the tree to control overfitting and bring about high performance [13] - [14]. The algorithm uses the same input data set of models.

3.4 Neural Network Models

We use Feedforward Neural Network models with the input variables and training data set as above. A-hidden-layer network architecture with class size of 10 and Sigmoid activation function is used. At the same time, the usual Neural network with 3-hidden-layer network architecture, in which: the first hidden layer has a size of 10; The second hidden layer has a size of 8 and the third hidden layer has a size of 5.

3.5 Results and analysis:

Run the forecast results for February 2018 (the month of the Lunar New Year) to assess the degree of error of the models

3.5.1 The model with input is the load of the last day, last week, last month

Processed historical data (power consumption, capacity, temperature recorded at 24 cycles - 60 minutes each) with the Standardized load Profiles (SLP) will be included in modules to build regression functions under SVR, Neural Network and Random Forest algorithms to build regression functions (Figure 6).

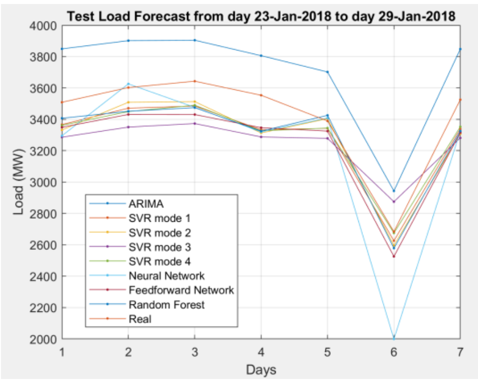

Figure 6: *Regression models test*

Table 2 - Results of checking errors of regression models

Date	Ytr	Yts1	Yts2	Yts3	Yts4	YtNN	Ytfeed	YtRF
23/1/18	9.71	4.05	5.02	6.35	4.19	6.09	4.55	2.91
24/1/18	8.30	3.65	2.61	7.00	4.25	0.65	4.76	4.19
25/1/18	7.17	4.35	3.57	7.42	4.21	4.58	5.84	4.63
26/1/18	7.10	6.20	6.77	7.48	6.39	6.58	5.82	6.44
27/1/18	9.22	1.37	0.44	3.27	1.33	0.56	1.91	1.06
28/1/18	9.68	2.16	3.28	7.12	0.32	25.51	5.89	3.93
29/1/18	9.15	5.30	6.17	6.92	4.91	5.71	5.96	5.67

We choose the regression function with the smallest error will be used as regression function for the next forecast phase (Table 2). The model Yts4 is selected to be a forecasting model.

- Forecast results for February 2018

Considering the forecast results for February of the model, we see a big difference between reality and forecasting (Figure 7). The reason is that we used the historical data of January 2018 (7-14-30 days before the forecasting date) as the input for the training model.

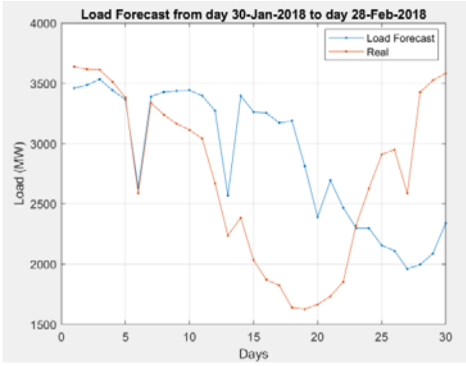

Figure 7: *Forecast results for the next 30 days*

3.5.2 SLPF - SVR combination model

Processed historical data (power consumption, capacity, temperature recorded at 24 cycles - 60 minutes each) with the Standardized load Profiles (SLP) will be included in modules to build regression functions under SVR, Neural Network and Random Forest algorithms to build regression functions

- Results of testing SVR models (Figure 8)

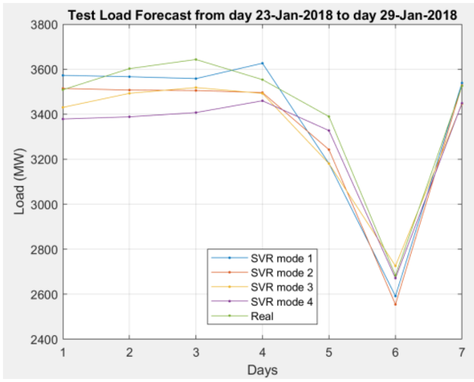

Figure 8: *SVR models test*

Table 3 - Results of checking errors of SVR models

Date	Yts1	Yts2	Yts3	Yts4
23/1/18	1.15	0.64	2.22	3.87
24/1/18	1.70	2.12	2.95	6.19
25/1/18	3.03	3.30	3.38	6.68
26/1/18	1.35	1.04	1.76	2.76
27/1/18	6.77	4.56	6.42	1.56
28/1/18	4.18	5.09	1.81	0.76
29/1/18	0.24	0.12	2.69	2.14
MAPE	2.63	2.41	3.03	3.42

