Short-term Load Forecasting based on Neural network and Moving Average

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Abstract: Load forecasting is an important problem in the operation and planning of electrical power generation. To minimize the operating cost, electric supplier will use forecasted load to control the number of running generator unit. Short-term load forecasting(STLF) is for hour to hour forecasting and important to daily maintaining of power plant.

Most important factors in load forecasting includes past load history, ca lender information(weekday, weekend, holiday, season, etc.) and weather information(instant temperature, average temperature, peak temperature, wind speed, etc.). The forecaster will treat past data as a time series and many kinds of approaches have been applied on this problem.

In this paper, we use a BP networks and moving average model for STLF. Temperature factor are also discussed in detail. Best 24-hour forecasting is 3.5% error and Best 24-hour forecasting is 1.24%

Keywords: STLF, Short-term load forecasting, neural network, modular neural network

1. Introduction

Electrical load forecasting plays a central role in the operation and planning of electric power. The countrywide energy estimation, the planning of new plant, the routine maintaining and scheduling of daily electrical generation are all depended on accurate load forecasting in the future.

Due to different aim of forecasting, the load-forecasting problem can be classified in to some kinds.

Spatial forecasting is mainly about forecasting future load distribution in a special region, such as a county, a state, or the whole country.

Temporal forecasting is dealing with forecasting load for a specific supplier or collection of consumers in future hours, days, months, or even years. According to the forecasting length, there are three different kinds of temporal forecasting.

1. **Long-term load forecasting** (LTLF): mainly for system planning, Typically the long term forecast covers a period of 10 to 20 years. Key factors in LTLF

includes stock of electricity-using equipment, level and type of economic activity, price of electricity, price of substitute sources of energy, noneconomic factors such as marketing and conservation campaigns, and weather conditions.

2. **Medium-term load forecasting** (MTLF): mainly for the scheduling of fuel supplies and maintenance programmes. It usually covers a period of a few weeks.
3. **Short-term load forecasting** (STLF): for the day-to-day operation and scheduling of the power system.

In this paper, we will mainly talk about the STLF. The STLF forecaster calculates the estimated load for each hours of the day, the daily peak load, or the daily or weekly energy generation. STLF is important to clerical supplier because they can use the forecasted load to control the number of generators in operation, to shut up some unit when forecasted load is low and to start up of new unit when forecasted load is high.

A large variety of techniques have been investigated in STLF, and we can find many different approaches

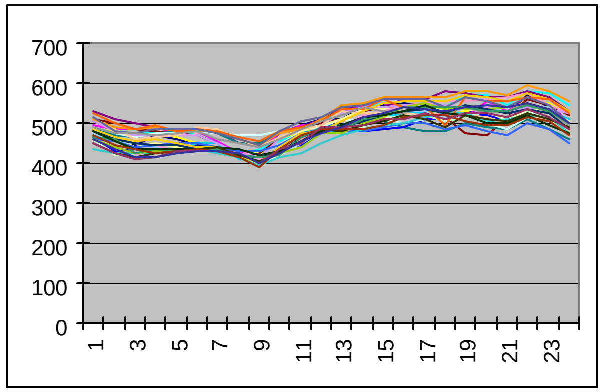
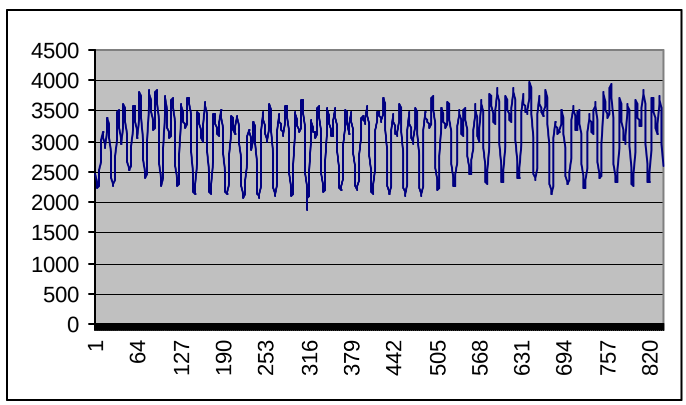
? Time-series / Regression approach
? Group Method of Data Handling
? Feed-forward Network Approach MLP,BP,RBF)
? Recurrent Network Approach
? Competitive Network Approach
? Evolutionary Network Approach
? Modular / Hierarchical / Hybrid Network Approach
? Fuzzy Approach
? Bayesian Network Approach

