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An Innovative Application Method of Monthly Load Forecasting for Smart IEDs

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Abstract – This paper develops a new Intelligent Electronic Device (IED), and then presents an application method of a monthly load forecasting algorithm on the smart IEDs. A Multiple Linear Regression (MLR) model implemented with Recursive Least Square (RLS) estimation is established in the algorithm. Case Study proves the accuracy and reliability of this algorithm and demonstrates the practical meanings through designed screens. The application method shows the general way to make use of IED's smart characteristics and thereby reveals a broad prospect of smart function realization in application.

Keywords: Monthly load forecasting, Multiple linear regression, Recursive least squares, IED

1. Introduction

In utilities and factories, Intelligent Electronic Devices (IEDs) are becoming more and more popular. The research on IED's smart characteristics can lead to a better fulfillment of practical needs [1]. So far in plants, it is easy to measure the consumed load at any time, yet the monthly load forecasting reports do not come along easily. After doing research on IED's smart characteristics, we developed a program applied on IEDs to improve the situation.

Out of economic consideration and installation requirements, the IEDs as the platform, are designed to be simple and cheap. The forecasting algorithm on IEDs is supposed to provide results quickly, thus this paper chooses classical regression method and builds a Multiple Linear Regression (MLR) model in the algorithm. The unknown parameters in this MLR model are estimated and updated by Recursive Least Square (RLS) estimation [2].

In Case Study, analysis and evaluation are presented to show the accuracy of the algorithm. Display screens are designed to show how the developed IEDs and the forecasting algorithm are going to work in practical situations. Through the algorithm, IEDs calculate and update the forecasting every hour, analyze the data, and then display the results immediately, along with the other measured values.

Using this application method, various smart functions can be implemented with IEDs, which will bring greater convenience and economic benefits to the users. Useful information can be reported to the users quickly and visually, leading to improvement of system security, reliability, maximization of economic profit and optimization of operation.

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2. An Innovative Application Method of Monthly Load Forecasting

2.1 Different approaches for load forecasting

In the latest few decades, different practical techniques to forecast load have been utilized in application. Most forecasting methods use statistical techniques such as regression and time series, or Artificial Intelligent (AI) algorithms such as Artificial Neural Networks (ANN), fuzzy logic and Support Vector Machines (SVM).

Due to the ability to learn complex and nonlinear relationships, AI techniques have received much attention in recent years [3, 4]. However, there are drawbacks for the complex algorithmic methods based on AI technique. For instance, they may converge slowly and even diverge in certain cases [5]. Their relatively high requirement of time and space confines their response speed to the latest information from measurements.

The conventional techniques, such as multiple regression and time series methods, which are broadly categorized into statistical methods, are relatively simple and mature.

Regression analysis is one of the most widely used statistical techniques in electric load forecasting. It is about the changes of dependent variable when any one of the independent variables is varied, while the other independent variables are fixed.

Time series models have many forms and represent different stochastic processes. Time series methods focus on statistical processing of history load data and ascribe the data variation to the time. Even though some papers claim that it is possible to input some weather information by expressing in transfer function form, generally the lack of weather input usually limits their application area [6].

2.2 An innovative application method of monthly load forecasting

Since the objective is to consider the information of the different factors, to accomplish the forecasting easily and to be able to update forecasting quickly in time, the classical multiple regression model is a good choice. Regression analysis may not be effective enough for the non-stationary, nonlinear load profiles because it assumes linear relationships during the prediction process. However making use of IEDs to renew the forecast every hour helps to compensate this inherent shortcoming [7].

In the field of power system automation, IED is a kind of device that performs versatile electrical protection functions, captures and stores locally measured signals, monitors the operating status, issues control commands, and provides adequate available data for network analysis [8]. In the paper, we designed a new IED, on which we applied our monthly load forecasting algorithm, making real-time forecasting results readily available. The new IED consists of a data processing element, a measuring element and a display element. It is easy to customize, produce, install, and manage.