- Results of testing machine learning models (Figure 9)

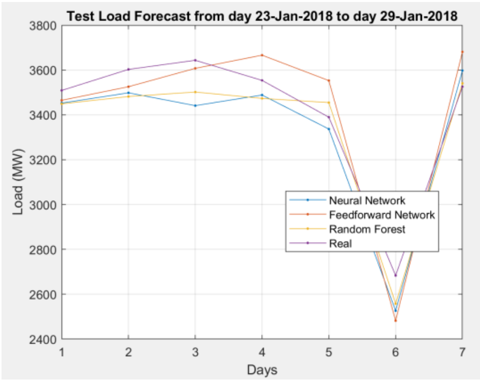

Figure 9: *Machine learning models test*

Table 4 - Results of checking errors of machine learning models

Date	YtNN	YtFeed	YtRF
23/1/18	1.25	1.61	1.70
24/1/18	2.14	2.90	3.36
25/1/18	0.99	5.55	3.89
26/1/18	3.16	1.84	2.26
27/1/18	4.81	1.56	1.92
28/1/18	7.51	5.85	4.68
29/1/18	4.41	2.05	0.43
MAPE	3.47	3.05	2.60

- Results of testing regression models (Figure 10)

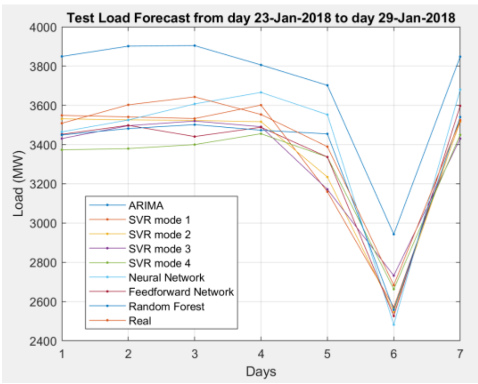

Figure 10: *Regression models test*

Table 5 - Results of checking errors of all models

Date	Ytr	Yts1	Yts2	Yts3	Yts4	YtNN	Ytfeed	YtRF
23/1/18	9.71	1.15	0.64	2.22	3.87	1.25	1.61	1.70
24/1/18	8.30	1.70	2.12	2.95	6.19	2.14	2.90	3.36
25/1/18	7.17	3.03	3.30	3.38	6.68	0.99	5.55	3.89
26/1/18	7.10	1.35	1.04	1.76	2.76	3.16	1.84	2.26
27/1/18	9.22	6.77	4.56	6.42	1.56	4.81	1.56	1.92
28/1/18	9.68	4.18	5.09	1.81	0.76	7.51	5.85	4.68
29/1/18	9.15	0.24	0.12	2.69	2.14	4.41	2.05	0.43
MAPE	8.62	2.63	**2.41**	3.03	3.42	3.47	3.05	2.60

We choose the regression function with the smallest error will be used as regression function for the next forecast phase (Table 3, 4 and 5). The model Yts2 is selected to be a forecasting model.

With the regression model selected above, combined with the SLP that has been developed for February 2018, we will have forecast results (Figure 11)

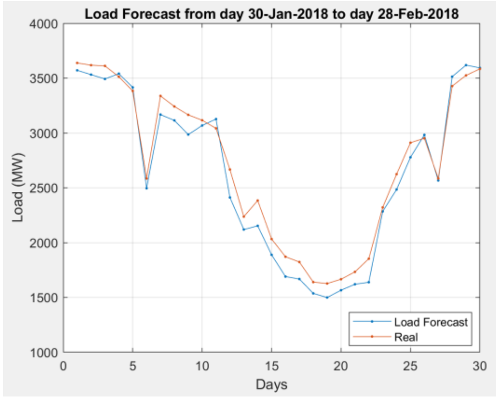

Figure 11: *Forecast results for the next 30 days*

4 Conclusion

Observe the experimental results in the forms of testing datasets (load data sets of the previous day, the previous week, the previous month and the dataset of Standardized Load Profile - SLP), we see the results of the SLP-SVR model's are closely to the actual value of February 2018, while the results of the old model are in quite large deviation.

Thus, through experimentation, we see that the use of Standardized Load Profile (SLP) as the input dataset for modules of the forecasting regression function is effective and give forecasting results with low errors. It solves the problem solve the problem of deviation between the solar and the lunar dates, especially in the months of lunar new year, as well as resolving the difference between the solar and lunar cycles.

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