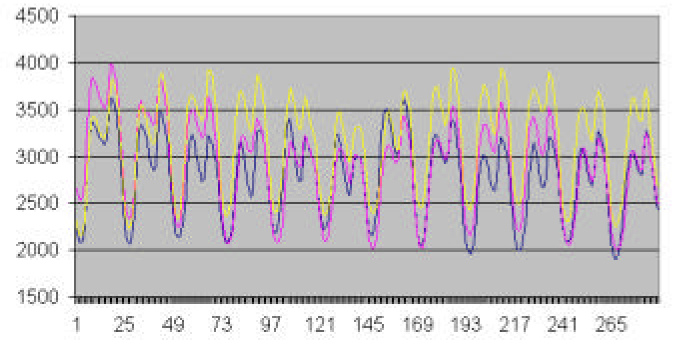
Among them, the statistical approach, including classical Multiply liner regression and ARMA (automatic regressive moving average), and Neural Network approach are the most detailed studied approaches. During the past ten years, neural network approach are the most frequently used approach, different kind of neural networks – feed forward net (perceptron, back propagation network, radical basis function network), recurrent network (e.g. Hopfield), competitive network (e.g. Self-organization Map), have been applied on this problem. Some of them are hybrid with genetic or fuzzy method.

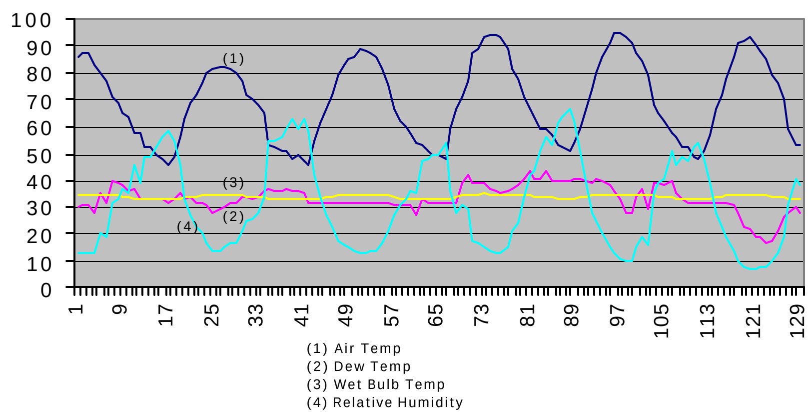
The whole paper is organized as following. In part 2 we will analysis the determining factors in STLF. In part 3 and 4 we will give a detailed description about neural network and moving average model for STLF. Temperature factor is also discussed in section 4. In Part 6 we summarize the result and give conclusion.

2. Demand-determining factors in STLF

The power system has a high complexity. Many factors are influential to the electric power generation and consumption. According to [George G Karady], the factors can be classified into economical, environmental, calendar, weather and random effectors. Some influential factors and examples are listed in following.

Calendar	Seasonal variation of load (summer, winter etc.)	–Change of number of daylight hours –Gradual change of average temperature –Start of school year, vacation
	Daily variation of load. (night, morning,etc)	 SIC5411, Aug 1,1996 , daily CONSUMPTION and temperature variance.
	Weekly Cyclic	Variation  Week circle in PSE data, 5 weeks, 1/1/1999 – 2/4/1999
		Saturday and Sunday significant load reduction
		Monday and Friday slight load reduction

<table>
<tr><td></td><td>Holidays (Christmas, New Years)</td><td>

Load around Christmas, from 12/20 to 12/31, in 1999, 2000 and 2001. We can find a apparent load different between Christmas day (the hour 121-145 in the figure) and other days. And similar different can be found in each year. Christmas Eve and 12/26 also different to normal load curve.</td></tr>
<tr><td>Economical or environmental</td><td colspan="2">Service area demographics (rural, residential)
Industrial growth.
Emergence of new industry, change of farming
Penetration or saturation of appliance usage
Economical trends (recession or expansion)
Change of the price of electricity
Demand side load management</td></tr>
<tr><td>Weather</td><td colspan="2">

