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-Smart Grid Technology: Prediction and Monitoring

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Abstract—Classical electrical distribution systems have been used to transport electrical energy generated at a centralpower plant by increasing voltage levels and then deliver it to the end users by gradually reducing voltage level.Traditional whole building energy modelling suffers from several factors, including the large number of inputs,required for building characterization, simplifying assumptions and the gap between the as-designed and as-built building. Prior work has attempted to mitigate these problems by using sensor based machine learning approaches to statistically model energy consumption, applying the techniques primarily to commercial building data, which makesuse of hourly consumption of data. It is unclear however, whether these techniques can translate to residential buildingssince the energy usage patterns may vary significantly. Until now, most residential modelling research only had accessto monthly electrical consumption data. Smart Grid structure will offer opportunities to progress within a layout byproviding many facilities and work to be done in the operation of the distribution network that is not limited to theenergy supply and demand balance, but to ensure providing the quality criteria of energy and energy measurement. Oneof the biggest challenge for Smart Grid application scenarios will be handling the massive amount of data that isexpected to be collected from various sources and treated to optimize its operation. In this respect, different machinelearning techniques such as artificial neural networks, fuzzy systems, evolutionary programming and other artificialintelligence methods and their hybrid combinations can significantly contribute to solve problems in Smart Grid. Amachine learning technique, Least Square Support Vector Machines method works best in this domain. It establishesperformance for predicting hourly residential consumption. Work shows that Least Square Support Vector Machine isthe best predictor.

Index Terms- Smart Grid, Regression, Least Support Vector algorithm, Forecasting, Power System.

I. INTRODUCTION

Forecasting of future loads is also important for network planning, infrastructure development and so on. However, power system load forecasting is a two dimensional concept: consumer based forecasting and utility based forecasting. Thus the significance of each forecast could be handled disjointedly. Consumer based forecasts are used to provide some guidelines to optimize network planning and investments, better manage risk and reduce operational costs. In basic operations for a power generation plant, forecasts are needed to assist planners in making strategic decisions with regards to unit commitment, hydrothermal co-ordination, interchange evaluation, and security assessments and so on. This type of forecast deals with the total power system loads at a given time, and is normally performed by utility companies. With the skyrocketing growth of power system networks and the increase in their complexity, many factors have become influential in electric power generation, demand or load management. Load forecasting is one of the critical factors for economic operation of power systems.

II. LEAST SUPPORT VECTOR MACHINE

Support vector machine (SVM) is a kind of maximum margin classifier which was originally proposed to solve theproblem of binary classification. Among a large number of training data vectors, only a few are selected as supportvectors that define the maximum margin. Only the support vectors are utilized in predicting the classes of the testing data vectors,

thus leading to a good generalization. Later, it was realized that SVM can be adapted to solve the problemof regression. Suykens and Vandewalle proposed a least-squares version of support vector regression (SVR) which is particularly suitable to solve regression problems in time series data. The least squares SVR tries to find the solution by solving a set of linear equations instead of a convex quadratic programming for classical SVMs. A brief description of the least-squares SVR is given in the below subsections.

III. AIMS AND OBJECTIVES

The overall vision for the Smart Grid is that it will possess the following qualities:

Intelligent: of sensing system overloads and rerouting power to prevent or minimize a potential outage; of working autonomously when conditions require resolution faster than humans can respond and cooperatively in aligning the goals of utilities, consumers and regulators.

Efficient: capable of meeting increased consumer demand without adding infrastructure (Optimized for best resource and equipment utilization).

Accommodating: accepting energy from virtually any fuel source including solar and wind as easily and transparently as coal and natural gas; capable of integrating any and all better ideas and technologies energy storage technologies, for example as they are market-proven and ready to come online.

Motivating: enabling real-time communication between the consumer and utility so consumers can tailor their energy consumption based on individual preferences, like price and/or environmental concerns (Interactive among customers, retailers, and markets).

Quality-focused: capable of delivering the power quality necessary free of disturbances and interruptions to power our increasingly digital economy and the data centres, computers and electronics necessary to make it run.

IV. EXISTING SYSTEM

For a planner to neither underestimate nor overestimate the load, convenient forecasting techniques with reasonable degree of accuracy need to be developed. Therefore there is a need for development of optimal and accurate based load forecasting models to improve (minimize) the forecast error. However, load forecasting is a difficult task because the consumption is influenced by many factors, such as weather conditions, vacations, economy status, and idiosyncratic habits of individual customers. Inaccurate load forecasts may increase operating costs. Evidently, a poor load forecast misleads planners and often results in wrong and expensive expansion plans.

