Overview of Contingency Analysis and Load Forecasting

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Abstract: *One of the key elements in the contemporary energy management systems is contingency analysis. The study of contingency analysis involves making accurate calculations of system performance from a set of simplfied system conditions in order to quickly estimate system stability right after outages. If the real-time analysis is carried out into the immediate future, contingency analysis can offer a potent insight into potential operational emergencies. Forecasted loads and generation, planned outages, and transmission dynamic ratings based on a weather forecast can all be used in predictive look-ahead analysis. The overview of contingency analysis and a discussion of load forecasting in the power system are provided in this paper.*

Keywords:. *Contingency Analysis, load forecasting, short-term load forecasting, Long-term forecasting, Medium-term Forecasting, etc.*

I. INTRODUCTION

A contingency is the loss or failure of a single piece of equipment, such as a generator or transformer, or a minor component of the power system (such as a transmission line). This is also known as an unanticipated "outage." Contingency analysis is a computer program that assesses the effects of each outage event and determines any overloads by using a simulated model of the power system. A "preview" analysis tool is what contingency analysis is all about. The effects of potential issues with the power system in the near future are simulated and quantified. When analyzing contingency events offline, CA is used as a study tool. It is also used online to show operators the effects of potential outages in the future. As a result, operators can use pre-planned recovery scenarios to be better prepared to respond to outages. [1].

One of the key elements in the contemporary energy management systems is contingency analysis. The study of contingency analysis involves making accurate calculations of system performance from a set of simplfied system conditions in order to quickly estimate system stability right after outages. One of the most crucial tasks faced by the planning and operation engineers of bulk power systems is contingency analysis. One of the crucial linear sensitivity factors, the Line Outage Distribution Factor (LODF), is crucial for determining the impact of critical contingencies and, as a result, for suggesting potential preventive and corrective measures to address system violations..

One of the "security analysis" applications in a power utility control center that distinguishes an Energy Management System (EMS) from a simpler SCADA system is contingency analysis (CA). Its goal is to analyze the power system to find overloads and other issues that might arise as a result of a "contingency." Analysis of contingencies is an abnormal situation in an electrical network. It stressed out the entire system or a specific area of the system. It happens as a result of a transmission line suddenly opening.[2].generator overload. Sudden generational shift Unexpected change in the load value. Tools for managing, creating, analyzing, and reporting lists of contingencies and related violations are provided by contingency analysis. When analyzing contingency events offline, CA is used as a study tool. It is also used online to show operators the effects of potential outages in the future.

A power system blackout is caused by a series of individual components failing one after the other in a very short period of time, with the first failure occurring unexpectedly. This can also be referred to as a high-order contingency event or an N-k contingency event. Literally, the term "N-k contingency" can refer to several component failures that happen almost simultaneously. True randomly multiple component failures, however, are incredibly uncommon. As a result, it does not reflect the fact that failures are connected, whereas the term "cascading failure" does. It is crucial to assess a power system's security to ensure that it will continue to operate even if one or more components stop working as intended.

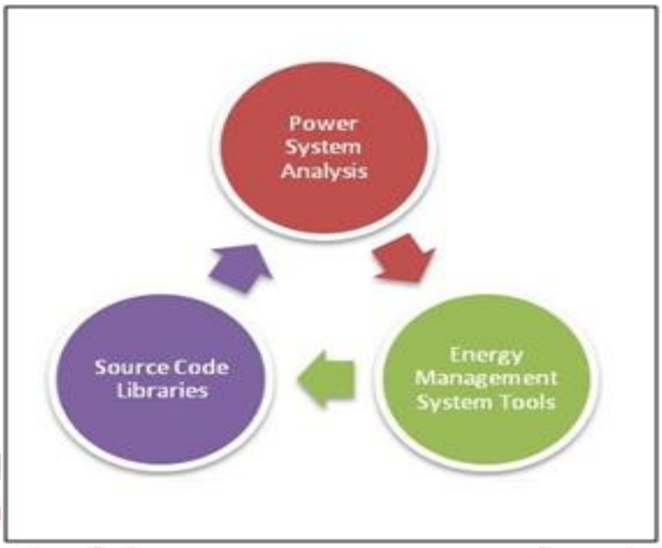

Figure 1 Security of Power System

Contingency is the inability of a device, such as a generator, transformer, transmission line, or another one, to function properly in the power system or the change in the device's state, which may include the potential for an unforeseen circuit breaker to open in a transformer substation. The contingency plan's goal is to monitor how the device will function differently after the fault element is removed.