We can find that not all weather factors are important. Some are typically random during a period of time, such as wind speed and thunderstorms. Also some factors are interrelated. For example, temperature is partly controlled by cloud cover, rain and snow. Among all those factors, temperature is the most important because it has direct influence on many kind of electrical consumption, such as air conditioner, heater and refrigerator. However, the leading weather influential factor for specific consumer may be different.</td></tr>
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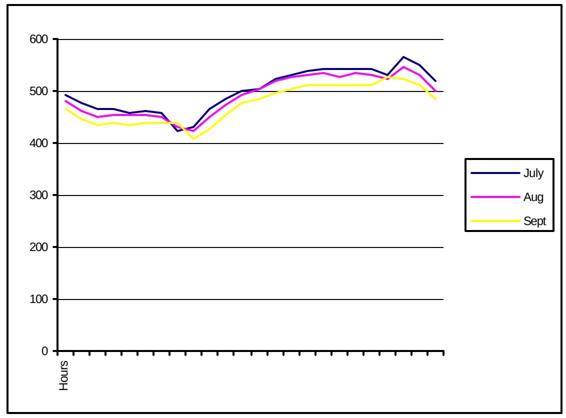
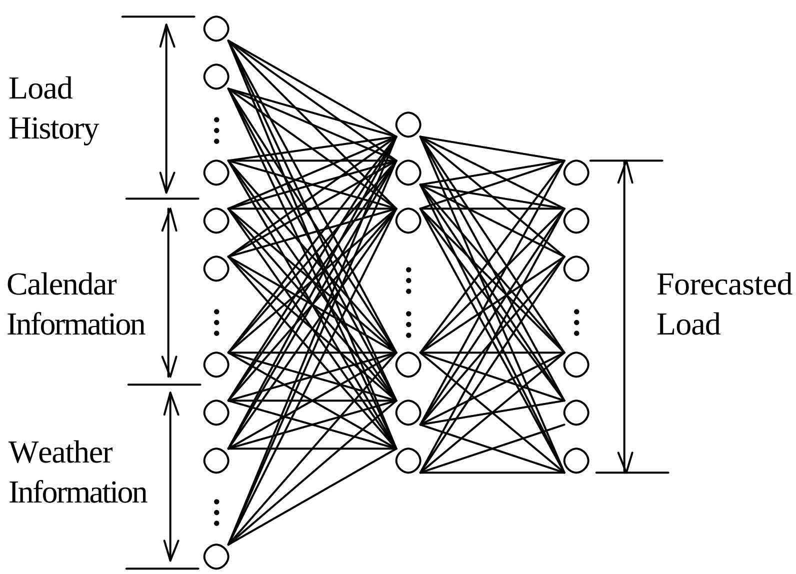
<table>
<tr><td></td><td>Temperature


Average temperature (City A, 1996), negative correlated with load in summer
July: 73.99, Aug: 70.84, Sept: 60.13</td></tr>
<tr><td></td><td>Humidity
Thunderstorms
Wind speed
Rain, fog, snow
Cloud cover or sunshine</td></tr>
<tr><td>Unforeseeable random events</td><td>Start or stop of large loads (steel mill, factory, furnace)
Widespread strikes
Sporting events (football games)
Popular television shows
Shut-down of industrial facility</td></tr>
</table>

3. STLF by neural network



The general neural network model for load forecasting is shown in the figure. The difference in different model is how to select load, calendar and weather information as input. Usually the output is forecasted load for future, and each node corresponds to forecasted load of specific hour.

We have developed two kinds of model: hour-ahead model and day-ahead model, according to the actually need for this problem. All load data is from Power Domain and weather data comes from Accu Weather.

3.1 hour-ahead model

Net Structure: 9 - 8 – 1

INPUT

1- hour : 1-24

2- Temperature: real (not the forecasted temperature)

3- load of last day, this hour

4- load of last hour

5- load of this hour

6- Weekend: 1,0

7,8,9 - Weekday: 001 - 111

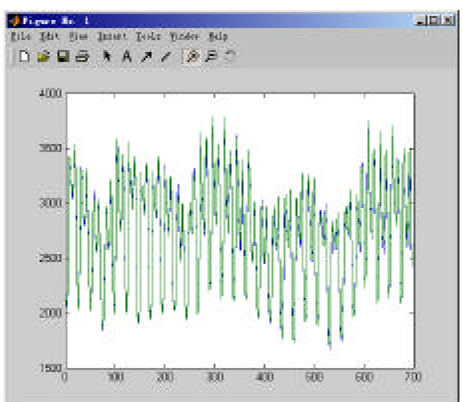
OUPUT

load of next hour

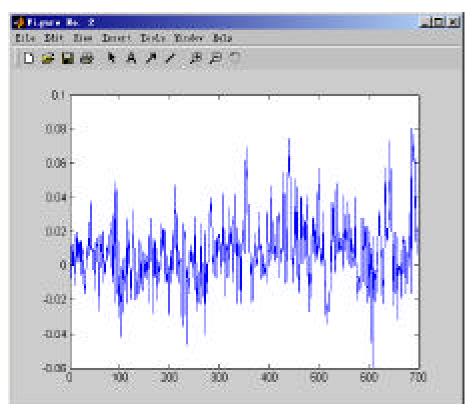
Training set: Jan 2- Jan 30 ,2002 (696 points)

