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AN APPROACH TO DISTRIBUTION SHORT-TERM LOAD FORECASTING

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An Approach to Distribution Short-Term Load Forecasting

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***Abstract* - This paper reports on the developments and findings of the Distribution Short-Term Load Forecaster (DSTLF) research activity. The objective of this research is to develop a distribution short-term load forecasting technology consisting of a forecasting method, development methodology, theories necessary to support required technical components, and the hardware and software tools required to perform the forecast. The DSTLF consists of four major components: monitored endpoint load forecaster (MELF), nonmonitored endpoint load forecaster (NELF), topological integration forecaster (TIF), and a dynamic tuner. These components interact to provide short-term forecasts at various points in the distribution system, e.g., feeder, line section, and endpoint. This paper discusses the DSTLF methodology and MELF component. MELF, based on artificial neural network technology, predicts distribution endpoint loads for an hour, a day, and a week in advance. Predictions are developed using time, calendar, historical load, and weather data. The overall DSTLF architecture and a prototype MELF module for retail endpoints have been developed. Future work will be focused on refining and extending MELF and developing NELF and TIF capabilities.**

I. INTRODUCTION

A. New Requirements on the Distribution System

A number of recent developments have resulted in several challenges to the electric power industry. Among the most influential factors are increased power flow on existing systems, the expansion of distributed automation and demand-side management (DA/DSM) activities, deregulation, and the installation of generation at the distribution level. Each of these factors has the potential to significantly alter the design, operation, and maintenance requirements of the distribution systems. A proposed method of alleviating anticipated technical difficulties is to automate the distribution system. Appropriate automation can increase operating flexibility and speed, defer requirements for costly transmission and generation improvements (by increasing utilization of available resources), and improve power reliability and quality.

The ability to make accurate short-term load predictions on distribution feeders will be vital to optimizing distribution system operations and maintenance. In particular, the ability to plan for system power requirements an hour to a week ahead is critical to a number of real-time control requirements (e.g., econoomic generating capacity scheduling, fuel purchase scheduling, security analysis, transaction evaluation, power flow and switching cycle optimization, and disribution reconfiguration). Such capability is necessary to ensure power system stability under high load demands, to perform DSM load management activities, to optimally configure the system for current/near-term conditions, and to economically optimize system operation with respect to power flow/generation.

B. Objective

The Pacific Northwest Laboratory (PNL) is currently conducting a multiyear research project to develop a core technology for building short-term load forecasters. These forecasters will accurately predict load requirements at the distribution level of the power system. The project supports a recently initiated research activity focused toward appropriately applying intelligent information technology (IIT) to the electric power industry transmission and distribution sector.

The Distribution Short-Term Load Forecaster (DSTLF) consists of four major components: monitored endpoint load forecaster (MELF), nonmonitored endpoint load forecaster (NELF), topological integration forecaster (TIF), and dynamic tuner . These components interact to provide short-term forecasts at various points in the distribution system, i.e., substation, feeder, line section, and endpoint. Loads will be predicted for a period of time between one hour and one week into the future.

Because load characteristics in a power system change over time as a function of economics, technology, conservation, and population demographics, the DSTLFs must be able to monitor their own performance and self-tune, should that performance fall below a specified threshold. This self-tuning capability will also increase flexibility during the installation process. It is also anticipated that as monitoring capabilities for distribution systems are upgraded, an insufficient amount of historical data will be available to pretrain DSTLFs for site-specific load characteristics. Self-tuning forecasters trained for a site with load characteristics similar to those for the desired location can be installed and allowed to improve their accuracy over time as experience is gained.

This paper reports on the first year of the DSTLF research efforts. The general DSTLF methodology and initial MELF development efforts will be discussed in detail.

II. LOAD FORECASTING BACKGROUND

Load forecasting is the process of predicting the electrical load on a power system for some period of time in the future. The forecasts are typically based on knowledge of system composition, historical load behavior, and weather. Load forecasts are made for both long and short periods of time. Short-term forecasts are used in near-term decision processes and to maintain the day-to-day operation of the power system. Applications requiring short-term load forecasting (STLF) capabilities include power system control, scheduling, and security.

A. Short-Term Load Forecasting (STLF) Methods

At the transmission level, STLF has traditionally been performed using either a time-series or regression method. Time-series methods treat the load pattern as a time-series signal with known periodicities and predict the future load by using various time-series analysis techniques such as Kalman filtering, autoregressive-moving average (ARMA), and Box-Jenkins [1]. In contrast, regression methods use a linear or piecewise-linear function to represent the functional relationship between pertinent variables (e.g., weather, customer usage) and system load. Load is predicted by inserting the weather information into the predetermined functional relationship [1].

