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Short-term Load Forecast of Integrated Energy System in Multi-station Fusion Scenario Based on Robust Model

Shanbnam Daparvar*

LJMU, Dept Elect & Elect Engn Comp Sci, Liverpool L3 3AF, Merseyside, England

**corresponding author*

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Abstract: Integrated Energy System (IES) is the development direction of energy consumption in the future. Through the coordinated design and planning of energy systems such as electricity, cooling, and heat, energy utilization can be effectively improved and the development of renewable energy units can be promoted. The purpose of this paper is to predict the short-term load of an integrated energy system in a multi-station fusion scenario based on a robust model. Convex Quadratic Loss Functions to Suppress Negative Effects of Outliers Non-convex Quadratic Loss Functions limit the maximum loss penalty for outliers. First, the loss function is expressed as the difference of two quadratic functions, and the corresponding robust model is built. Second, the optimization problem corresponding to the robust model is transformed into a system of linear equations using the CCCP technique and KKT conditions. Finally, the prediction accuracy of RLS-SVR model, SVR model and BP neural network model is compared. The results show that for cooling load prediction, the average relative error of the prediction model constructed by RLS-SVR is 1.05% and 1.12%, which is lower than other models.

1. Introduction

Energy is the basic substance for the survival and development of human society, which is related to the foundation and economic life of the country, and plays an important strategic role in the rapid development of the country. Energy is a function of society, and with the development of renewal, the dependence on energy is getting stronger and stronger [1]. However, at present, with the rapid development of social production, causing traditional fossil energy to face problems such as excessive abuse and reduction of reserves; and traditional energy systems mainly rely on fossil fuels, high energy consumption brings many environmental problems, especially climate In addition, in the current traditional energy supply areas, various energy systems are not related to each other, resulting in ineffective and waste of energy [2].

Due to the differences in the level of science and technology and national conditions, the starting time and focus of research on robust models are different in countries around the world. Albrecht S proposed a powerful MPC idea that could add uncertainty to existing knowledge about attacks. To this end, a new method is proposed to detect unknown attacks in inefficient systems, combined with a multi-level robust MPC system. Numerous case studies of non-distributed systems demonstrate the potential of this approach [3]. Kobayashi Y developed a robust model to predict the adsorption behavior of U(VI) on ferrihydrite under several environmental conditions. The surface U(VI) particles that dominate ferrihydrite are usually internal twins. However, previous complex surface models were unable to predict U(VI) visibility due to the lack of sufficient macroscopic adsorption data records to account for complex surface reactions. U(VI) adsorption data at 10 nM U(VI) concentration were obtained in NaNO3 solution with/without CO2 air at high pH, ionic energy and concentration. Newly determined adsorption data from direct and indirect luminescence measurements of U(VI) hydroxyl groups were used to determine the stoichiometric and equilibrium parameters of adsorbed U(VI) reactivity. The model can also predict properties under multiple solution conditions based on previous optical observations [4]. Gilanifar M proposes an enhanced MTL algorithm for Bayesian Spatiotemporal Gaussian Process (BSGP) models to characterize groups of distinct regions. It assumes the impact of environmental and traffic conditions on fires to improve short-term load forecasting. Additionally, a Low Waste Disposal Model (LRDM) is presented to demonstrate the effectiveness of the approach using real-time case studies from two residential companies in Tallahassee, Florida. Compared to other MTL systems, the proposed method goes beyond performing image prediction and compliance enforcement to provide knowledge transfer between communities [5]. The methods used in the above literature are all based on historical load data, and the prediction error is relatively large for the actual site load forecasting.

It is of great significance to build an integrated power system. Accurate load forecasting has a positive impact on the overall design, operation, control and utilization of power systems, and is a key technology to promote the development of energy products. However, there are few studies on load system capacity prediction. On the one hand, the research of integrated energy system is also in the developing stage. On the other hand, the energy composition of the integrated power system is more diverse. There is a mixed relationship between different burdens. The problem presented to us is that it is difficult to find a breakthrough in the characteristic load forecasting.

2. Research on Short-term Load Forecasting of Integrated Energy System in Multi-station Fusion Scenario Based on Robust Model

2.1. Robust Model

(1) Model uncertainty description

Uncertainty dynamic models are the basis of robust control theory. Some real parameter values in these uncertainty models cannot be accurately described, but the changing laws of these parameter values can be known [6-7]. The traditional robust controller is designed based on a linear dynamic model, which describes the dynamic process along a nominal steady-state operating point, and the uncertain part of the model is supplemented by the uncertain model parameters, which fully explains the standard. Call the difference between a linear model and a real process. These uncertain dynamic models are often referred to as robust models or uncertain state-space models [8-9].

