Fuzzy Modeling Technique with PSO Algorithm for Short-Term Load Forecasting

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Abstract. This paper proposes a new modeling approach for building TSK models for short-term load forecasting (STLF). The approach is a two-stage model building technique, where both premise and consequent identification are simultaneously performed. The fuzzy C-regression method (FCRM) is employed at stage-1 to identify the structure of the model. The resulting model is reduced in complexity by selection of the proper model inputs which are achieved using a Particle Swarm Optimization algorithm (PSO) based selection mechanism at stage-2. To obtain simple and efficient models we employ two descriptions for the load curves (LC's), namely, the feature description for the premise part and the cubic B-spline curve for the consequent part of the rules. The proposed model is tested using practical data, while load forecasts with satisfying accuracy are reported.

1 Introduction

Short-term load forecasting (STLF) plays an important role in power systems. Accurate short-term load forecasting has a significant influence on the operational efficiency of a power system, such as unit commitment, and interchange evaluation [1-5, 7-10].

The PSO algorithm [11] is a new evolutionary computation stochastic technique. In this paper, a selection mechanism is suggested based on PSO algorithms. This tool provides a means to selecting the past daily LC's that should be considered in the premise part of the model obtained at the previous stage. Since the selection of the most significant past inputs is of great importance in STLF, PSO helps establishing a correct mapping between the past LC's and the LC of the day to be forecasted. At this stage we obtain a reduced fuzzy model having a simple structure and small number of parameters. The simplicity and flexibility of PSO helps not only to simplify the implementation but also to combine with any kinds of estimators easily; in addition, it reduces the time cost of model selection a lot and has superior performance.

In this paper, the entire load curve (LC) of a day is considered as a unique load datum. Our intention is to create a fuzzy model mapping the LC's of past input days to the LC of the day to be predicted. The paper tackles all problems related to the structure and parameter identification of the model with TSK Fuzzy modeling and PSO.

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2 Model Identification

The model building method is a two-stage procedure, dealing simultaneously, with two important issues relevant to fuzzy modeling, namely, structure identification, input selection.

Stage-1: At this stage the structure identification problem is tackled. It comprises the following two tasks that are related to each other: (a) partitioning the input space, that is, determining the fuzzy sets of the model inputs (premise identification), and (b) calculating the parameters of the consequent regression models (consequent identification). The modeling algorithm suggested in this paper is based on the fuzzy C-regression model (FCRM) method. The FCRM is a modified version of the FCM clustering algorithm, FCRM develops clusters whose prototypes are regression models, hyper-planes etc. Hence, FCRM method suits the type of fuzzy models considered here. In our case, the cluster prototypes are LC-shaped CBS curves. The identification objective is to separate the daily load data into c fuzzy clusters and determine the LC-shaped prototypes. The resulting fuzzy partition is then assigned to the premise variables, which permits defining the premise fuzzy sets. Note that each cluster corresponds to a fuzzy rule.

Stage-2: Based on the initial fuzzy model generated at stage-1 and a candidate input set, a PSO is developed in this stage. The goal of PSO is to select a small subset comprising the most significant model inputs. At the end of this stage we obtain a reduced fuzzy model with simple structure and small number of parameters.

3 Load Forecasting Fuzzy Models

A. Framework of the fuzzy model

The load of next day is output of the model and the corresponding load influencing factors such as history load data, temperature information are the input data of the model. The training data is supplied by history database. The final target is to find an enough simple and accurate mapping function from influencing factors to future load with a good generalization.

B. Definitions and notation

The suggested method is employed to develop TSK fuzzy models for the forecasting of the next day's hourly loads of the Chinese Henan Interconnected Power System. To obtain an economical forecast model with reduced parameter complexity, we considered four day types: the Weekday (Tuesday, Wednesday, Thursday, Friday), Saturday, Sunday and Monday. So fuzzy models are generated for the forecasting of the whole week. For each day type a separate fuzzy model is generated to perform hourly based load forecasting for the time period of interest.

For the identification of a fuzzy model we employ two data sets, the training and the checking set. The training data set contains historical load and weather data from a time period of six months, starting from 1st May and ending at 31st October and is used to develop the fuzzy models. The forecasting capabilities of the obtained models are evaluated by means of the checking data set that contains load and weather data of the year 2001.

4 Test Results and Conclusions

The fuzzy models obtained by the suggested method are employed for STLF of the Chinese Henan interconnected power system. Table 1 summarizes the four day types' forecast APE and weekly forecast APE. The suggested modeling method generated fuzzy models with three or four clusters (rules). In the great majority of cases, the CBS curves are described by eight control points with the interior knots set at the time instants where the load extremals occur. The forecasting results on May 23 2001 are shown in Table 2.

Table 1. Simulation results for the fuzzy models developed by our method: Four day types' forecast APE and weekly forecast APE

Day Type	Monday	Weekday	Saturday	Sunday	Week
APE(%)	2.01	2.26	1.95	2.32	2.14

Table 2. The forecasting results on May 23 2001

Hour	Actual load /MW	forecasting load /MW	Error/%
1	5051	5125.9	1.48
2	4905	5123.0	4.44
3	4883	4899.9	0.35
4	4884	4712.1	-3.52
5	4781	4758.7	-0.47
6	4988	5012.0	0.48
7	5314	5388.0	1.39
8	5677	5802.4	2.21
9	6425	6171.0	-3.95
10	6591	6409.8	-2.75
11	6646	6434.6	-3.18
12	6581	6420.1	-2.44
13	6419	6377.2	-0.65
14	6296	6221.0	-1.19
15	6238	6047.1	-3.06
16	6105	6296.1	3.13
17	6193	6408.8	3.48
18	6982	6925.9	-0.80
19	7725	7588.1	-1.77
20	7862	7636.3	-2.87
21	7628	7305.8	-4.22
22	7187	7011.1	-2.45
23	6168	6361.5	3.14
24	5482	5266.1	-3.94
APE(%)			1.98

From the above discussion, the resulting model is reduced in complexity by discarding the unnecessary input variable and is optimized using a richer training data set. This method is used to generate fuzzy models for the forecasting of the Chinese power system. The simulation results demonstrate the effectiveness of the suggested method.

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