Both time-series and regression methods involve complex modeling techniques and have heavy computational requirements resulting in long computational times and a tendency to experience numerical instabilities. These inherent drawbacks have stimulated development of forecasters based on artificial intelligence (AI). Both expert systems and artificial neural networks have been applied to the load forecasting problem.

Expert systems use the knowledge of a human expert to develop rules for forecasting. Artificial neural networks (ANNs) do not rely on human experience but attempt to draw a link between sets of input data and observed output. Although the accuracy of load predictions made by expert systems and ANNs is relatively the same, the difficulty in acquiring and transforming the knowledge of an expert to a set of rules makes ANN technology slightly more attractive for STLF applications.

ANN technology has proven to be a viable option to statistical techniques such as regression analysis, time-series prediction, and classification. The advantages of ANNs in statistical applications include robustness to probability distribution assumptions, their ability to classify in the presence of nonlinear separation surfaces, and their ability to perform reasonably well with incomplete data [2]. ANN technologies have been selected to form the basis of PNL's distribution system MELF development. An overview of ANN technology can be found in [1 - 4].

Although a significant amount of research has been conducted in the past five years with respect to the use of ANNs in short-term load forecasting, much of the development has been focused on predicting load at the transmission level. Inherent differences in the makeup and operating characteristics of distribution and transmission systems will prevent the direct transfer of traditional transmission-level statistical techniques and AI STLFing technologies to the distribution level. The development of an efficient method of predicting loads at the distribution level will depend on an understanding of distribution system characteristics that complicate the short-term load forecasting process.

B. Distribution Short-Term Load Forecasting Issues

The unique features of the distribution system could impede DSTLF development efforts. Distribution system characteristics that will complicate the development of DSTLFs include the lack of historical data, dynamic changes in distribution system configuration, sparse sensing, and the increased randomness associated with single endpoint load shapes.

Independent of the forecasting technique used, the fundamental requirement for successful STLF is access to historical hourly data of the proper quality and quantity. Presently, distribution systems can be characterized as data-poor with respect to both data quality and quantity. ANN (and other) STLF techniques are based on knowledge of the load shape provided by historical hourly load and weather data. The ANN training data needs to be as accurate and complete as possible.

An additional difficulty associated with predicting distribution system loads is the dynamic nature of the distribution system physical configuration. To maximize the reliability of the system and maintain services to the customer, the physical layout of the distribution system is reconfigured. This reconfiguration is performed manually or automatically, often with little warning. The number and nature of endpoints on a feeder can change, thus changing characteristics of the loadshape. A DSTLF must be able to adapt, in real time, to any topological changes in the distribution network. The concept of the TIF component of the DSTLF and the self-tuning capability were developed to address the issues associated with the dynamic nature of the distribution system.

Finally, the very nature of the load at the distribution level complicates development of a DSTLF. The number of individual loads represented by a distribution feeder is much smaller than the number of individual loads that comprise a transmission line. Load forecasts made at transmission levels benefit from the larger number of endpoints based on the law of large numbers. The law of large numbers dictates that the impact of unusual characteristics and anomalies tends to be minimized when a large number of data points is included in the analysis, thus increasing the accuracy of predictions. In addition to the statistical difficulty associated with analysis of a large number of endpoints, the load shape of a single endpoint will have larger relative changes in load and will be significantly affected by unusual events or sudden changes.

Current developments in the power industry are bringing the need for automated short-term prediction capabilities to the forefront of distribution system improvement efforts. The unique features of the distribution system will complicate STLF development efforts. The success of the DSTLF core technology will depend, in part, on how well the DSTLF methodology and its associated elements (MELF, NELF, TIF, and dynamic tuner) address the limited monitoring, dynamic state, and variability of load.

III. DSTLF METHODOLOGY

PNL has defined a DSTLF methodology that addresses the changing utility industry's needs and the unique distribution system forecasting environment. The methodology is designed to facilitate the development of a core forecasting technology that is pervasive across all distribution systems and independent of a utility's monitoring scheme, physical layout, and endpoint characteristics. The capabilities required to develop the methodology elements include a load forecasting method, load shape group/type identification, endpoint load aggregation, and dynamic self-tuning.

A. Methodology Basis

Methods for forecasting load at any level of a power system are constrained by the type and amount of data gathered from the network. Because of the lack of data at the distribution level, the forecasting method is based on limited monitoring of endpoint loads but will accommodate and, in fact, be more accurate with increased monitoring. In a limited monitoring environment, a certain percentage of endpoints is continuously monitored. Loads for the monitored endpoints are directly forecasted from the gathered data. Loads for nonmonitored endpoints are estimated based on analysis of load characteristics of similar monitored endpoints using a group/type characterization scheme that matches endpoints with similar properties and load shapes.