(2) Linear matrix inequality

Linear matrix inequalities play a key role in the framework of robust control theory. It is a very efficient computational tool in dealing with a variety of matrix-variable problems that arise in systems and control theory, using analytical or frequency-domain-based methods to transform the problem into a linear (or affine) finite set matrix inequality constraints for convex optimization problems [10-11]. Benefiting from the progress of interior point optimization problems, convex optimization problems including LMI are now more tractable, which are characterized by high accuracy and high efficiency [12-13].

2.2. Primitive Space Support Vector Machine

The standard support vector machine model is a quadratic programming problem with inequality constraints. When introducing support vector machines, most literatures usually solve the dual optimization problem by introducing a function to get the optimization problem in the dual space. The constraints in the dual problem are easier to deal with in form and the nonlinear mapping in the dual problem can be implicitly represented by a kernel function, so that the kernel function or kernel matrix can be directly used in the solution to participate in the operation [14-15]. In recent years, with the deepening of the research on the original space optimization problem, a large number of literatures point out that the support vector machine can directly solve the original space optimization problem. The corresponding optimization problem must be transformed into an unconstrained optimization. This problem is solved by classical unconstrained optimization algorithms such as Newton's method, vehicle joint gradient method, etc. [16-17].

2.3. Short-term Forecast of Multiple Loads in the Integrated Energy System

Therefore, before using the model for prediction, the original data should be analyzed in detail, and the information contained in the data should be fully explored suitable input vector. Moreover, there are many influencing factors of multiple loads in the integrated energy system, which have a great influence on the load fluctuation. Therefore, it is necessary to do a correlation analysis between the load and the influencing factors, and select the appropriate influencing factors. In the selection of prediction models, a model with strong nonlinear mapping ability should also be selected for prediction [18].

3. Model Construction for Investigation of Short-term Load Forecasting of Integrated Energy Systems in Multi-station Integration Scenarios

3.1. Data Preprocessing

Before load forecasting, it is necessary to preprocess the sample data, including data normalization and correction of abnormal data. Due to the interference of the data acquisition device, some abnormal values are usually generated. These dimension values are significantly different from normal values. If used to model a model without features, it will negatively affect the predictive model, thereby reducing the accuracy of the prediction. Due to the different dimensions and value ranges of different input features, directly using the original data for model training may have poor prediction effect. Therefore, it is necessary to normalize the features in the data set before making predictions.

3.2. The Steps of Ies Multi-load Short-term Forecasting

The forecasting model is selected first, and the input and output vectors are determined according to the characteristic analysis and actual demand. The general steps are shown in Figure 1.

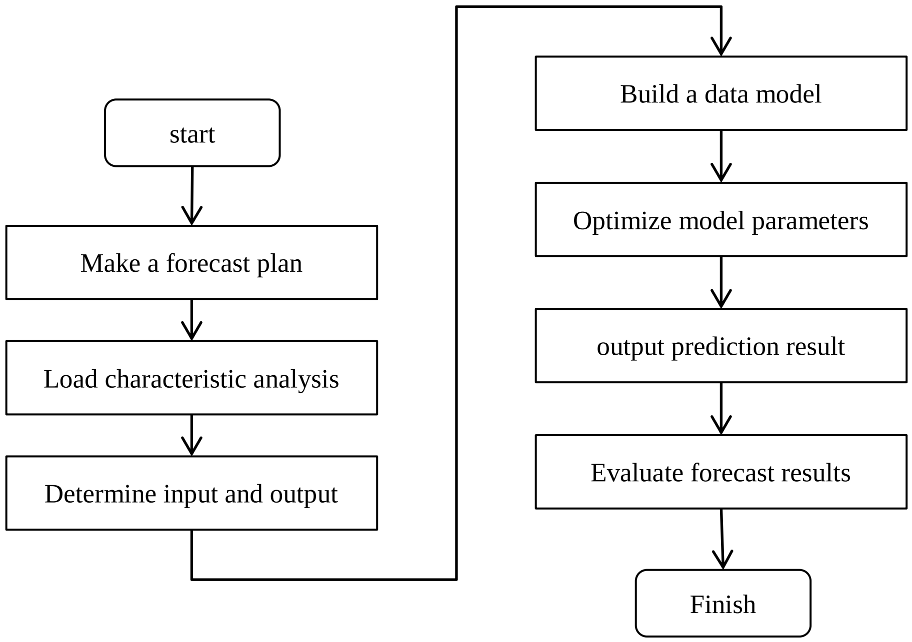

Figure 1. IES multi-load short-term forecasting steps

3.3. RLS-SVR Solution and Algorithm Implementation

Based on the non-convex quadratic loss function, the following robust model is established:

$$\min_{\omega,b} L = \frac{1}{2}\|\omega\|^2 + \frac{C}{2}\sum_{i=1}^{n} l_g(r_i) \tag{1}$$

in: $r_i = y_i - f(x_i)$. Because it is non-convex, it is impossible to directly solve the optimization problem with the classical convex optimization method. (1) The non-optimization problem is transformed into a series of convex optimization problems with the help of CCCP criterion.

