TECHNICAL MEMORANDUM

ELECTRICAL LOAD FORECASTING
USING MACHINE LEARNING TECHNIQUES

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SUMMARY

Load modeling and forecasting are essential for operating power utilities profitably and securely. Such activities have become increasingly important since the rise of the competitive energy markets through privatization and deregulation of power systems in may parts of the world. Conventional statistical methods have long been used for this purpose, but modern machine learning approaches; e.g. neural networks, can handle a larger number of input variables, require less user intervention and are better in handling nonlinearities and in dealing with data uncertainties and inaccuracies. This Technical Memorandum proposes the use of abductive networks machine learning for performing modeling, analysis, and forecasting tasks for the electrical load generated by power utilities. Compared to neural networks, the proposed abductive networks technique offers a number of advantages, including simplified and more automated model synthesis requiring less user intervention, and analytical input-output model relationships that automatically highlight significant input parameters and provide better explanation facilities.

The proposed work should be of interest to the Ministry of Industry and Electricity and the electrical power utilities of the Kingdom. Resulting applications include the development of fast and accurate tools for the short-term forecasting of the daily peak load, hourly day load curve, or total daily energy. Analytical model relationships generated from historical data will clearly identify influential input parameters and their individual contributions to the load function. This should allow better insight into the load relationships and enable comparison with previously used statistical or empirical relationship. The work can also help classify load patterns over the year in various regions of the kingdom.

Following a brief introduction in Section 1, the objectives of the work are presented in Section 2. A description of the problem is given and the proposed approach is outlined in Section 3. Section 4 describes various aspects of the proposed work. Relevant CAPS experience in using the proposed approach and other statistical technique in similar and related areas is outlined in Section 5.

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SECTION 1 INTRODUCTION

Load forecasting has always been an important requirement for operating power utilities economically and reliably. Increase load capacities and the more competitive nature of the market brought about by deregulation and privatization have increased the need for faster and more accurate forecasts, as well as better understanding of the factors influencing load demand. Traditionally, statistical tools in the form of univariate time series analysis or multivariate regression analysis have been used for this purpose. The first category ignores important weather effects on the load and therefore gives poor accuracy, particularly during sudden weather changes. The second approach tends to assume linear relationships for simplicity, while the relationship between the load and weather parameters are known to be complex and nonlinear. Moreover, the methods are computationally intensive and require considerable user intervention in determining the form of the model relationship. In many cases, the form assumed may not be the most appropriate one.

Data-based machine learning modeling techniques offer a better approach to solve this problem. They automatically discover complex and nonlinear relationships that actually exist between the electric load and explanatory inputs such as previous load values, weather variables, and social factors through training on collected data. They utilize abundantly available historical data for offline training and provide fast-executing forecasting models that are suitable for online use. Since the late eighties, artificial neural networks (ANNs) have been used for load forecasting. However, neural networks suffer from a number of limitations, including long training times, difficulties in determining optimum network topology, and the black box nature that gives poor explanation facilities. To overcome the above limitations, this Technical Memorandum proposes using the alternative abductive networks approach for the rapid development of accurate models for the electric load in various regions of the kingdom. In addition to their use as forecasting tools in a production environment, the models shall give insight into load-influencing factors and the input-output relationships involved.

SECTION 2 OBJECTIVES

We propose the application of abductive network data-based modeling to the important area of electrical load modeling and forecasting in power utilities of the kingdom. Resulting applications will serve the following objectives:

- Develop transparent and accurate load forecasting models to assist in the economic and reliable operation of power utilities.

- Compare the structure and performance of resulting models with currently used models and forecasting techniques.

- Improve our understanding of daily, weakly, and seasonal variations in the electrical load in various regions of the kingdom.

- Determine the factors that influence the electrical load, including social, economic, and weather conditions and quantify their effects in various regions.

- Introduce the use of modern computational intelligence techniques for modeling, forecasting, and data mining applications in the electrical power industry of the kingdom.

- Develop platforms for training junior engineers in load forecasting and scheduling.