In the event that a contingency materializes, there are three levels of issues:

• None – In this situation, the power system can be balanced without overloading any other components.
• Severe – This category includes damage caused by overloading of various elements, such as lines and transformers.

• Critical – When there is a high and immediate risk of a power system collapsing because of its instability.

Every electric appliance must be able to recover from a first contingency in order for it to function and also recover from a second contingency in the future..
Before a scheduled outage is implemented, CA is used to perform one last check on the system. The system operator or dispatcher proceeds with the outage in the control center using the data acquisition and control (DAC) applications to isolate a number of pieces of equipment from the primary power system if no issues are found. If no issues are found, the outage is sanctioned by the outage coordinator or the network engineer.

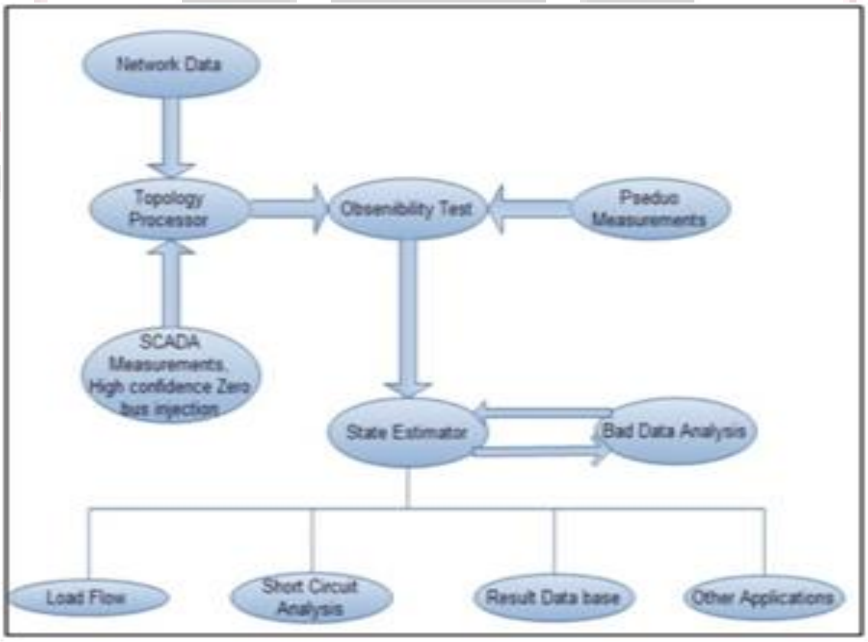

Figure 2 Contingency analysis protocol

In order to determine whether steady-state operating limits have been violated in the event of a contingency, the network model is subjected to contingency analysis (CA). The power flow base case obtained from State Estimator (SE) solution is typically used to run "(N-1)" outage analysis in real-time contingency analysis (RTCA). However, the power system real-time and forecast data available present a chance to conduct a more thorough look-ahead study in order to improve operators' situational awareness..

II. LOOK-AHEAD CONTINGENCY ANALYSIS

Traditional RTCA uses the real-time estimated solution under the presumption that the pre-contingency state and the load in the power network will not change at the time of the studied outages. In reality, the large power system's network state, loads, and generation vary depending on the time of day, and in the event of bad weather, the power system's pre-contingency state may change significantly.

To get ready for the market the following day, some market operators and reliability coordinators conduct offline studies 24 hours in advance. However, only one real-time point is used for the real-time analysis. Enhancing the real-time horizon and carrying out multi-time point studies of the near future in real-time can be helpful for operations. The condition of the power network in the near future can be extrapolated using information on load forecast, interchange plans, and generation forecast or electricity market target. In order to make sure that the proper topology is used in the predictive analysis, the scheduled outages are transferred into the look-ahead study.[3].

The power network's current state and electrical issues as they arise are assessed using historical tracking and proactive monitoring of high severity contingencies. Forecasts for short-term individual generation can be obtained from market participants or estimated from unit commitment. With an average accuracy of 1-2 percent, the short-term load forecast provides hourly forecasts for area load based on weather. Based on the load area forecast distributed among the various stations, the load forecast for each station can be determined. By comparing their historical values to the values for the area loads, it is possible to calculate the distribution factors for individual loads. Constant and varying components make up conforming loads. The latter is determined by calculating the contribution of each load to the overall area..