Because current distribution systems are poorly monitored, the development of a robust group/type characterization scheme is essential for forecasting load at the distribution level. At this time, a proven group/type method that characterizes load shapes of endpoints based on the load behavior of other endpoints in the same group/type does not exist. PNL's research will answer a fundamental question: can grouping schemes be developed that cluster endpoints with similar load shapes to a degree that meets the industry's performance requirements?

Once both monitored and nonmonitored endpoint loads have been predicted, line, feeder, and substation loads can be estimated by employing an aggregation method that sums endpoint loads located on the respective line sections and feeders. Line losses should be accounted for in the summing process.

The self-tuning feature allows the DSTLF to adapt to the changing network environment. Self-tuning is a gradual process. Following a change in the physical configuration or in the nature of the loads on the system, the accuracy of the DSTLF will decrease and then improve as tuning progresses. Because of the initial decrease in performance, the DSTLF system should be able to anticipate potential configuration scenarios. An automated configuration management system is necessary to support DSTLF activities and provide the information necessary to pretune the DSTLF based on expected physical layouts.

The DSTLF development process and core components were defined to address the issues associated with the limited monitoring environment as well as the group/type, aggregation, and dynamic self-tuning requirements that form the basis of DSTLF methodology.

B. Methodology Description

The DSTLF methodology is described in terms of the data requirements, the processes the data undergoes, and the DSTLF components that perform the data processing activities. Layered data process modules are used to illustrate the interactions between the data and core component processing elements, the interactions between the various core component processing elements themselves, and the process flow required to obtain the desired forecasted load.

The input data required by the DSTLF, shown in Fig. 1, is dependent on the forecasting technology, the group/type theory, and the aggregation and self-tuning methods. Input data typically consists of historical load, historical temperature, current load, current temperature, and the forecast request.

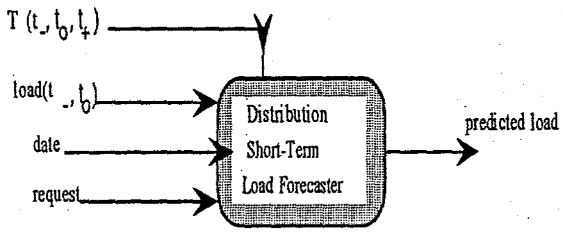

Fig. 1. DSTLF

The approach for predicting a load is to estimate the load of monitored endpoints, use the resulting forecasts, in conjunction with group/typing schemes, to predict the loads of nonmonitored endpoints, and aggregate the individual endpoint forecasts, as necessary, to estimate line and feeder loads. These processes are performed by the monitored endpoint load forecaster (MELF), nonmonitored endpoint load forecaster (NELF), and topological integration forecaster (TIF), respectively.

The MELF consists of a forecasting element based on ANN technology trained from historical data to predict the load of an endpoint (or a specific location on a distribution system). The MELF ANN design and development processes have been conducted with the goal of eventually automating the process. The MELF's ANN has two operational modes: a learning mode, during which the weights associated with the interconnecting nodes are optimized, and a forecasting mode, during which requested load forecasts are made. The learning mode is invoked prior to integration with the other DSTLF elements and as needed by the dynamic tuner element.

The MELF-predicted forecasts are used either directly (if the load is for a monitored endpoint) or as input to the NELF. The relationship between the MELF and NELF is shown in Fig. 2. The NELF consists of a group/typing scheme and one or more transform algorithms. A NELF operates by using a group/typing scheme to identify MELF(s) with similar behavior characteristics. The forecast, generated by the MELF, and the nonmonitored endpoint historical and real-time data are analyzed by the NELF to identify the transform algorithm needed to forecast the desired endpoint's load. If the group/type analysis determines that an endpoint belongs to multiple groups, additional transform algorithms will be required to individually assess the contribution of each group to the endpoint's total load.

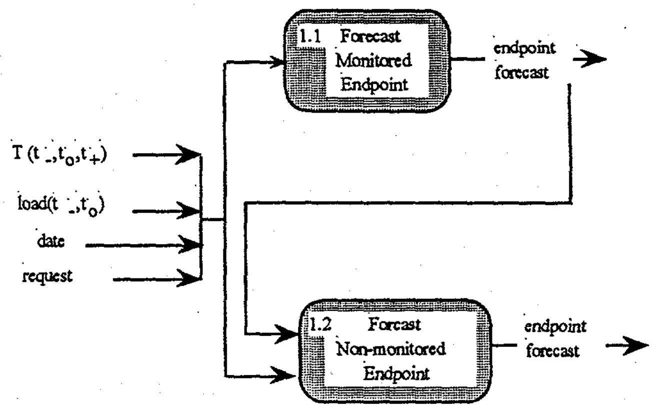

Fig. 2. NELF

If the requested load is for a point in the distribution system that consists of multiple endpoint loads (e.g., a line section, feeder, or substation) and the point is not directly monitored, the TIF estimates the load by summing the endpoints associated with the location. The TIF uses a topological model to identify the endpoints associated with a specific location in the distribution system. The model describes the system in terms of endpoints, cable, and switches, fuses, and other components that can change the configuration. Predictions can be made for both the current and potential physical configurations. The TIF also address issues associated with the aggregation process such as line losses. Fig. 3 shows the relationship between endpoint, line, and feeder forecasts.