Finally, according to the KKT condition, the regression decision function is obtained:

$$f^{(t+1)}(x) = \sum_{i=1}^{n}(\alpha_i - s_i^{(t)})k(x_i, x) + b \tag{2}$$

4. Analysis and Research in Multi-station Fusion Scenario Based on Robust Model

4.1. Comparison of Prediction Accuracy

In order to more intuitively evaluate the advantages and disadvantages of the three models, the average relative error, the maximum relative error and the root mean square difference are used as the measurement standards to predict the multivariate load in the next three days. , Figure 2 is the cooling load prediction error. EMAPE is the mean relative error, EMAX is the maximum relative error, and RMSE is the root mean square error. M1 is the RLS-SVR model, M2 is the SVR model, and M3 is the BP neural network model.

Table 1. Electric load prediction error

Date type	Emape(%)			Emax(%)			Rmse(%)		
	M1	M2	M3	M1	M2	M3	M1	M2	M3
Working day	1.04	1.23	1.56	2.25	3.12	3.64	0.44	0.54	0.87
Off day	1.13	1.57	1.89	2.42	3.12	4.21	0.34	0.45	0.56

As shown in Table 1, for power load forecasting, the average relative errors of the RLS-SVR forecasting model are 1.04% and 1.13%, the maximum relative errors are 2.25% and 2.42%.

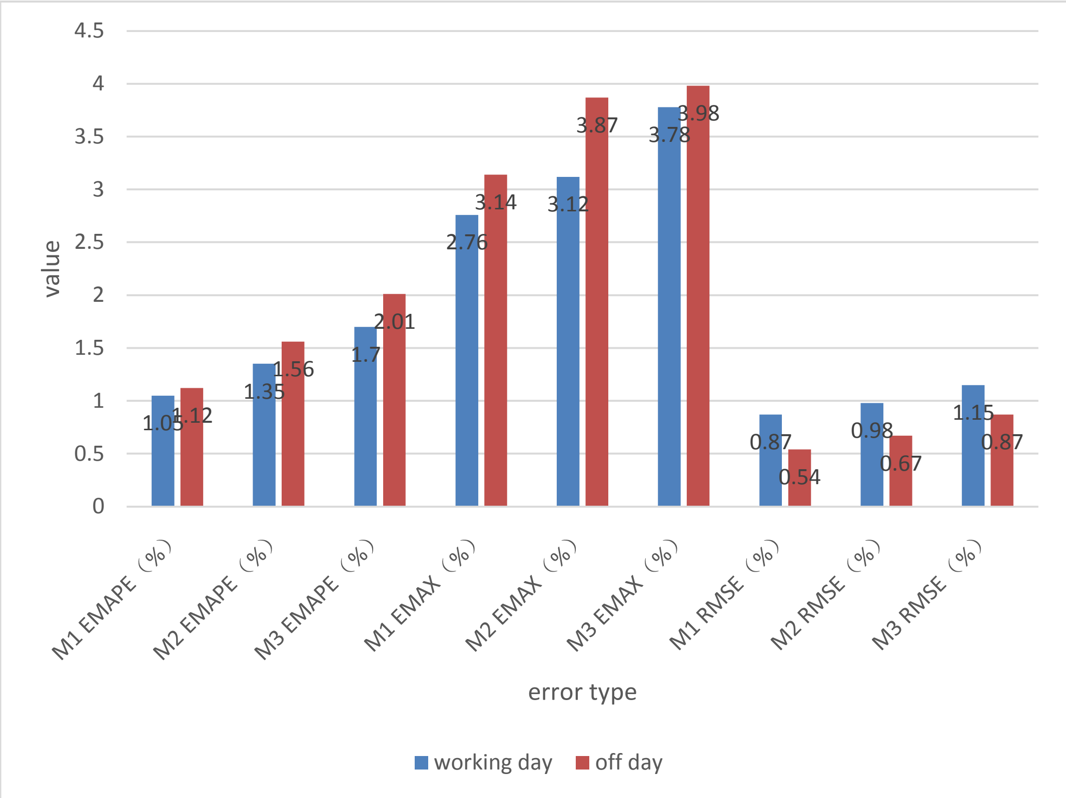

Figure 2. Cooling load prediction error

As can be seen from Figure 2, for the prediction of cooling load, the average relative errors of the prediction models constructed by RLS-SVR are 1.05% and 1.12%, the maximum relative errors are 2.76% and 3.14%. Through the comparison of the above data, it is further proved that the RLS-SVR model has certain practical value for the high precision of summer multivariate load forecasting.