SECTION 3 DISCUSSION OF THE PROBLEM

3.1. Description of the Problem

Accurate load forecasting is one of the key problems that need to be solved for the planning and economic and secure operation of modern power systems. Long-term forecasts (five to 20 years) are required for system planning, procurement of generating units, and staff hiring. Medium-term forecasts (one month to five years) are used for purchasing enough fuel and revising electricity tariffs. Short-term load forecasting (STLF) (one hour to one week) [1] is important for scheduling functions, such as generator unit commitment, hydro-thermal coordination, short-term maintenance, fuel allocation, power interchange, transaction evaluation, as well as network analysis functions, such as dispatcher power flow and optimal power flow. Another area of application involves security and load flow studies, including contingency planning, load shedding, and load security strategies. Very short-term load forecasting (few minutes to one hour) is becoming increasingly important for security assessment, handling of special events, and online energy trading. This document is primarily concerned with STLF load forecasting.

Accurate STLF forecasts translate into improved security and efficiency of utility operation. Overestimation of the short-term load may involve the startup of unnecessary reserves, which increases operating costs. On the other hand, underestimation may lead to the deployment of expensive peaking units or the purchase of generation at higher cost. It was estimated that an extra 1% in the forecast error increased the operating cost of a UK power utility by 10 M sterling pounds in 1985 [2]. With the ever-increasing load capacities, a given percentage forecasting error amounts to greater losses in real terms. Recent changes in the structure of the utility industry in many parts of the world due to deregulation and increased competition highlight the need for better forecasting accuracy even further. Mean absolute percentage errors of 2-3% appear to be the lower bound of acceptable accuracy for STLF forecasts. In addition to accuracy, STLF forecasters must be adaptive to changing situations and should utilize the most recent data available. They should accommodate special conditions such as measurement errors, power outages, and special days. They should be as simple as possible to reduce design and operation time and the computational overhead. They should also be easy to use and need to be accepted as practical working tools by the operation staff in power utilities.

STLF activities include forecasting the daily peak load, total daily energy, and daily load shape as a series of 24 hourly forecasted loads. Traditionally, power utilities have relied in the past on a few highly experienced in-house human experts to perform judgmental forecasts [3] manually using techniques such as the similar-day method [4]. Increased demand on the accuracy, speed, and frequency of the forecasts have gradually led to forecast automation. Conventional techniques for forecasting the load shape included both static and dynamic methods. Static methods model the load as a linear combination of explicit time functions, usually in the form of sinusoids and polynomials [5]. The more accurate dynamic models attempt to take into consideration other important factors such as recent load behavior, weather parameters, and random variations. Techniques in this category include univariate time series models such as the autoregressive moving average (ARMA) [6], the Box-Jenkins integrated autoregressive moving average (ARIMA) [7] for non-stationary processes, as well as the Kalman filtering technique [8]. Univariate time series methods suffer from limited accuracy as a result of ignoring weather effects, are time consuming, require extensive user intervention, and may be numerically unstable [9]. Multivariate causal models use multiple regression to express the load as a function of exogenous inputs including weather and social variables [10]. In addition to the complexity of the modeling process, regression models are often linear devices which attempt to model distinctly nonlinear relationships [11]. This causes poor forecasting accuracy during rapidly changing weather conditions [12]. Even when a nonlinear relationship is attempted for the model, it is difficult to determine empirically the correct complex relationship that actually exists between the load and the other explanatory inputs.

A recent trend in handling such problems that are difficult to solve analytically has been to resort to artificial intelligence and machine learning techniques. These techniques range from knowledge-based expert systems to data-driven approaches such as fuzzy logic, genetic algorithms, and neural networks. Although rule-based expert systems have been developed for load forecasting, e.g. [13], this approach has not been widely adopted due to the difficulty in elucidating knowledge from domain experts [14] and the considerable development time and cost. The availability of huge amounts of historical load and weather data in utility data bases encourages the use of data-based modeling approaches such as neural networks [15]. Such techniques are non-parametric, i.e. the user does not need to explicitly specify the model relationship. This enhances their use in knowledge discovery by freeing them from bias or influence by previous assumptions. With neural networks, complex nonlinear input-output relationships can be modeled automatically through supervised learning using a database of solved examples. Once synthesized, the model can generalize to perform predictions of outputs corresponding to new cases; previously unseen during training. Neural networks modeling offers a number of advantages over conventional approaches, including reduced development time and increased tolerance to noise, uncertainty, and missing data, reduced need for knowledge on the modeled phenomenon, freedom from assumptions on the probability distributions of input variables, relative ease of updating the model through re-training, and the fact that no programming is needed. Intensive computations are required only once during model synthesis, while predictions by the models synthesized are fast and straight-forward, making them ideal for online use.