The main idea of the algorithm is updating parameters in MLR model every hour by RLS estimation, thereby updating the forecasting results. When there are some general changes from year to year, the program will analyze the history data and further improve the forecasting. The algorithm is simple enough to implement on the IEDs. It does not need the initial input; it learns the load characteristics by the time and it is suitable for a lot of sites.

The monthly load forecasting algorithm in this paper introduces an innovative application method for smart IEDs. Firstly, due to the fast communication ability of IEDs, information can be renewed in time. The algorithm tracks the trajectory on its best by updating the forecasting every hour. Secondly, with the smart processors, IEDs can do data processing for the users. Smart IEDs calculate the expected power cost and give recommendation about the load consumption when they do the forecasting. Thirdly, all the forecasting results, cost evaluation and recommendations will be sent out timely and displayed on the screens clearly and directly.

The application method shows the general way to exploit IED's smart characteristics. Not only the load forecasting, but also various other applications can be implemented in a similar way. This is a useful application method for system planning, monitoring and control. It will also contribute a lot to the development of smart grid, which is the way ahead to the modern society and better human life.

3. Load Forecasting Algorithm with RLS Estimation Based on Regression Model

Multiple regression models are used to model the relation between load consumption and affecting factors such as weather, day type, etc. The final accuracy of a load forecast algorithm depends on not only the model selected, but also the accuracy of the coefficients assigned by the relevant estimation technique [9]. In this paper, the coefficients are determined recursively every hour by RLS estimation, a well-known elaborated estimation methodology.

In some years or some months, supply or demand fluctuation due to reasons such as changes of weather conditions and energy price may result in apparent load changes. The algorithm proposes a useful approach to adjust the forecasting results by using the history forecasting data.

In the following we explain our MLR model and detail the forecasting methodology.

3.1 MLR model

MLR method is an approach to modeling the relationship between a scalar (dependent) variable y and more than one explanatory (independent) variables denoted as x. The general expression is in the form as

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \varepsilon \tag{1}$$

As to monthly load forecasting, y is referred to as monthly load. $x_i \left(i = 0, 1, \ldots, k \right)$ are the affecting factors. ε represents the noise in application. $\beta_i \left(i = 0, 1, \ldots, k \right)$ are the unknown parameters that need estimation, in which β_0 is the constant term in the model [10].

The unknown parameters β_i in the MLR model should be classified in a reasonable way that would not only detail the different effects but also avoid overlap from each other. On the basis of life experience, the load profile highly depends on the temperature. The algorithm forecasts the monthly load through measuring the load so far and forecasting all the hourly loads left in that month. Therefore the differences brought by time, day type and month should also be included. Overall the parameters should at least encompass the influence of day type, time, month and temperature [11]. These affecting factors are expressed by the variables defined by a kind of 3-layer class in this paper. In the first layer, different days of the week are divided into 4 sets based on 4 day types which are Monday; Tuesday to Friday; Saturday and Sunday. In the second layer, for each of the 4 day-type sets, 24 subsets corresponding to 24 hours in one day is specified. In the third layer, to each of the 24-hour subsets, there is 1 parameter for constant term, 12 parameters for monthly effect and 1 parameter for temperature. The parameter setting structure is displayed in Table 1.