III. LITERATURE REVIEW

Transmission switching (TS) has proven to be a useful tool for controlling power flow. TS can lower system costs, increase system dependability, and better manage sporadic renewable resources. This paper develops an AC-based real-time contingency analysis (RTCA) package with TS to solve the state-of-the-art TS problem. The software is tested using actual power system data from PJM, TVA, and ERCOT's energy management systems. The findings demonstrate that post-contingency corrective switching is a transformational technology that is ready for implementation and offers significant reliability gains. The developed RTCA package's reported in-paper computational speed and effectiveness are both promising [4].

The method of contingency analysis is frequently used to foresee outcomes of outages, such as failures of apparatus, conductor, etc., and to demand necessary actions to maintain the facility system's security and dependability. Given the sheer number of components in a power system, conducting an offline analysis to determine the effects of each individual contingency could be time-consuming. This review paper provides several contingency analysis techniques, and it also cites the use of artificial neural networks for contingency analysis. [5].

The researchers present their ongoing work to create a generative-adversarial (GA) model for quick and accurate grid contingency analyses, and they briefly review earlier applications of machine learning (ML) in power grid analyses. Our review indicates that the need for an extensive amount of training data is the continuing limitation of traditional ML techniques in grid analyses. This requirement is necessary for model generalization and precise predictions. A small training set is used by GA models to first learn the true data distribution, which is then used to generate new samples that incorporate the true data with some variations. [6].

For the planning and expansion of the power system, load forecasting is always necessary. Forecasting load and its management has become a top priority for researchers with the advent of the smart grid. Forecasting loads has proven difficult for developed and industrialized countries as well as developing ones. The best methods for load forecasting have been identified based on time, inputs, outputs, and error type in this paper, which includes a systematic review of the methods of load forecasting based on 126 research papers. Time series analysis and machine learning algorithms are the approaches that are being compared. By selecting the appropriate model from their problem, researchers can make an informed decision with the aid of this meta-analysis. [7]

Forecasting electricity demand has proven to be a significant challenge for power system scheduling across a range of energy sectors. The electricity market has used a variety of computational intelligence techniques and methodologies for short-term load forecasting, but there is little information about their viability given the type of data and other potential factors. This work introduces several scientific and technical justifications for short-term load forecasting techniques based on the findings of earlier energy researchers. To illustrate how effective each method is in different situations, the fundamental advantages and disadvantages of these approaches are discussed. Finally, a hybrid approach is suggested. [8].

Deep learning is a development in machine learning that is evolutionary. The method has been used in a number of fields where intelligent decisions are expected to be made by computers after processing large amounts of data. In the field of biometrics, where patterns within distinctively human traits are recognized, deep learning has important applications. Deep learning has recently been used by many systems and applications for biometric systems. The deep network is trained on a wide variety of patterns, and after it has absorbed all the distinct characteristics from the data set, it can be used to identify related patterns. Recognition based on a person's face, fingerprint, iris, ear, palm print, voice, and gait are all examples of biometric technology that is frequently used in security applications..This paper gives a brief overview of a few systems and applications that used deep learning to classify biometric systems based on their biometric modalities. We are also evaluating the system and performance indicators that are currently in place. We reach our conclusion after thoroughly examining various existing strategies that combine deep learning techniques with biometric systems. [9].

In order to model STLF in an MG environment, [10] provides an overview of the most recent analytical and approximation techniques reported in the literature. This article primarily focuses on a review of significant techniques used to forecast the availability of renewable energy sources, energy demand, and price and load demand. Different models are evaluated and critically analyzed in terms of their primary goals, methodology, error rate, and other factors. We have highlighted the key details in the form tables for easy reference. By reading this review paper, the researchers can quickly define and frame their research problem related to the LF area..