3.2. Proposed Approach

In spite of the wide-spread use of feed-forward neural networks trained with error back-propagation for load modeling and forecasting, the technique suffers from a number of limitations, including difficulty in determining optimum network topology and training parameters [16]. There are many choices to be made in determining numerous critical design parameters with little guidance available [11] and designers often resort to a trial and error approach [17] which can be tedious and time consuming. Such design parameters include the number and size of the hidden layers, the type of neuron transfer functions for the various layers, the training rate and momentum coefficient, and training stopping criteria to avoid over-fitting and ensure adequate generalization with new data. Another limitation is the black box nature of neural network models, which makes them lack on explanation facilities, providing little insight into the modeled relationship and the relative significance of various inputs [18]. The acceptability of, and confidence in, an automated load forecasting tool in an operational environment appear to be related to its transparency and its ability to justify results to human experts [4].

To overcome such limitations, we propose using abductive networks [19] as an alternative machine learning approach to electric load forecasting. The approach has been successfully used at CAPS for forecasting the monthly domestic energy consumption at the Eastern Province over one year [20], as well as in the related field of forecasting the minimum and maximum daily temperatures [21,22]. Other application areas at CAPS included nuclear spectroscopy [23,24], monitoring of machine vibrations [25], and medical informatics [26,27]. Compared to neural networks, the method offers the advantages of faster model development requiring little or no user intervention [19], faster convergence during model synthesis without the problems of getting stuck in local minima [16], automatic selection of relevant input variables, and automatic configuration of model structure [16]. With the resulting model represented as a hierarchy of polynomial expressions, analytical model relationships can be derived. These provide insight into the modeled phenomena, highlight contributions of various inputs, and allow comparison with previously used empirical or statistical models. The technique automatically avoids over-fitting by using a proven regularization criterion based on penalizing model complexity [19], without requiring a dedicated validation data set during training, as is the case with many neural network paradigms.

A database consisting of an adequate number of solved examples is required to develop and evaluate the abductive network model. The dataset should include input variables that are likely to influence the output parameter to be modeled, as well as corresponding values of the output parameter. The model is synthesized through training on a training dataset and is then evaluated through examining its performance on a separate evaluation data set. The proven model can then be tried for load forecasting in a real production environment. Feedback from client staff during the trail period will guide efforts for improving both the performance and acceptability of the final product. Work on the project involves coordination with the client engineers in identifying a suitable application area, determining relevant input parameters, obtaining the required historical data from client data bases, performing data pre-processing to ensure good quality of the training and evaluation data, as well as in model integration with other systems at the client site. Model performance will be analyzed and compared with that of existing forecasting methods that are currently being used by the client.

SECTION 4 STATEMENT OF WORK

The proposed work includes the following tasks:

4.1. Problem Identification

The proposed technique can be used for load modeling and forecasting for the short, medium, or long term. The most important application for the day-to-day operation of power utilities is forecasting the load shape one day in advance, in the form of 24 hourly load forecasts. However, applications for forecasting the peak load and the total energy for the day are also reported in the literature. Consultations with the client would identify a specific application of interest to them, for which adequate historical data exists for the load, weather, and other factors that are deemed important.

4.2. Selection of Input Variables

A wide range of factors influences the electrical load, including:

- Seasonal effects, including daily, weekly and seasonal variations, as well as vacation and holiday periods.

- Meteorological and climatic factors, including temperature, humidity, wind speed, cloud cover, day light duration, etc.

- Economic and social factors, including economic and population growth, business hours, electricity pricing and tariff structures.

- Random disturbances.