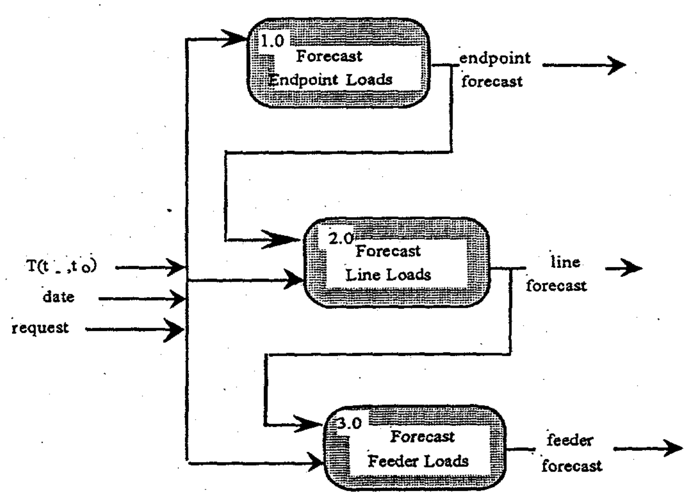

Fig. 3. TIF

Input data is used directly by the line and feeder forecasters if the line or feeder is directly monitored. Endpoint forecasts are used as input data if they are not directly monitored.

C. *AI Technology Requirements*

A number of AI technologies will be used to develop the DSTLF capability. Previous research experience in building intelligent software systems has indicated a benefit associated with integrating diverse AI paradigms. The DSTLF will employ ANNs, fuzzy logic, and model- based reasoning.

Because the nonlinearity and statistical nature of endpoint load profiles are well suited to prediction by neural networks, ANNs form the basis of the load forecasting technology used by the MELF.

Fuzzy logic is well suited for forecasting the loads of nonmonitored endpoints because of the subjective group/type schemes and issues associated with membership. The group/type theory will provide a crisp definition of ideal group types. However, actual endpoints will most likely not be ideal and may share properties with more than one group/type. Fuzzy logic is an appropriate technology for capturing inexactness in grouping processes and provides logical inferencing and computation capabilities.

The TIF will use model-based reasoning techniques to identify the preferred configuration for a given set of operating conditions and requirements. The TIF will examine models representing the current and potential physical layouts of the distribution system and power system analysis models representing the current and potential operating conditions of the distribution system.

Model-based reasoning technology will be used also in developing a dynamic self-tuner. The basic approach will be to combine a performance reasoner with the ANN learning algorithm. The performance reasoner will detect the need for adjusting the weights of the MELF and, based on this detection, will implement the learning algorithm. Subsequent to implementing the new weights, the performance will be compared to the existing forecaster's accuracy. Based on the results of the comparison, the revised weights will be substituted for the current weights, or further evaluation and training will take place.

IV. SUMMARY

Accomplishments during the first year of the DSTLF development include the establishment of a DSTLF concept, partial development of an overall DSTLF methodology, and completion of proof-of-concept prototype MELFs.

The first year of DSTLF research has provided sufficient proof of concept to continue development efforts. In addition, it has produced a framework to guide future development efforts. Ongoing efforts that will be continued include general MELF prototype development and completion of the DSTLF methodology. Remaining elements of the DSTLF that will also be pursued include the group/type theory, NELF, topological integrator, and self-tuning capability. Because of the distribution industry's nearly universal limited endpoint monitoring environment , near-term activities will focus on development of a group/type theory.

V. BIOGRAPHIES

Trav Stratton received his B.S. in Physics and M.S. in nuclear engineering from Texas A&M University in 1971 and 1975, respectively. He joined Pacific Northwest Laboratory in 1987. His interests include artificial intelligence research and application development for reasoning about physical systems with a focus on the diagnosis of components.

Krista Gaustad received her B.E.E. and M.S. in electrical engineering from Auburn Univeristy in 1989 and 1991 respectively. She joined Pacific Northwest Laboratory in 1991. Her interests include the application of intelligent information technologies to the electric power industry.

VI. ACKNOWLEDGMENT

The concept of utilizing group/typing theories to estimate the load at nonmonitored endpoints was developed by Dr. Keyhani of Ohio State University. The proposed D-STLF methodology is based in part on a methodology conceived by Pacific Gas &Electric staff in conjunction with Dr. Keyhani.

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