Test set: Jan 31- Feb28, 2002 (696 points)

normalization : to N(0,1)



Forecasted result:



Forecasting error (percent)

Total Error: 1.53 %

3.2 1- 24 hour ahead model

use 24 NN to forecast, forecasting length 1 - 24 hour

Net Structure: 8 - 8 – 1

INPUT
1- hour : 1-24
2- Temperature: real
3- load of two days ago, forecasting hour
4- load of one day ago, forecasting hour
5- load of 12 hours ago
6- load of last hour
7- load of this hour
8- Weekday: 0 - 7
9- Weekend: 1,0

OUPUT
load of x hours later (x = 1..24)

Training set: Jan 3- Feb 4,2002 (792 points)
Test set: Feb 5- Mar 9, 2002 (792 points)
normalization : to N(0,1)

Te result is list in following table. We also use a naïve ensemble way to reduce error. For example, to make 12-hour forecasting, we will make forecasting from 12 to 24 hour and then average he forecasting result.

	Single net Average error (%)	Single net Maximal error (%)	Ensemble net Average error (%)	Ensemble net Maximal error (%)	Reduction on Average error (%)	Reduction on Maximal error (%)
1.	1.66	9.35				
2.	3.21	21.69	4.60	20.29	-43.30	6.45
3.	4.33	38.13	4.72	20.40	-9.01	46.50
4.	4.50	21.24	4.80	20.67	-6.67	2.68
5.	5.36	31.05	4.90	20.80	8.58	33.01
6.	5.71	30.25	4.93	20.99	13.66	30.61
7.	5.88	30.20	4.98	21.44	15.31	29.01
8.	6.73	35.57	5.00	21.21	25.71	40.37
9.	6.00	38.83	4.98	20.81	17.00	46.41
10.	5.46	36.66	4.97	19.85	8.97	45.85
11.	5.60	29.74	5.00	18.65	10.71	37.29
12.	5.26	21.06	5.02	17.97	4.56	14.67
13.	5.80	26.72	5.08	18.32	12.41	31.44
14.	6.38	32.08	6.09	19.17	4.55	40.24
15.	5.90	24.57	5.06	18.86	14.24	23.24
16.	6.31	26.85	5.07	18.94	19.65	29.46
17.	6.53	26.86	5.07	18.79	22.36	30.04
18.	6.60	53.82	5.05	17.75	23.48	67.02
19.	6.68	58.55	4.96	19.64	25.75	66.46
20.	7.85	41.83	5.01	21.93	36.18	47.57

21.	5.68	38.00	5.11	20.17	10.04	46.92
22.	5.44	28.76	5.24	21.09	3.68	26.67
23.	6.15	32.59	5.49	23.24	10.73	28.69
24.	5.45	22.52				

4. STLF by moving average

By observing load curve, we can find cycle at different level

1- daily cycle
2- weekly cycle
3- yearly cycle

so we can use some moving average model to forecast future load.

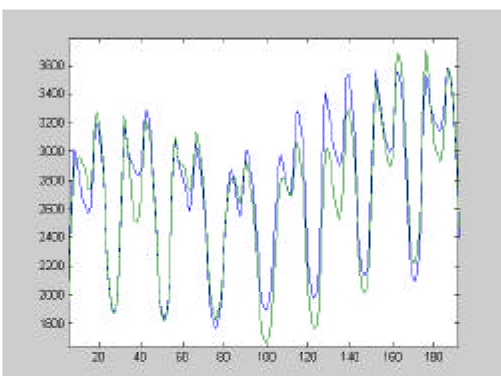
$$L = ?_{i} \; w_i L_i$$

L_i is load at past reference point, eg. a week ago , w_i is its weight

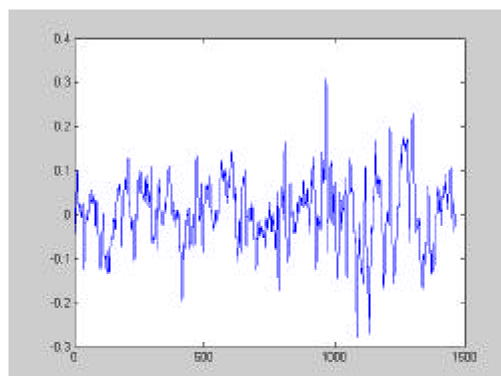
4.1 Day-Ahead Forecast

To forecast load of 24 hours later, based on load of 6*24 hour before and adjust it with error between now and 7*24 hours ago.