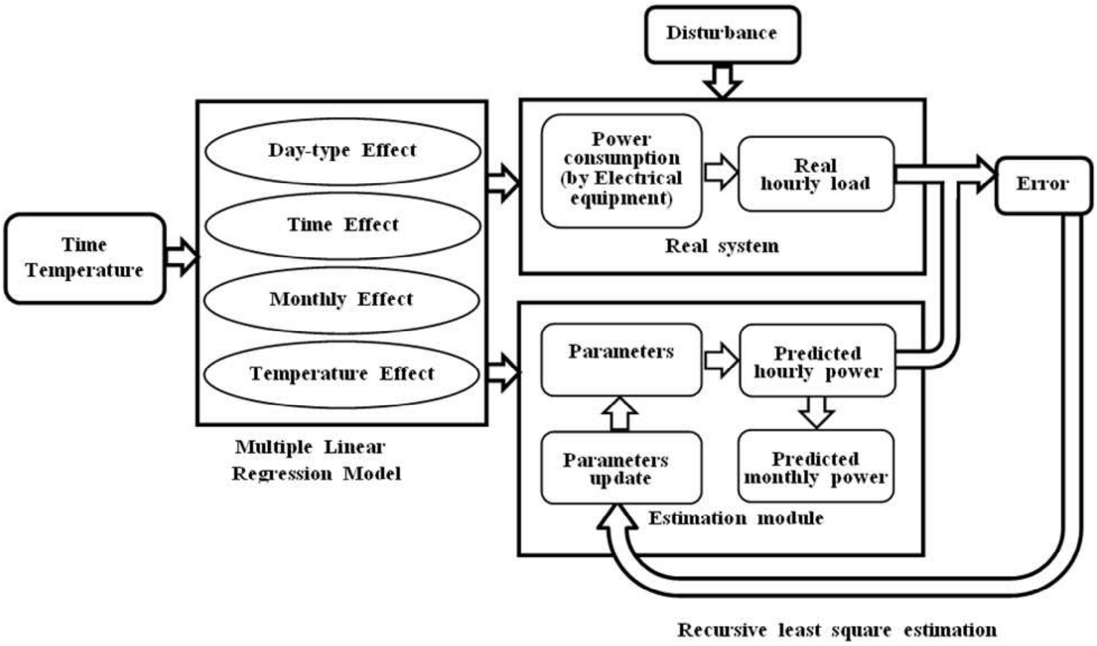

Fig. 1. Scheme of RLS estimation in forecasting

Table 1. Structure of the parameter settings

Layer	Parameters		
1	Days Type (4 sets)		
2	24 Hours(24 sets)		
3	Constant term (1 parameter)	Months (12 parameters)	Temperature (1 parameter)

For each subset, 14 parameters are classified. β_0 , $\beta_1 \sim \beta_{12}$, β_{13} respectively present parameters for constant term, 12 monthly effects and temperature. Predicted hourly load will be expressed using these parameters [12].

3.2 RLS estimation employed in load forecasting

The estimation of the parameters $\beta_i\left(i = 0,1, \ldots ,k\right)$ in MLR model is essential to the accuracy of the forecasting results [9]. To make use of the advantage of smart IEDs, RLS estimation is employed for the parameter estimation and updating. RLS, just as its name implies, is supposed to recursively find the parameters that minimize the sum of weighted least squares of the errors [13, 14]. The certain forgetting factor is given to each of the equations to assure that the newer data gets more weight.

The scheme of the RLS estimation applied on the MLR model with the parameter setting discussed in the last part is as shown in Fig. 1. With smart IEDs, the input signals to make a new equation added to the equation set can be obtained every hour. RLS estimation updates the parameters recursively every hour. Hence the optimal forecasting up to then is always assured.

3.3 Monthly factors differing from year to year

If a second year is so common that it is generally alike with the previous year in load consumption amount and composition, there will be a strong possibility that the load forecasting for the second year is accurate enough from the first day for each month. Because the initial parameters inherited from the previous year are in fact close to the final optimal solution this year. When some modest fluctuations take place, as what happens commonly in real life, forecast error is also not so large and it will decrease quickly by RLS estimation. But for some years, considering the actual conditions maybe the weather is warmer or cooler which brings about a higher consumption of electricity. Or maybe some events or policy changes take place and bring electricity demand change to some or all of the months in one year. These potential changes always augment or reduce the load by a certain percentage during the whole month. If we know how much this year changes from the previous year for the first several days of this month, we can adjust the forecasting on the assumption that the remaining days have the same change tendency.