Selection of input variables that represent the above factors during model synthesis plays an important role in data-based modeling, as the model relationship is derived based on the input-output information presented. It is recommended that only relevant inputs are used, since too many inputs increase training time, lead to complex models that may not generalize well with new data in actual use, and require proportionally larger training sets to avoid the resulting model over-fitting the training data. Additional irrelevant inputs have been shown to degrade the performance of neural network load forecasters [28]. In many situations, the inputs are selected through engineering judgment, previous experience with manual and automated load forecasting, as well as trial-and-error experimenting. Statistical techniques have also been used to select input variables, including input-output correlation analysis [14,29,30], regression analysis [14], load autocorrelation functions [31], principal component analysis [17], phase-space embedding [32], and singular value decomposition [17]. The objective is to select a parsimonious set of independent inputs that are strongly correlated with the load but are not mutually correlated among themselves to avoid redundancy [17].

Load-affecting factors vary from one application to another depending on the climatic conditions and load characteristics. However, the following input variables would generally be required to construct a global model for forecasting the hourly load curve on any day of the year:

1. Historical load values with time lags reflecting strong autocorrelations [31] and seasonalities

of the load time series.

2. Historical, and possibly forecasted, weather parameters. Hourly and minimum and maximum daily temperatures appear to be the most relevant [4], although other parameters may also be useful, including humidity, wind speed, cloud-cover, and rainfall [33]. Time lags here reflect the delay between the change in weather and its effect on the load; e.g. due to the insulation of dwellings [34].

3. Day-of-week indication, to take into account different load profiles that characterize various days of the week. It is often adequate to classify weekdays as working days or weekend/holidays. A binary code with only 1 bit active at a time is suitable for this purpose [35].

4. Day-of-year indication, to take into account cyclic seasonal load variations over a year's interval. Sinusoidal functions of the form $\sin(2\pi i/365)$ and $\cos(2\pi i/365)$, where i is the day index, are sometimes used for this purpose [36].

As an example of the number of inputs used, a global model for forecasting the 24 hourly loads for tomorrow [37] uses 79 inputs detailed as follows: 24 actual hourly loads of yesterday, 24 actual hourly temperatures of yesterday, 24 forecasted hourly temperatures for tomorrow, and a 7-bit binary code representing the day-of-week.

4.3. Selection of Data Sets for Model Development

To obtain good load forecasting models, the training and evaluation data sets should be a good representation of the problem space. The larger the amount of good training data we use, the better we expect the resulting models to be, provided that extending the data set does not introduce incoherencies or inconsistencies that are not accounted for by the input variables. Also, testing the models on a large set of representative evaluation data increases confidence in the resulting model and improves the statistics of the evaluation analysis performed. Various load patterns should be uniformly represented in the data to avoid model bias towards patterns seen more frequently during training. Neural network load forecasting models have been synthesized using training data from one year [38] up to five years [39]. Evaluation is usually performed on data for one to two years.

There are two basic modeling approaches adopted for load forecasting: building a global model for a general day of the year [12], or building a set of dedicated seasonal models, each, for example, is for a given day type in a particular season [40] or for a given interval within each such day [41]. A global model is trained on the full set of yearly training data and includes inputs that describe the forecasting day. Dedicated models are trained only the relevant set of examples representing the particular season and week day. In some studies, groups of days having a similar load profile are first identified automatically, e.g. using a Kohonen's classifier neural network, and a forecasting model is then developed separately for each group [42]. To ensure adequate number of training examples for such models, the training set for the model often has to span multiple years. Dedicated models handle a subset of the overall modeling problem, and therefore are simpler and have fewer inputs compared to global models. This makes them faster to train and more accurate. However, the management and updating of a large number of dedicated models (60 models in [41]) could be inconvenient in an operational setting.

4.4. Data Preprocessing

Data gathered shall be examined to check for completeness and avoid obvious errors. Missing data values are substituted through interpolation or the whole data row is discarded. Obvious outliers are treated similarly. Additionally, a number of preprocessing steps are usually performed on the raw data prior to use in model synthesis or evaluation. Examples include:

1. **Trend Adjustment:** When the training data used span multiple years, trend effects are removed by adjusting the load values to take into account the average annual load growth [41,43,44].

2. **Normalization**: Data for the input variables and the load output are normalized individually to the same range, e.g. 0 to 1 [44], or as Z scores of zero mean and unity standard deviation [39]. Normalization is based on the minimum and maximum values, and the mean and standard deviation values for the individual variable, respectively. An opposite operation restores the predicted load output to the original problem space.