Jan 9 – Mar 10, 2002
Average error = 5.74% , Maximal error = 30.74%,

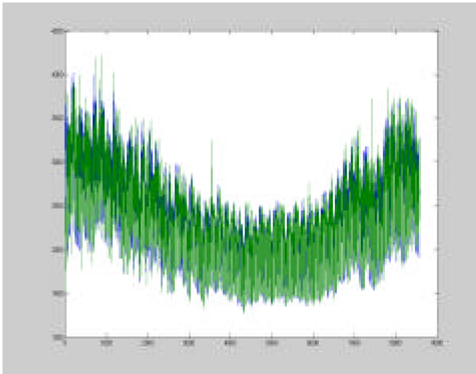


Part of the result

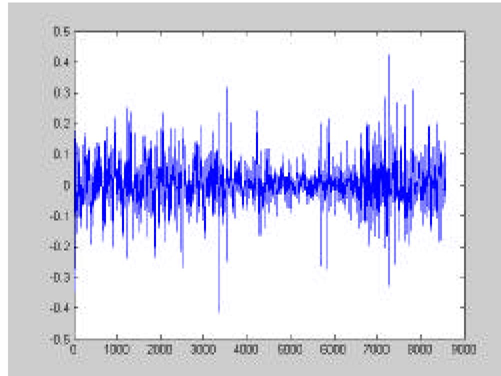


Error

on whole year data of 2001, use past weeks data 75% last week + 25% last last week
average error = 4.62%, max error = 42.38%



Part of the result

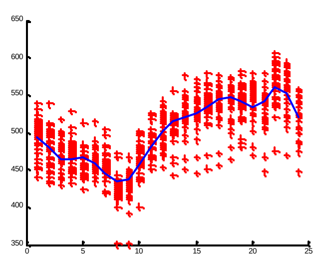


Error

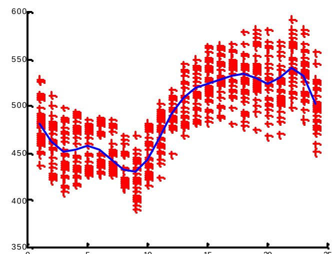
4.2 Temperature shifting factor

Temperature is the most important factor in the forecasting. We can find temperature as a shift factor for average load.

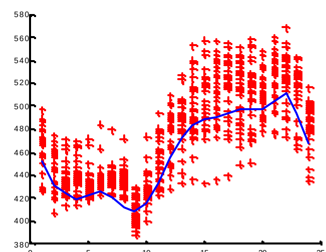
Those figures show the difference of average hour load in a month. We can find the average temperature is positively related during summer



July



Aug

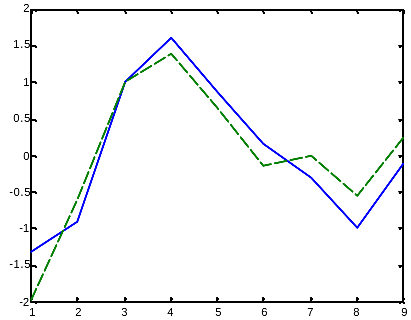


Sept

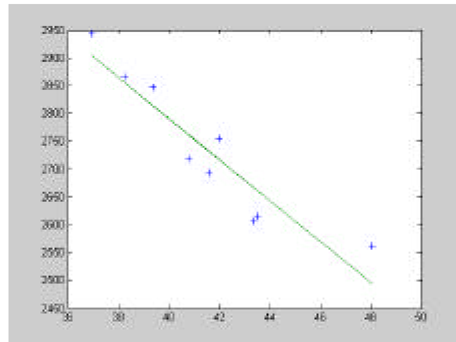
Basic pattern for SIC5411,ID143 in July, Aug and Sept , 1996
Average temperature: July: 73.99, Aug: 70.84, Sept: 60.13

To find the detailed relationship between temperature and load, we conduct some regressive analysis on average load and temperature.