For a certain month, this algorithm proposes to get the error between the real load and the load calculated by using the previous-year final parameters, and then use this error to adjust the original forecasting result this year. Because the original forecasting tracking ability is turning to be good enough as time passes by, the adjustment should be multiplied by a forgetting factor at the same time.

After doing the adjustment to certain months having significant changes, the forecasting will be improved observably. The final forecasting algorithm is able to track the real load profile very well.

4. Case Study

The MLR model and the forecasting algorithm using RLS estimation have been expounded previously. Two simulative cases are studied to verify the accuracy of the algorithm in this section. Display screens can possibly be utilized to show how well this approach can work.

4.1 Performance of the algorithm

The algorithm sets all the parameters to zero initially and then recursively gives the parameters that minimize the sum of weighted least squares of the errors every hour. If an apparent change appears in a second year, the mechanism to adjust the forecasting results based on the estimation of the previous year will be activated.

The first case is set in January, 2011. Random disturbance is involved as noise. Real hourly load is obtained from smart IEDs. Real monthly load is assumed to be known from the beginning for evaluating the algorithm. The real loads and forecasting results at 12:00 (24-hour format) on weekdays (only the weekdays from Tuesday to Friday) are recorded to make the profiles. The profiles of hourly and monthly load forecasting with disturbance are shown in Fig. 2 and Fig. 3.

In Fig. 2, the first point is recorded at 12:00 (24-hour format) on the first weekday. The predicted value is far away from the real load and the error is very large at that time. Through estimation for several days, the forecasting is improved and becomes good enough. After then the insignificant errors in the forecasting are mainly due to the disturbance from the real load, this implies that the algorithm is incapable of tracking the noise. In Fig. 3, there is also a large error between the estimation and real load at first. As time passes by, the forecasting becomes better and better. The forecasting error goes to almost zero by the end of this month.

The second case is set in January, 2011 and January, 2012. A step change in monthly load is set to take place in 2012. Likewise, real monthly load is assumed to be known

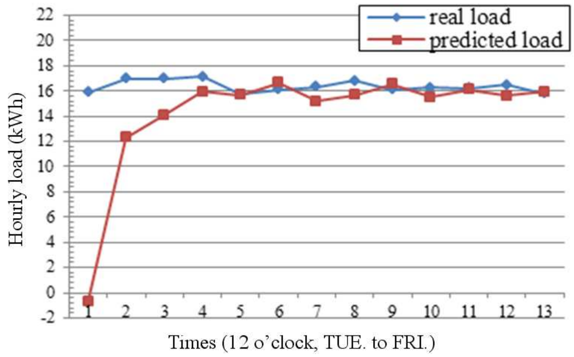

Fig. 2. Hourly load profile (1 month in 1 year)

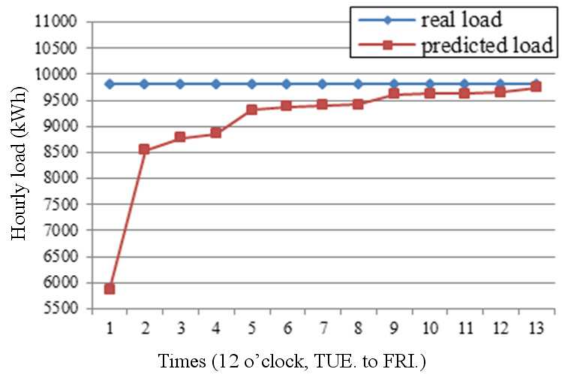

Fig. 3. Monthly load profile (1 month in 1 year)