3. **Transformations:** The raw data for some variables may be transformed to generate new variables that better assist in modeling the load function, e.g. by explicitly representing a known non-linearity. Examples of such new variables include:

- An equivalent temperature that embodies a number of weather parameters, including dry bulb temperature, relative humidity, and wind speed [37,45].

- A squared temperature variable that reflects the effect of the cooling and heating loads. The variable has zero value when the temperature is within the comfort zone (no heating or cooling required) and is equal to the square of the difference between the temperature and the cooling and heating threshold temperatures for colder and hotter weathers, respectively [46].

4.5. Model Development

Records constituting about 70% of the total data are used for synthesizing an abductive network model that describes the input-output relationship. A model is synthesized for each variable declared as ‘output’. The remaining 30% are reserved for model evaluation.

Abductive network models take the form of layered feed-forward networks of functional elements (nodes) [19]; see Figure 1. Elements in the first layer operate on various combinations of the independent input variables (x's) and the single element in the final layer produces the predicted output for the dependent variable y. Both the element type and the combination of inputs to it from all previous layers are selected automatically for best prediction performance. Networks are limited to four layers, and training is stopped automatically at a point in time that strikes a balance between model complexity (which ensures adequate learning of the training data set) and model simplicity (which results in better generalization in predicting new cases when the model is put to actual use). Neural networks usually use a separate validation dataset to prevent over-learning, which reduces the number of cases available for actual training.
The following main functional elements are supported:

(i) A white element consisting of a constant plus the linear weighted sum of all outputs of the previous layer, i.e.:

"White" Output $= w_0 + w_1x_1 + w_2x_2 + w_3x_3 + ... + w_nx_n$

where $x_1, x_2,..., x_n$ are the inputs to the element and $w_0, w_1,..., w_n$ are the element weights.

(ii) Single, double, and triple elements implementing a 3rd-degree polynomial expression with all possible cross-terms for one, two, and three inputs, respectively; for example,

"Double" Output $= w_0 + w_1x_1 + w_2x_2 + w_3x_1^2 + w_4x_2^2 + w_5x_1x_2 + w_6x_1^3 + w_7x_2^3$

This allows taking into account nonlinear combinations of the input variables automatically as required. Substituting the equations of the functional elements of the various layers gives a polynomial expression relating the modeled output to the input variables.

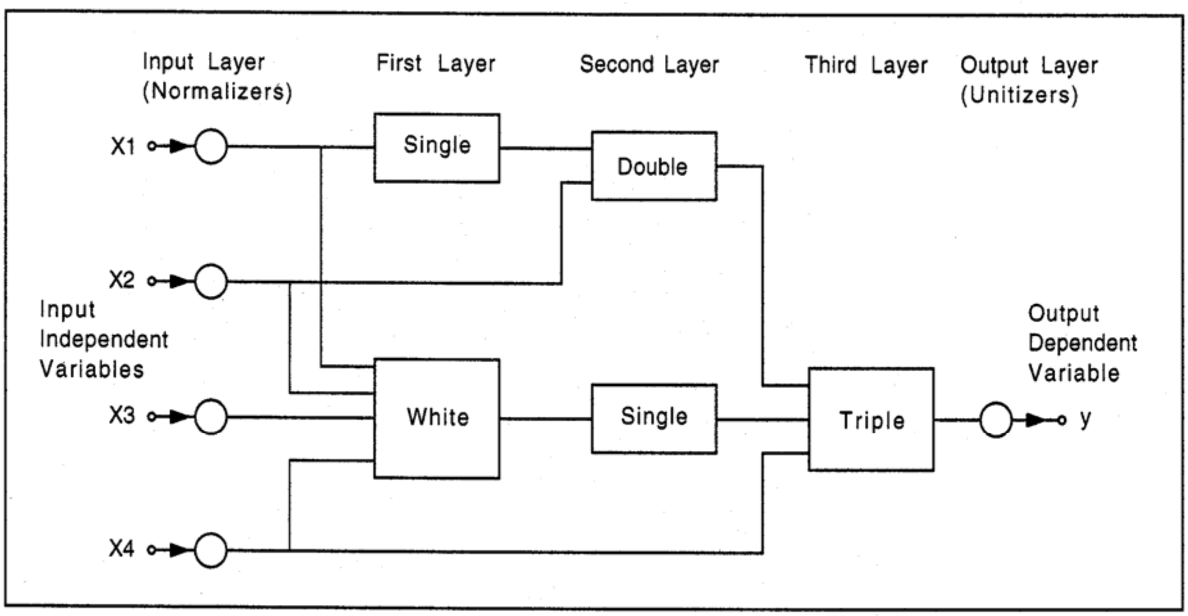

Figure 1. A typical abductive network model showing various types of functional elements

