Household Electricity Consumption Prediction: Comparing Neural Fitting Optimization Algorithms

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***Abstract*—This work compares neural fitting optimization algorithms for predicting household electricity consumption. Leveraging gas consumption, income, season, and occupants as inputs, Bayesian Regularization, Scaled Conjugate Gradient, and Levenberg-Marquardt were assessed. The findings illuminate the most effective algorithm for forecasting accurate and efficient electricity consumption.**

***Index Terms*—Consumer electronics, neural network, Optimization, prediction,**

I. Introduction

Forecasting household electricity consumption is vital for energy management and sustainability. Despite smart meters and the Internet of Things (IoT) advancements, accuracy remains challenging due to diverse influencing factors. This work proposes comparing neural fitting optimization algorithms to enhance prediction accuracy. Leveraging neural networks, the aim is to optimize fitting processes for more efficient energy management [1].

Comparing various neural fitting optimization algorithms allows us to identify the most suitable techniques for handling complex energy data. The study seeks to enhance energy efficiency, reduce prediction errors, and provide a basis for selecting optimization algorithms for consumer electricity consumption prediction [2].

II. Methodology

As indicated in Fig. 1, the prediction fitting model evaluated using MATLAB R2019b student version was set as *fitnet* with 3 inputs, 10 hidden layers, and 1 output layer.

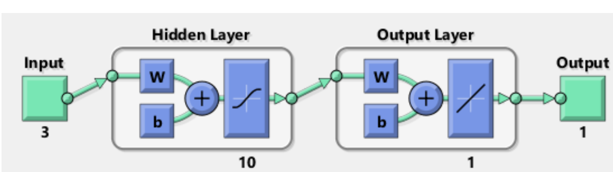

Fig. 1. Predictive Network Architecture showing the number of neurons in the fitting network's hidden layer. The fitting neural network is defined as fitnet for the Domestic Electricity Consumption (output) based on three (3) input variables.

The three inputs are (i) the Gas consumption alternative of the consumer, (ii) the number of occupants in the household, and (iii) the income of the principal occupant being responsible for the payment of the electricity consumption bill. On the other hand, the output is the prediction of the electricity consumption per month.

The data was collected from volunteer households in Gumi, South Korea between 2020 to 2024. The 48 months of data comprised variables such as electricity consumed, gas consumed, number of occupants in the household, and income variation of the principal during the period under review.

Using MATLAB *nftool*, the training, validation, and testing data were randomly divided as 70%, 15%, and 15% respectively. The three algorithms compared were Levenberg-Marquardt, Bayesian regularization, and Scaled conjugate gradient as available in the MATLAB Neural Network fit tool.

Justification of the Input variables [3]:

1) Gas consumption: Gas consumption can be correlated with electricity usage, especially if gas is used for heating, cooking, or hot water.
2) Household income: Household income can indirectly affect electricity consumption by influencing the affordability of energy-efficient appliances, home insulation upgrades, or renewable energy investments.
3) Season of the year: Seasonal variations in weather conditions can significantly impact electricity consumption, especially for heating and cooling purposes. Including the season as an input factor allows the model to capture seasonal trends and adjust predictions accordingly.
4) Number of occupants: The number of occupants in a household can affect electricity usage through factors such as the frequency of appliance usage, lighting needs, and hot water demand. More occupants generate higher electricity consumption, although the relationship may not be linear.

III. Performance Evaluation

Performance evaluation metrics are (i) mean squared error (MSE) showing the average squared difference between outputs and targets. Lower values are better. (ii) regression R values quantify the correlation between outputs and targets. A perfect correlation is denoted by an R of 1, indicating a close relationship, while an R of 0 signifies a random relationship. The summary is presented in Fig. 2 and Fig. 3.