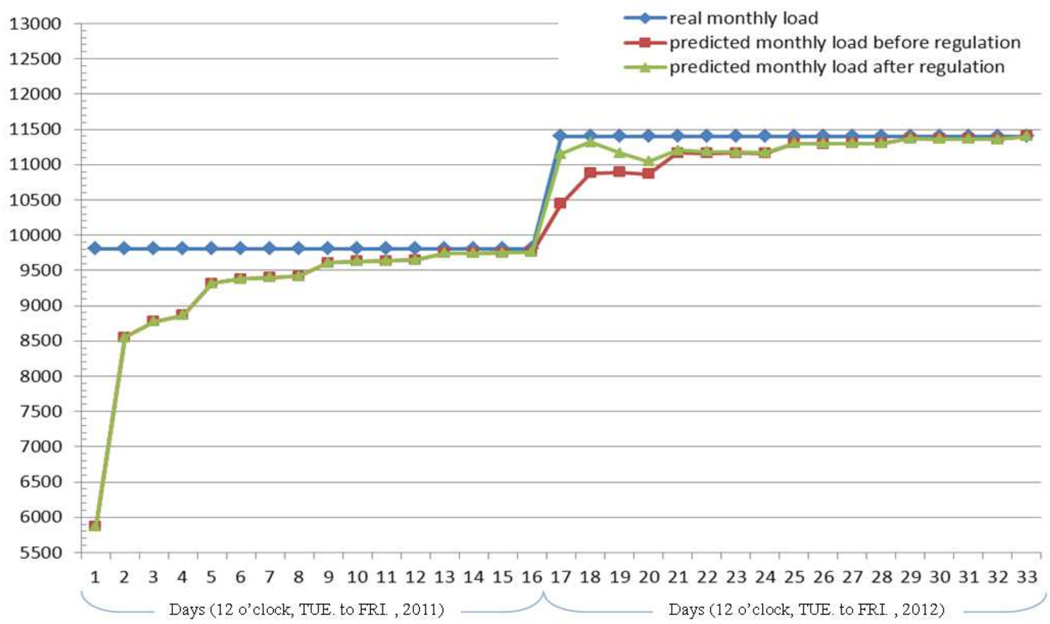

Fig. 4. Monthly load profile (with step change of monthly effect for same month in 2 years)

from the beginning and forecasting results at 12:00 (24-hour format) for weekdays (only the weekdays from Tuesday to Friday) are recorded. The profiles of the real monthly load, predicted monthly load before and after regulation are shown in Fig. 4.

In January, 2011, the forecasting has large error at first and then becomes better until it is good enough. In January, 2012, the forecasting before regulation has a sharp change as the step change appears, after that the error decreases towards zero slowly because of the tracking ability of the RLS estimation. To improve the performance when the apparent change takes place, the regulation mechanism is introduced into the forecasting. After the regulation, the forecasting for the first several days in January, 2012 is clearly improved and better than before.

From Fig. 2 and Fig. 3, profiles show the good tracking ability in hourly load and monthly load forecasting within one year. It learns the characteristics from the beginning without initial input, which means it suits any plant. In Fig. 4, a step change is given to real load in the second year. Due to the step change in real load, there will be a large forecasting error during the first few days. In this case we introduced the regulation mechanism to the algorithm. From the profile it is clear that the forecasting is improved and the sharp error is reduced to a reasonable small range after regulation. And the error tends to be around zero as time passes by because of the contribution of RLS estimation. In conclusion, the algorithm is simple, fast and accurate enough.

4.2 Applications of the algorithm

At the moment, what we have in the factories and plants are mostly the devices that give the measured value while what we need is something can dynamically provide much more information. Applying this algorithm on smart IEDs will offer a simple and accurate way to different questions in load consumption and economic evaluation. Because based on the forecasting results, IED can give recommendation on load consumption and calculate the electricity cost, etc.

In this paper, display screens are designed to show how the smart IEDs communicate data visually. On the designed display screen, real consumed load up to then is displayed at the left side, so are the predicted monthly load and cost. The right side shows the system state such as normal, warning and breach according to contract. For example, 8000kWh is set as a load consumption limit in a contract. The price is 150 Won per kWh below the limit. If the contract is breached, the price is increased to 200 Won per kWh and the company will be imposed extra penalty of 100 000 Won. Three conditions are displayed in the following three screens, which are normal, warning and breach state, respectively.