First 9 weeks in 2002, relationship between average weekly load and temperature is shown as (they are normalized and temperature is reverted):



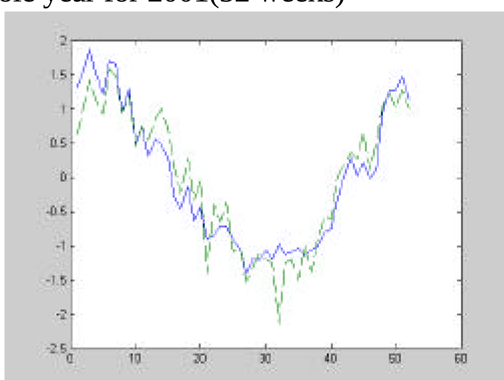
Weekly average load



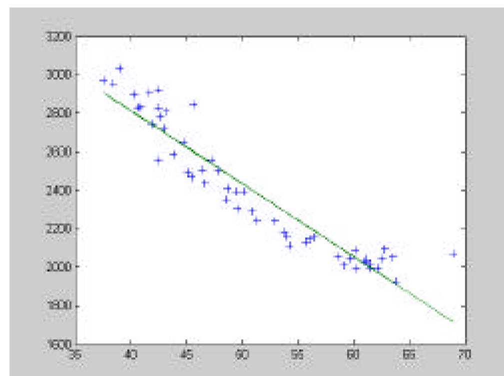
Weekly average temperature

Function: -38.8 T + 4264.5 = L

Whole year for 2001(52 weeks)



(a)

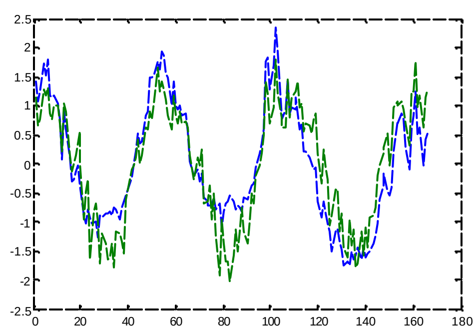


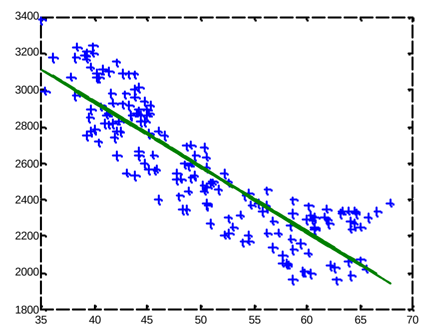
(b)

(a) Normalized average load and temperature (dashed line) for every week

(b) linear regressive -38.0 T + 4332.5 = L

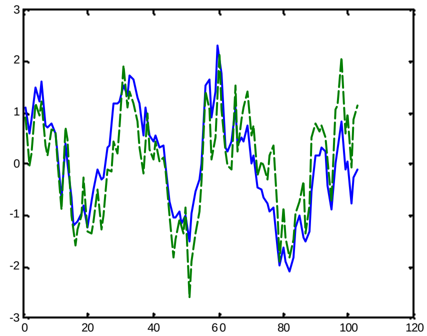
Three years (166 weeks, Jan 1,1999- Mar, 2002) -35.4T + 4352.2 = L

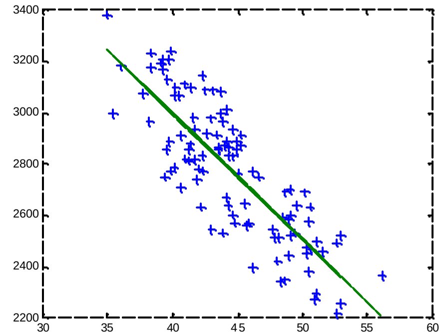




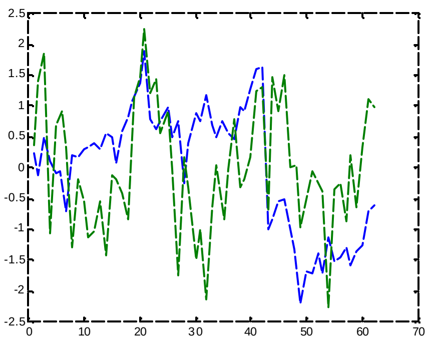
We can find good nearly linear relationship between weekly average temperature and load. However, the summer pattern may be different to that of winter pattern. The regressive analysis of summer and winter is shown as following:

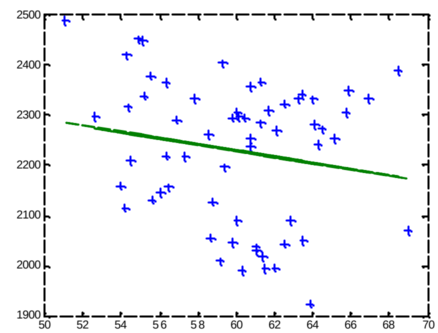
Three winter (1999- 2002) -49.2T + 4967.5 = L