Bayesian Regularization: This method often demands increased computational time yet offers robust generalization

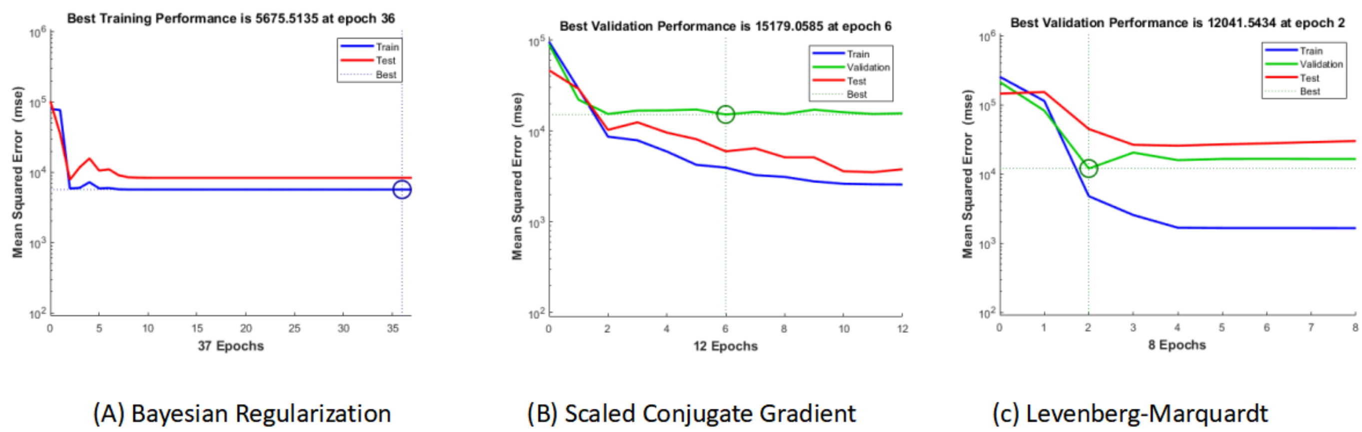

Fig. 2. Comparing the impact of Fitting optimization algorithms on the electricity consumption Prediction accuracy.

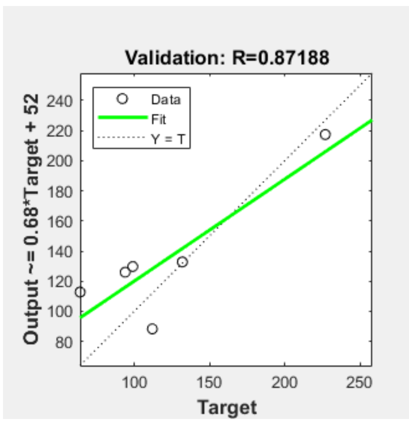

Fig. 3. Visualization of the Prediction Fit (green fit line) of the Bayesian Regularization Algorithm. Note that the R = 87%

capabilities, particularly suitable for challenging, limited, or noisy datasets. The training process concludes upon achieving adaptive weight minimization, facilitating regularization. The Bayesian regularization algorithm minimizes the following objective function: $E(\omega) = 1/2 \sum_{i=1}^{N} (t_i - y(x_i, \omega))^2 + \lambda/2 \parallel \omega \parallel^2$ where ω represents the weights of the neural network, t_i is the target output, $y(x_i, \omega)$ is the predicted output, N is the number of training samples, and λ is the regularization parameter.

Scaled Conjugate Gradient This algorithm demands reduced memory usage. Training ceases automatically when further generalization improvements are halted, discerned through a rise in the mean square error of the validation samples. It is an iterative optimization method that updates the weights based on the gradients of the error function. The weight update equation is as follows: $\omega^{(k+1)} = \omega^{(k)} + \alpha_k \rho^{(k)}$

where $\omega^{(k)}$ is the weight vector at iteration K, α_k is the step size, and $\rho^{(k)}$ is the search direction obtained through conjugate gradient iterations.

Levenberg-Marquardt: This algorithm tends to consume more memory resources while demanding less computational time. Training halts automatically when generalization ceases to improve, as signaled by an uptick in the mean square error of the validation samples. It minimizes the sum of squares error function using a combination of gradient descent and Gauss-Newton methods. The weight update equation is: $\omega^{(k+1)} = \omega^{(k)} - [J^T J + \lambda I]^{-1} J^T \varepsilon$ where J is the Jacobian matrix, ε is the error vector, λ is the damping parameter, and I is the identity matrix. More details on these fitting algorithms can be seen in [2].

IV. Conclusion

This work used gas consumption, household income, season of the year, and number of occupants as input factors to predict electricity consumption. These factors influence energy usage patterns in households. Nevertheless, the efficacy of these predictors may fluctuate based on the unique context and dataset characteristics. Three optimization algorithms were investigated with Bayesian regularization outperforming scaled conjugate gradient, and Levenberg-Marquardt based on the independently collected data in Gumi, South Korea.

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