In Fig. 5, the operation is normal under contract. The predicted monthly load is 7499.70 kWh, less than the limit of 8000 kWh.

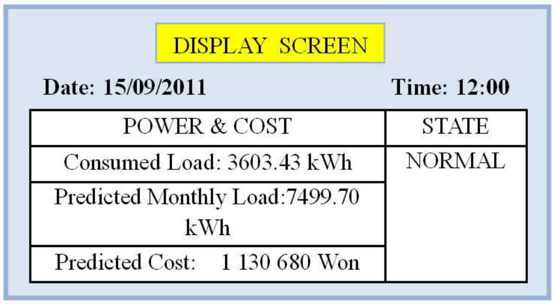

Fig. 5. Designed screen with system under normal state

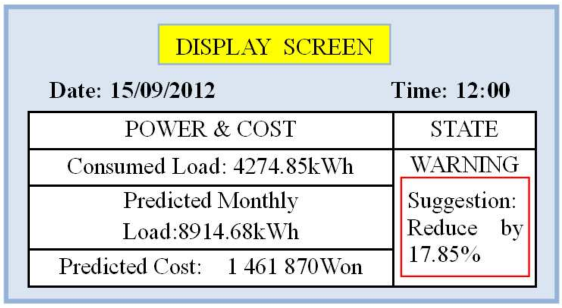

Fig. 6. Designed screen with system under warning state

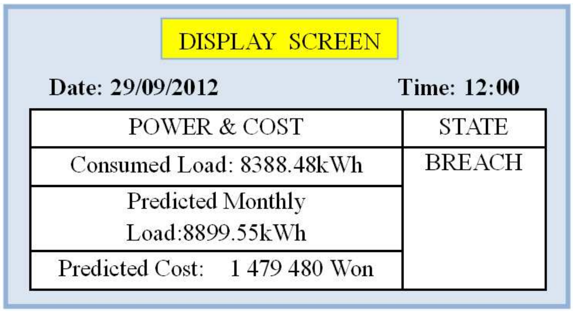

Fig. 7. Designed screen with system under breach state

In Fig. 6, the forecasting result shows that the predicted monthly load 8914.68kWh will exceed the limit. The operation state then has a danger to breach the contract. A warning is given and a recommendation of how much load should be reduced in the following days is given along. The predicted cost here includes the possible penalty in case that the recommendation is not adopted.

In Fig. 7, the consumed load by then has already exceeded the limit in the contract. Definitely the contract has been breached. If the system goes on operating like this, the predicted cost will be 1 479 480 Won including penalty.

In this way, the information that people are concerned with can be sent out, including prediction and analysis results besides the traditional measuring values like consumed load, time and date. All of them are displayed on screens visually together, which is very convenient in practice.

5. Conclusion

Load forecasting plays an essential role in electrical industry, as they provide the basis for making decisions in power system planning and operation. The studies on smart IEDs prompt the development of forecasting techniques and diversified application.

Different forecasting approaches are briefly introduced in section 2.1. Prior to explaining the algorithm, the advantages of this algorithm and the meanings of the application method are described particularly in section 2.2: the IEDs are simple and cheap; the algorithm for the IEDs is fast and accurate; forecasting performance is improved; analysis is made at the same time and output visually.

In section 3, the algorithm on IEDs is explained in detail. With the data from smart IEDs expediently, the algorithm gives the best forecasting results on its own every hour. It learns the load characteristics by the time, with no need of the initial input. When some yearly or monthly changes take place, the algorithm is able to do regulation accordingly.

In case study, tests demonstrate the robustness and accuracy of the algorithm at first. Applications of the algorithm reflect the advantages and meanings claimed in section 2, through the examples of designed screen.

By making better use of the smart capabilities of IEDs, not only can load forecasting be improved, but also many other smart functions can be achieved in similar way in practice. The application method of this algorithm reveals a broad prospect of applications capitalizing on smart information from IEDs.

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