "TX_trip" and "TX_LTR" is used to create Group C. A graph in Group C is depicted in Fig. 17, which consists of four graph lines displaying the results from 00:00 to 23:30. In Graph 1, the red dotted line depicts the rating of the loading transformer. Between "TX_trip" and "TX_LTR" before the 1-day trip event date, the total data of the MW load is displayed on the second graph line, which is the blue line. The forecasting sum using the TEMA technique method for MW load is displayed on the green line on the third graph line. This sum is calculated between "TX_trip" and "TX_LTR" on the day of the transportation event. Utilizing the MW load HWS method, the forecast sum data between "TX_trip" and "TX_LTR" on the day the trip takes place is displayed on the fourth line of the graph, which is the black line. A display is also made of the maximum MW load data for each of the four graph lines. The Pyauto2 method produces a MW load graph as close to reality as possible on the day of the loading transformer trip event. This is an improvement over the previous method, which involved the operator at the control center using MW load data from the last day to plan LTR. To calculate the forecast results, Pyauto2 employs the HWS with the L-BGFS method, which is more accurate than the HWS with the grid search method that Pyauto1 employs. Because the MAE calculation yielded a result of 0.4576, the MSE was 0.3996, and the RMSE was 0.6084. The processing time of Pyauto2 is 64.88 s on average, significantly faster than that of Pyauto1, which is 172.51 s on average. The operator at the control center uses the MW load totals graph data obtained from Pyauto2 between "TX_trip" and "TX_LTR." Considering that if the sum is greater than the red dotted line or the rated equipment line, the control center operators are required to inform the distribution center to bring the power outage MW load from other external loading transformer substations. This prevents loading transformer trips with overload relays immediately following LTR. The automatic transmission of trip event data to the individuals involved in repairing and editing the loading transformer and the operator at the control center is one of the advantages of Pyauto2. This will result in a reduction in the amount of time that is spent on the LTR process being carried out. Figs. 18 and 19 show the results of Group C data, and Fig. 20 shows the data from pyauto2 displayed on the operator's mobile phone in the utility control center.

XIII. CONCLUSION

The LTR procedure is a procedure that the utility control center utilizes to restore energy if a 115/22 kV loading transformer trip occurs from the electrical system. To resolve the issue of reducing the amount of time required for the LTR process, this study incorporates three different tools: FTA, HW with the L-BFGS optimization algorithm (HWS), and Line Notify. Shortening the amount of time spent in the LTR process will reduce the amount of time customers are subject to power outages. In the analysis process, the FTA technique takes the place of the operations that the operator currently performs at the utility control center. Numerous abnormal message alarm occurrences occur on the SCADA system to differentiate and confirm the loading transformer event. These occurrences occur in six steps (A1–A6), which are reduced to 10 s. FTA will minimize the number of person-hours operators need to put in and produce more accurate results than using humans for analysis. The process of locating MW load data to calculate the load transfer from one loading transformer to another is an essential step in the LTR process to achieve the closest possible prediction of the MW load following a trip event. EMA, which is utilized to calculate changes in short-term data, and HWS, which is employed to calculate changes in data that have a recurring pattern over time, are the two methods proposed in this study for MW load forecasting. This forecasting technique will replace the previous method, which used 1 day's historical data to calculate load transfer. The rationale behind this change is to ensure that overload trip problems are avoided after the LTR step. This study proposes a method to find and extract distorted MW load data to get the correct MW load data sent to the EMA and HWS forecasting methods that will be calculated in the subsequent step. This intends to resolve the problem of distorted MW load data that has been occurring in Thailand's central region electrical system. For screening, the technique involves first bringing all the imported data to estimate the EMA value and then bringing the EMA value created to create the upper and lower lines. The HWS forecasting technique is suitable for use with the data on electricity usage from 22 kV power distribution points. These points show recurring changes around the pattern of electricity usage and temperature changes that occur seasonally and annually. Calculating the values of α, β, and γ, which are parameters in HWS, is accomplished by utilizing the L-BFGS optimization algorithm in this study. If the optimal parameter is obtained, HWS will compute the most precise forecast with the least amount of forecasting error. Because it can replace two operators for all LTR procedures and takes less time than conventional methods, the Pyauto2 can reduce the number of person-hours taken into consideration. Pyauto2 will automatically detect the SCADA abnormal message alarm, and it will then take the time to analyze the message on the loading transformer trip out of the electrical system. The values of the MW load forecast for the TX_trip and TX_LTR will be displayed. Pyauto2 will carry out this. Because of the ease with which this graph can be read, the control center will be able to view the information after the trip, which will prevent the loading transformer trips from overloading after the LTR.

Finally, as a methodological extension of this work, we plan to study several issues, such as Issue 1: Reduce the effects of the variance on the renewable solar plant with an installed capacity of less than 8 MW linked into a 22 kV electrical system, which could potentially impact the forecast error. Issue 2: Develop Pyauto2 to be able to analyze other equipment, such as analyzing main bus trip events, 230/115 kV loading transformers, or substations with a breaker and a half bus arrangement that is equipped with multiple protection relays. Many types and more complex functions include breaker failure relay, bus differential relay, or distance relay zone backup. Issue 3: develop the fuzzy relation technique to analyze the SCADA alarm instead of the FTA to solve the problem of the FTA's limitations in the issue of the protective relay not working properly as designed. Malfunctions or some digital point alarms are not sent to be displayed on the SCADA at the utility control center.

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