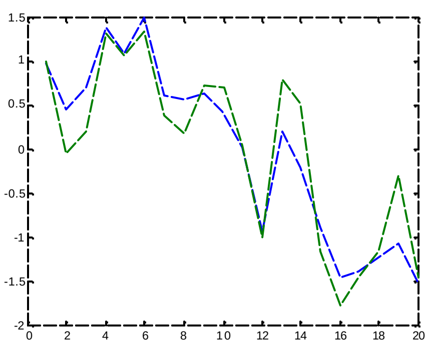
Three summers (1999- 2002) -6.1T + 2595.3 = L - hardly any linear relationship

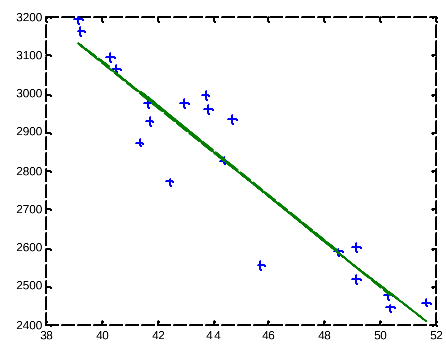




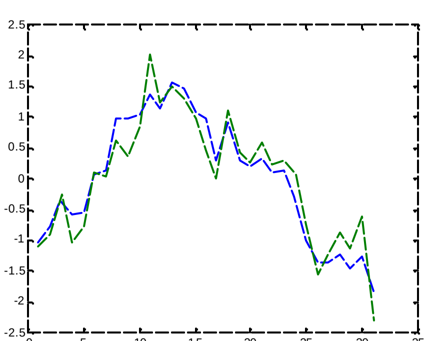
each winter

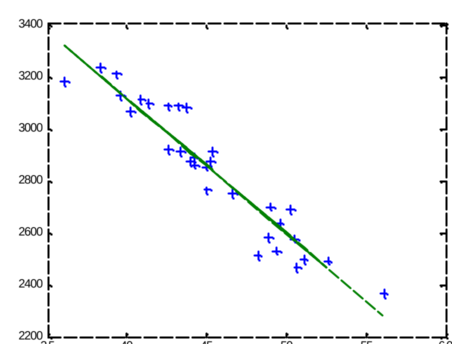
1999(first 20 weeks) -58.4 T + 5424.0 = L