4.6. Model Evaluation and Analysis

The resulting model is evaluated on the evaluation set of the database, previously unseen during training. Various procedures for forecasting error analysis will be employed, including:

- Mean absolute percentage error (MAPE)

- Error variance
- Minimum and maximum errors
- Number of large errors
- Error histograms

Model performance will be compared with that of existing models or forecasting methods that may be currently used by the client as well as some standard or well-accepted simple method such as the ‘average day’ forecast in order to verify model advantage.

In addition to predicting the modeled output from measured inputs, the resulting abductive network models provide useful information on the modeled relationships. The model automatically selects input parameters that contribute most to the modeled output and can provide simplified analytical expressions for the model relationship that reveal significant input variables and their relative importance. With neural networks, this information is not readily available, and can only be derived through tedious inspection of large weight matrices. Such results allow interesting comparisons with known concepts on factors influencing the load. Derived model relationships will be compared with empirical or regression analysis relationships that may exist for the load function.

4.7. Model Integration

The resulting model is ported onto the computer system at the client site. Depending on the application, the model may be integrated to operate with other software programs and database applications. In situations where inputs to the model include load or weather data acquired online, the model should be interfaced to the software that runs the measurement apparatus. This part of the work requires close coordination with engineers and technicians at the client’s site.

4.8. Performance Assessment

Evaluate the performance of the model in realistic operational settings for extended duration. Study the level of acceptance of the new model by the client’s work team. Solicit and implement recommendations from the client team for product improvement. Investigate the need for model updating and re-training to accommodate long-term drifts in the training data.

4.9. Documentation

Full documentation will be provided on the data sets used, pre-processing employed, model synthesis, resulting model structures and input-output relationships, model evaluation analysis, and model integration.

SECTION 5 RELEVANT EXPERIENCE AT CAPS

CAPS has the resources and expertise to develop machine learning solutions for modeling and forecasting the electrical load for the kingdom's power utilities. CAPS researchers have previously used the technique as well as conventional statistical methods for medium-term forecasting of the monthly domestic electrical energy consumption in the Eastern Province, in the similar and closely-related area of modeling and forecasting daily weather parameters, and in forecasting patient volume in Al-Khabar primary care clinics. Following is a brief description of some applications:

5.1. Modeling and forecasting monthly electric energy consumption in eastern Saudi Arabia using abductive networks [20]:

Abductive networks were used to model the monthly energy consumption in terms of key weather parameters and demographic and economy indicators. Models synthesized on data for 5 years of were used to forecast new data for the 6th year with an MAPE of 5.6%. Compared to regression relationships previously developed on the same data, the models are more accurate, use fewer input variables and are much easier and faster to develop. Figure 2 shows a plot of both actual and predicted values over the training and evaluation periods.