[11] focuses on the use of Deep Learning (DL) techniques to precisely predict building (residential, commercial, or multiple) power consumption using the readily available historical big data. To evaluate how effective the research findings are and to support their potential use in the future, they are compared to cutting-edge statistical models and AI techniques from the literature. The objective of this work is to review current DL approaches that have been proposed, to highlight the state of the research, to identify new problems and potential future directions. Residential building load forecasting was found to be of greater interest, accounting for 47.5 percent of the relevant literature from 2016 to the present and focusing on short-term forecasting horizon in 55 percent of the referenced papers. The latter was attributed to the lack of publicly accessible datasets for experimentation in various building types, as it was discovered that in 48.2% of the related literature, the same historical data regarding residential buildings load consumption was used..

IV. LOAD FORECASTING

As civilization enters the third millennium, technological advancements made in recent years have essentially evolved into basic necessities. All of these developments rely almost entirely on a reliable and ongoing supply of electricity. The utilities must carefully and continuously plan in order to achieve this stability and continuity. Only by anticipating demand expectations and proactive production planning will this be possible. Governments and utilities both attempt load forecasting for various time frames. In order for utilities and governments to plan service expansion, long-term load forecasting (LTLF) is used to forecast expected demand growth for several years in the future. [12].

Large-scale demographic and urban development predictions are the mainstay of LTLF. For future periods up to a few years, medium-term load forecasting (MTLF) is typically done in order to implement fuel supply agreements or plan significant maintenance tasks. The MTLF relies on forecasts of seasonal weather variations and may incorporate significant load-affecting events (like an exhibition or a globally hosted event) into its prediction models..

On the other hand, short-term load forecasting (STLF) has a very brief forward projection time frame and is frequently used to plan responses to anticipated impending variations in supply and/or demand. The timeframe for STLF is typically a few hours to possibly a few days in advance. By anticipating changes in weather and demand, STLF typically aims to maintain supply quality while potentially achieving cost savings. This is especially true if the system's generation mix includes renewable resources. Additionally, STLF is preferred for potential load-shifting and load-scheduling applications that lessen extremely high demand peaks. [13].

The primary requirement of an electrical power generation system is a continuous and reliable supply of power. By examining past behavior, current trends, and other factors that affect load, these systems determine the need to meet load demand. This process is known as load forecasting (L.F). Finding the supply and demand gaps for the production of electrical power is regarded as being essential. Understanding the various factors affecting energy consumption, augmentation, and waste benefits the management. Furthermore, since it is fundamental in bridging the gap and concerns for energy demand, it is equally important for power control and exchange in various interconnected power systems [14].

Weather variables like irradiance, rain, temperature, humidity, and wind speed have a rigid and dependent relationship with load forecasting that should be taken into account with respect to the geographical region when developing any forecast model [14]. An extensive analysis of the electrical load has shown that it exhibits seasonal patterns with some uncertainties, which are not always cyclic. Therefore, due to the limitations of the traditional approaches used in regular load forecasting models, they are unable to handle the uncertainties present in a power utility with different generation modalities (DGM) or grid-isolated generations..