4.2. Stability Test of RLS-SVR Model

In addition, in order to further test the stability of the RLS-SVR model, the electric load and cooling load in one week were predicted respectively, and the average relative error EMAPE, the maximum relative error EMAX and the root mean square error RMSE were used as the evaluation criteria. The specific analysis results are shown in the table 2.

Table 2. One week electric load forecast error

Date	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	Average
Emape(%)	1.21	1.17	1.01	1.15	1.16	1.17	1.21	1.15
Emax(%)	2.87	2.64	2.54	2.41	2.63	2.74	2.52	2.62
Rmse/kw	0.61	0.59	0.54	0.48	0.54	0.37	0.34	0.50

It can be seen from Table 2 that for the electrical load, the average prediction error within a week varies from 1.01% to 1.21%, the maximum prediction error varies from 2.41% to 2.87%. Changes in the range of ~0.54kW, the average of the three above are 1.15%, 2.62% and 0.50kW in one week, respectively.

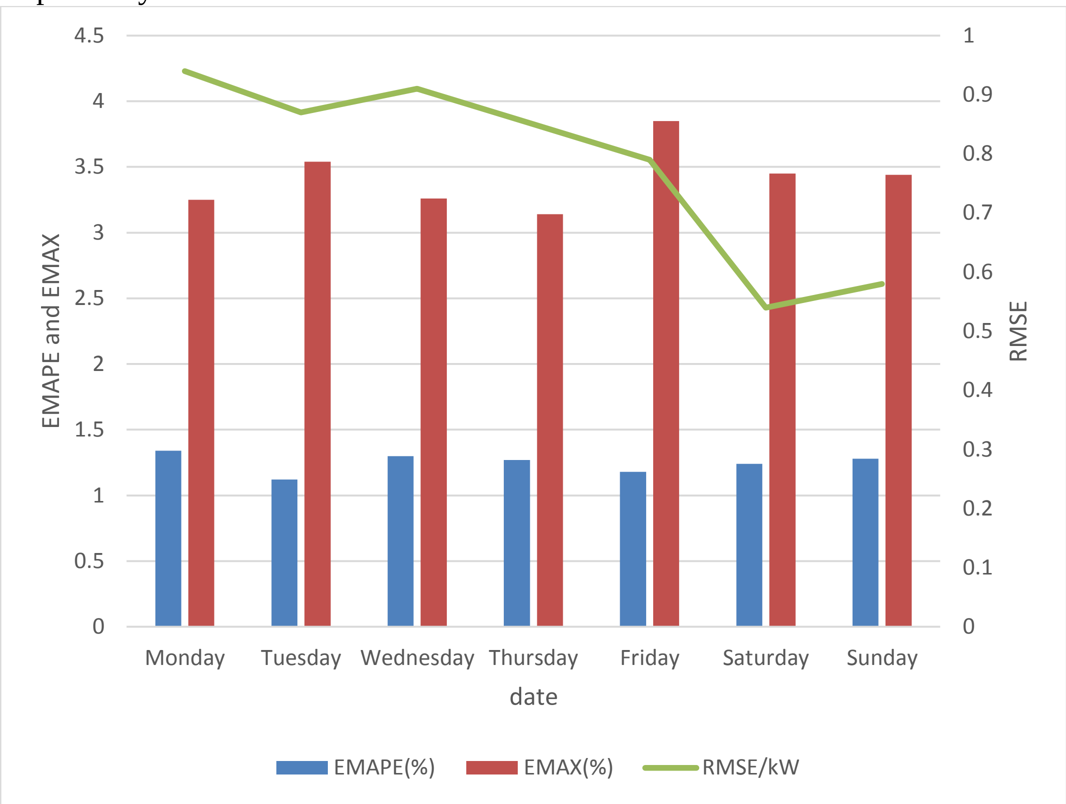

Figure 3. One-week cooling load forecast error

As can be seen from Figure 3, for the cooling load, the average prediction error within a week varies from 1.12% to 1.34%, the maximum prediction error varies from 3.14% to 3.85%. Changes in the range of ~0.94kW, and the average values of the above three in one week are 1.25%, 3.42% and 0.78kW respectively; through the above analysis, it can be seen that the RLS-SVR model proposed in this paper has better performance in predicting the multiple loads in the next week. good stability.

5.Conclusion

This paper proposes a robust model-based short-term load forecasting in the multi-station fusion scenario. From the perspective of power management, many loads in the future can be effectively predicted by accumulating and analyzing numerous loads of an integrated power system, and by modeling and learning the internal relationships and external factors of loads. Subsequent system planning and scheduling are of great significance.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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