V. PROBLEM STATEMENT AND SCOPE

To develop optimized Support Vector Regression-based model for Short-Term Load Forecasting and apply the resultedmodel to a real life cases to evaluate the performance of the proposed approach and provide one month ahead forecast.In the research, we will focus on a specific problem of forecasting the peak load (i.e., the maximum electricity usage) ofa particular consumer entity for a future time unit. The consumer entity in question can be of various granularity levels.For example, it can be a smart meter (for a household), a cluster of smart meters (for a neighbourhood), a powersubstation (for a town or city), or a power station (for an entire grid covering a large geographical area). Similarly, thetime unit in question can be of different lengths. It can be 5 minutes, 15 minutes, 1 hour, 1 days, 1 week, etc. In thiswork, we will study a system to forecast the daily peak loads of individual smart meters. However, it should be notedthat the same principles and techniques used in our studies are generally applicable to any load forecasting problemswith any combinations of consumer entities and time granularities. A number of methods based on different techniquessuch as time series analyses (like autoregressive integrated moving average (ARIMA) method), fuzzy logic, neurofuzzymethod, artificial neural network (ANN), and support vector regression (SVR) have been proposed. Among thesevarious techniques, support vector regression (SVR) is one of the latest developments. SVR could provide better resultsthan the older methods like artificial neural network (ANN) could.

VI. PROPOSED SYSTEM

For each target peak load value in the historical record, we construct a feature vector covering the above mentioned attributes associated with the target. Then, we train our least square SVR system using a set of ¡feature vector, target pairs for a large enough number of days. The result of this training

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process is a least-squares regressor model. We can use the resultant regressor model to forecast the peak load value Pd of a given day d. For that, we have to construct a feature vector for the day d in the same manner as in the training step. In constructing the feature vector, we need to know the forecasted temperature of the day d (if it is in the future) and whether it is a holiday (which can be easily known in advance). Then, the feature vector of day d is supplied to the regressor model to generate the forecasted peak load value of that day. After the day d is already passed and its actual peak load value (the target) already known, the regressor model is updated with the feature vector, actual target pair for the day d, thus resulting in a fresh model which best reflects the latest trend of events.

VII. METHODOLOGY

The system load, in power operation context, is the sum of consumers load at the time. A consumer load trend is as different as chalk and cheese and influenced by a thousand of factors. There is no any engineering rule that guides the selecting of these factors. Thus this process is mainly based on experience gained from the correlation analysis between the load and potential influencing factors.

The only existing criterion is that load forecasting in power systems can generally be divided into three different time

horizons: short, medium, and long term load forecasting. However, factors affecting the load at different time horizons are not necessary the same. The variation in the short-term load depends heavily on time factors i.e. hour of the day, day of the week etc. Medium to long term load is determined by factors such as population growth, per capital income,

demographic factors, gross domestic product (GDP) and so on. Most utility companies use this distinctive dependence in selecting the input variables.

Most of demand or load management programs used by electric utilities comprise STLF units. Every utility intends to have a reliable STLF system for economical operations of power systems. The reliability and robustness of the system primarily depend on the accuracy of the forecasts. Though, there are other important requirements for a good STLF system. These requirements take account of:

- Fast speed
- Accuracy
- Automatic data access
- Friendly interface
- Timely forecast
- Automatic performance evaluation of the obtained forecast
- Automatic bad data detection and forecasting report generation.

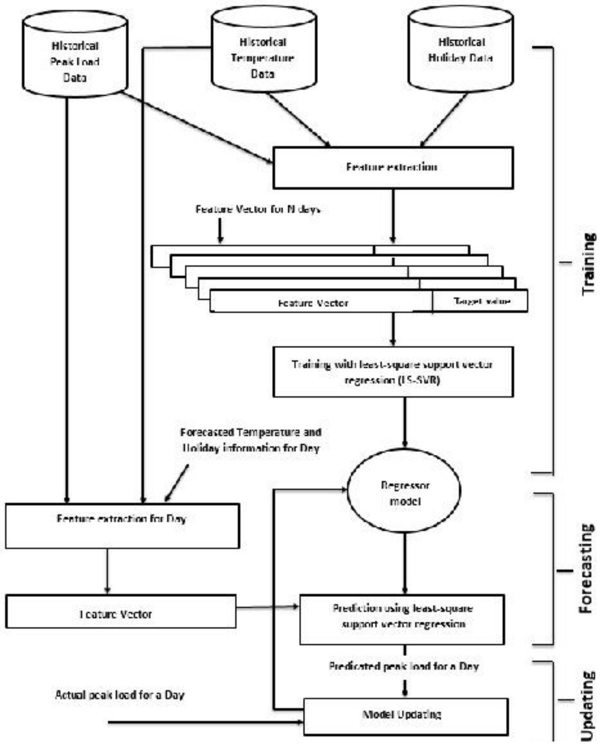

Fig 1. SVM Data Processing

Suykens and Vandewalle derived the least squares version of the SVM classifier by reformulating the minimization problem as below:

$$\min J_2(w,b,e) = \mu\left(\frac{1}{2}\parallel w\parallel^2\right) + \zeta\left(\frac{1}{2}\sum_{i=1}^{n} e_i^2\right)$$