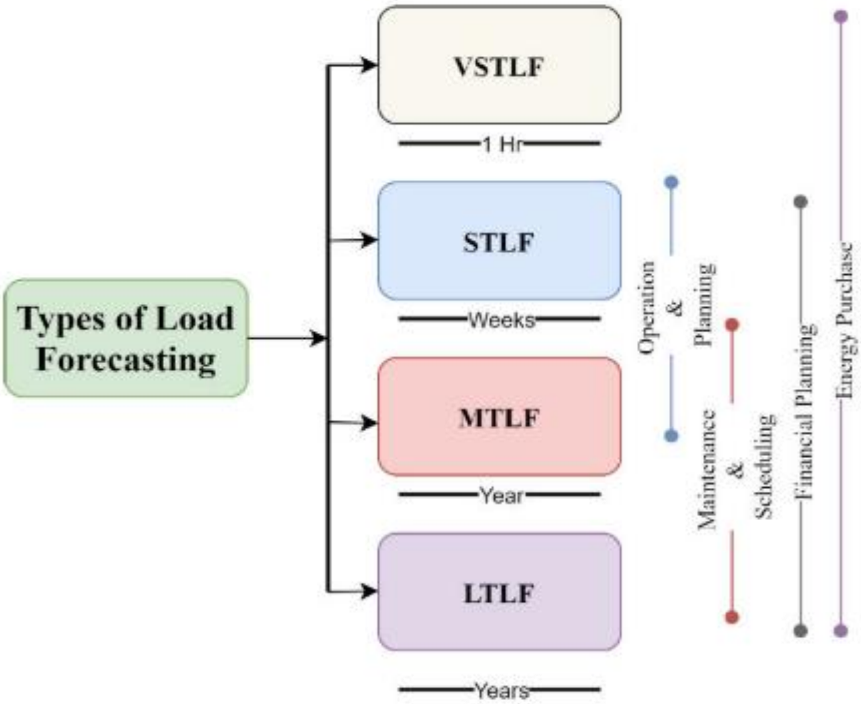

Figure 3 Electrical Load Forecasting Categories

A. Short Term Load-Forecasting (STLF)

The STLF timeframe ranges from a few minutes or hours to one day or a week in advance. The STLF addresses real-time control and security assessment while aiming for efficient dispatch and the best commitment of generator units. Power system short-term load forecasting is a crucial component of the daily power sector dispatch. The reliability, economy, and safety of power system operation are directly impacted by how accurately short-term load forecasting is performed. As a result, academics both domestically and internationally have always focused their research on short-term load forecasting techniques. Artificial neural networks have received a lot of attention recently as a smart algorithm used in the field of forecasting short-term power loads [15].

Conditional short-term load forecasting compares the load fluctuation trend over the upcoming period to the recursive process, demonstrating how external constraints have a greater influence on forecast outcomes than internal constraints do. These constraints must be measured using the appropriate technical methods if there is no basis; they cannot simply be assumed. In order to set conditional constraints for short-term load forecasting, we must first decide on a target, define the constraint with the precise number of concepts, and then forecast the daily weather, working day types, holidays, and other external conditions. predicting consistent data of daily load fluctuations through load forecasting The development of efficient and reliable operation of the relevant power sector benefits from high-precision load forecasting.

B. Long Term Load-Forecasting (LTLF)

Planning for the generation, transmission, and distribution of energy requires accurate long-term load forecasting. Traditional studies for long-term load forecasting relied on regression techniques, which were unable to accurately depict the behavior of the power system in a precarious electricity market. A solid understanding of load and the available forecasting techniques for modeling a specific type of load are necessary for LTLF techniques. We categorize loads as residential, commercial, and industrial because they respond to load factors differently and display growth or decline patterns differently [16].

Long Term Load Forecasting (LTLF), which can be extended to a horizon of a few decades, provides peak demand and energy forecasts for one or more years. Long-term forecasts from 20 to 50 years in the future are typically produced by utilities [17]. When there were no high resolution data available a few decades ago, the majority of utilities today still adhere to the LTLF practices that were established at that time.. The forecasters might not be able to use enough explanatory variables to capture all the important characteristics of the electric load because the low resolution data used in the conventional approach only offers a finite number of observations for predictive modeling. The model may still produce some significant errors when given the actual values of the weather and economic variables to re-forecast the loads under the current scenario, which can be challenging for forecasters to explain.

C. Medium Term Load-Forecasting (MTLF)

The ability to predict medium-term load is largely dependent on growth factors, or variables that affect demand such as significant occurrences, the addition of new loads, seasonal variations, demand patterns for large facilities, and maintenance needs of significant consumers. Additionally, this type of forecast uses hourly loads to estimate the peak load for upcoming days or weeks. With this knowledge, decisions can be made regarding the scheduling of major tests and commissioning activities, the timing of plant and major equipment outages, and whether or not to take certain facilities or plants offline for maintenance during a specific period of time. Although there is less need for accuracy, the analysis techniques used for this type of forecast are similar to those used for short-term forecasts.[17].In other words, it can be said that medium-term forecasting is less sensitive to power system operations than short-term forecasting. The planning and operation of the electric power system includes a crucial stage called medium-term load forecasting. It is used to schedule maintenance, prepare for outages, and organize significant power system renovations.

V. CONCLUSION

A contingency is the loss or malfunction of a single piece of equipment, such as a generator or transformer, or a minor component of the power system (such as a transmission line). This is also known as an unanticipated "outage." A power system blackout is caused by a series of individual components failing one after the other in a very short period of time, with the first failure happening unexpectedly. This is sometime also referred to as N-k contingency event or high-order contingency event. Forecasted loads and production, planned outages, as well as transmission dynamic ratings relying on a weather forecast can all be used in predictive look-ahead assessment. This paper provides a general idea of contingency analysis and sheds some light on power system load forecasting.

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