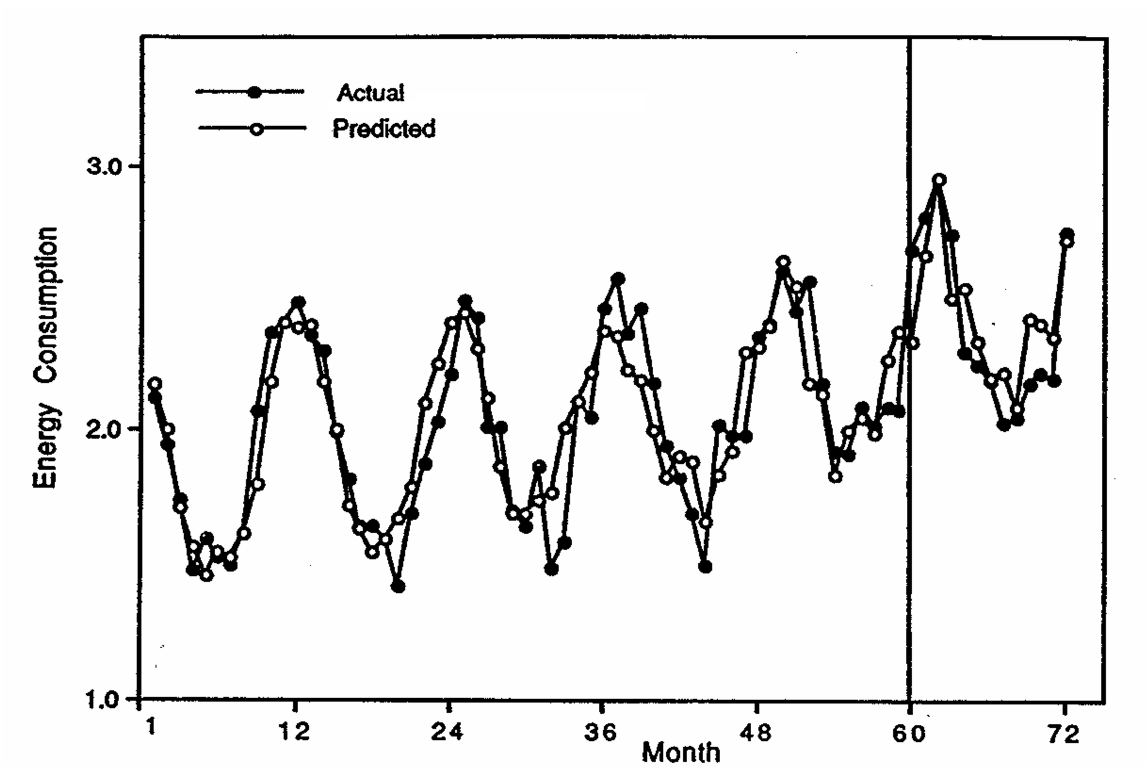

Figure 2. Actual and predicted values of monthly domestic energy consumption in the Eastern Province in GWH during the training interval (months 1 to 60) and the evaluation interval (61 to 72). Month 1 is August 1987.

5.2. Modeling monthly electric energy consumption in eastern Saudi Arabia using univariate time series analysis [47]:

Univariate autoregressive integrated moving average (ARIMA) models were developed for the monthly energy consumption time series described above. The optimum model is a multiplicative combination of first-order seasonal and non-seasonal parts, following first differencing at both the seasonal and non-seasonal levels. This model forecasts the 6th year data with an MAPE of 3.8%.

5.3. A machine-learning approach to modeling and forecasting the minimum temperature at Dhahran, Saudi Arabia [21]:

Abductive networks were used to model the minimum daily temperature in terms of other 18 weather parameters using data for one year. Evaluated on data of another year, the model predicts the minimum temperature with an error within ± 3% for 99% of the days, as compared to 67% of the days for a regression model. Another abductive model forecasts tomorrow's temperature using the corresponding values for the past three days with the same error bounds for 92% of the days.

5.4. Modeling and forecasting the maximum temperature using abductive machine learning [22]:

Abductive networks were used to model the maximum daily temperature in terms of other 18 weather parameters using data for one year. Evaluated on data of another year, the model predicts the maximum temperature with an error within ± 3% for 97% of the days. Another model forecasts tomorrow's temperature using the corresponding values for the past three days with the same error bounds for 77% of the days.

5.5. Modeling and Forecasting Patient Volume at a Primary Health Care Clinic Using Univariate Time-Series Analysis [48]:

Univariate time-series analysis was used to model and forecast the monthly patient volume at a primary health care clinic. Based on nine years of data, an ARIMA model forecasts data for the following two years with an average and maximum absolute errors of 1.86% and 4.23%, respectively. Another approach that extrapolates the growth curve of annual means using a polynomial fit gives the better figures of 0.55% and 1.17%, respectively.

Abductive networks and other statistical modeling techniques have also been used at CAPS in a variety of other applications in science, medicine and engineering, including:

- Identification /determination of radioisotopes from gamma ray spectroscopy [23].
- Peak fitting in nuclear spectroscopy [24,49].
- Online monitoring of vibrations in vacuum pumps [25].
- Medical informatics [26,27,50].
- Direct estimation of noisy sinusoids.

- Modeling for oil and gas reservoir characterization.
- Modeling of petrochemical processes.

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