Subject to the equality constraints:

$$y_i(w.\phi(x_i) + b) = 1 - e_i, \qquad i = 1, \cdots, n$$

The least-squares SVM classifier formulation above implicitly corresponds to a regression interpretation with binary targets y=±1. Both μ and ζ are parameters to tune the amount of regularization versus the sum squared error. The solution does only depend on the ratio γ=μ / ζ, therefore the original formulation uses only γ as tuning parameter. Therefore, we have:

$$\min J_2(w,b,e) = \frac{1}{2} \parallel w \parallel^2 + \gamma \frac{1}{2}\sum_{i=1}^{n} e_i^2$$

The solution of the least-squares regressor is obtained after the Lagrangian function is constructed as follows:

$$L_2(w,b,e,\alpha)$$

$$= J_2(w,b,e) - \sum_{i=1}^{n} \alpha_i \left(y_i(w.\phi(x_i)+b) - 1 + e_i\right)$$

$$= \tfrac{1}{2} \parallel w \parallel^2 + \gamma \tfrac{1}{2} \textstyle\sum_{i=1}^{n} e_i^2 - \sum_{i=1}^{n} \alpha_i \left(y_i(w.\phi(x_i)+b) - 1 + e_i\right)$$

Where α∈ ℝ (i=1,⋯,n) are the Lagrange multipliers. Again, the conditions for optimality are:

$$\frac{\partial L_2}{\partial w} = 0 \Rightarrow w = \sum_{i=1}^{n} \alpha_i y_i \phi(x_i)$$

$$\frac{\partial L_2}{\partial b} = 0 \Rightarrow \sum_{i=1}^{n} \alpha_i y_i = 0$$

$$\frac{\partial L_2}{\partial e_i} = 0 \Rightarrow \alpha_i = \gamma e_i, \qquad i = 1,\cdots,n$$

$$\frac{\partial L_2}{\partial \alpha_i} = 0 \Rightarrow y_i(w.\phi(x_i)+b) - 1 + e_i = 0,$$

$$i = 1,\cdots,n$$

By the elimination of w and e, we will have a linear programming problem instead of a quadratic programming one:

$$\begin{bmatrix} 0 & y^T \\ y & \Omega + \gamma^{-1} I_n \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ 1_n \end{bmatrix}$$

where y=,y$,⋯,y*- , 1*=,1,⋯,1-, α= ,α$,⋯,α*-, and I* is an n×n identity matrix. Here Ω∈ R^{n*n} is the kernel matrix whose individual element $\Omega_{i,j,<}$ (i,j=1,⋯,n) is defined as follows:

$$\Omega_{i,j} = \phi(x_i.x_j) = K(x_i,x_j)$$

VIII. ANALYSIS

The Smart Grid Architecture Framework aims at offering a support for the design of Smart Grid Block Diagrams with an architectural approach allowing for a representation of the current implementation of the electrical grid and future implementation of the smart grid.

Operational Feasibility: The Application will reduce the time consumed to maintain manual records and is not tiresome and cumbersome to maintain the records. Hence operational feasibility is assured.

Technical Feasibility: Minimum hardware requirements: - 1.5 GHz Pentium Processor or Intel compatible processor. 4 GB RAM or above. Internet Connectivity.100 GB hard disk space.

Economical Feasibility: Once the hardware and software requirements get fulfilled, there is no need for the user of our system to spend for any additional overhead. For the user, the Application will be economically feasible in the following aspects: The Application will reduce a lot of labor work. Hence the Efforts will be reduced. Our Application will reduce the time that is wasted in manual processes. The storage and handling problems of the registers will be solved.

IX. FUTURE SCOPE

The smart grid mission increases the involvement of customer in the power supplying system. The opportunity of service contributor has been limited in the power transmission and distribution systems across the world. However the wish to improve the service quality of the power delivery system has led to incorporation of new features in the system. Smart grid is consider as the next generation power grid, which supply bi-directional flow of electricity and information, with better power grid reliability, security, and efficiency of electrical system from generation to transmission and to distribution. As smart grid continues to develop, realization of a reliable and stable system is necessary. This paper reviews on the future scope in smart grid and failure in protection mechanism.

X. CONCLUSION

The smart grid paper gives information on costs, demands and supply of power. It explains how consumers will bothreceive and contribute power to the smart grid from ultimately anywhere in the world. It gives information on how todevelop technologies for new applications in distribution, communication, analysis and control and how millions onnew products and devices will be required.

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