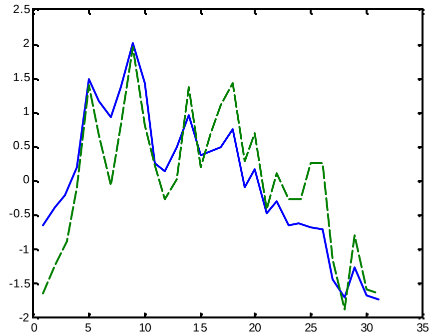


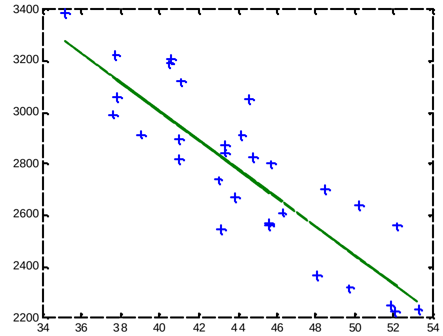
1999-2000 -51.7 T + 5182.9 = L



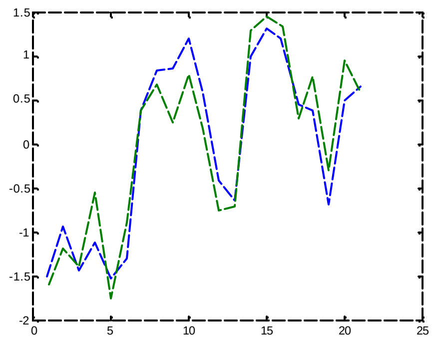


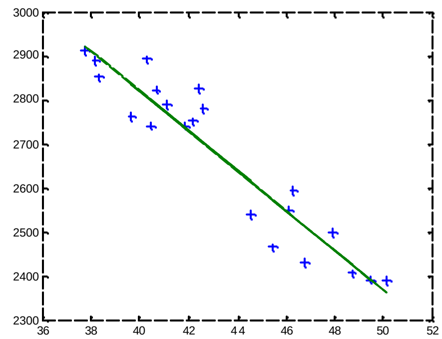
2000-2001 -56.1 T + 5246.4 = L





2001-2002   -45.4 T + 4640.4 = L



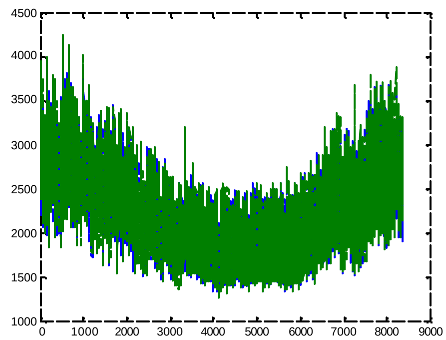


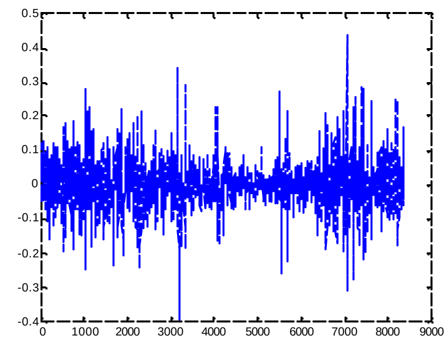
we can find there is apparent linear relationship during winters but no strong linear relationship during summer.

So we can modify original moving average with temperature shifting factor. Modified 7-days-ago load with (T1-T2)*38. where T1 is average temperature of past 7 days and T2 is average temperature from 7 days to 14 days ago. 38 is temperature coefficient

Test on whole year 2001, we have:
average error = 4.39% maximal error = 43.22%
on Jan – Mar 2002:
average error = 5.08% maximal error = 31.35%

If we only adjust winter load, we get
Average error = 4.22%, maximal error = 43.86%, 90% error = 7.01%





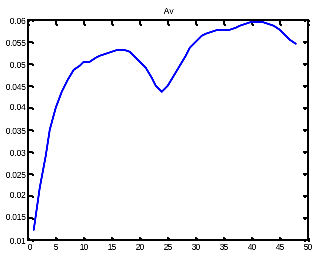
4.3 1-48 hour forecasting by weekly moving

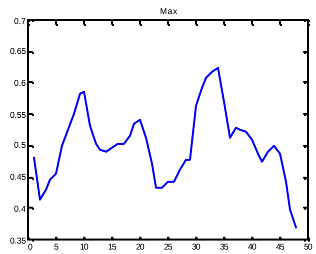
Use same model to make 1-hour to 48-hour forecast on year 2001:

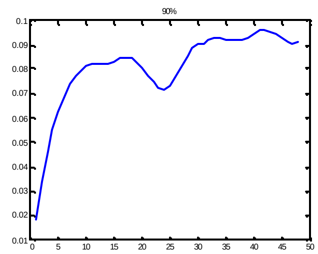
Forecasting span	Average error	90% error	Maximal error	Average error with no temperature adjusting	90% error with no temperature adjusting	Maximal error with no temperature adjusting	Average error in 3.2 (%)
1.	0.0124	0.0186	0.4790	0.0124	0.0186	0.4786	1.66
2.	0.0216	0.0334	0.4151	0.0216	0.0337	0.4143	3.21
3.	0.0290	0.0460	0.4306	0.0291	0.0462	0.4286	4.33
4.	0.0352	0.0552	0.4452	0.0353	0.0556	0.4427	4.50
5.	0.0400	0.0628	0.4544	0.0402	0.0634	0.4567	5.36
6.	0.0438	0.0684	0.4996	0.0440	0.0695	0.5029	5.71
7.	0.0466	0.0736	0.5265	0.0468	0.0742	0.5305	5.88
8.	0.0485	0.0774	0.5504	0.0487	0.0775	0.5517	6.73
9.	0.0497	0.0796	0.5841	0.0499	0.0802	0.5859	6.00
10.	0.0503	0.0812	0.5859	0.0506	0.0813	0.5884	5.46
11.	0.0508	0.0817	0.5315	0.0511	0.0825	0.5339	5.60
12.	0.0513	0.0819	0.5033	0.0516	0.0829	0.4956	5.26
13.	0.0518	0.0817	0.4940	0.0521	0.0830	0.4856	5.80
14.	0.0523	0.0823	0.4904	0.0527	0.0839	0.4744	6.38
15.	0.0528	0.0829	0.4970	0.0534	0.0843	0.4791	5.90
16.	0.0531	0.0843	0.5034	0.0538	0.0855	0.4841	6.31
17.	0.0531	0.0846	0.5018	0.0540	0.0862	0.5171	6.53
18.	0.0527	0.0848	0.5163	0.0537	0.0866	0.5581	6.60
19.	0.0520	0.0825	0.5337	0.0530	0.0848	0.5785	6.68
20.	0.0507	0.0801	0.5424	0.0519	0.0822	0.5882	7.85
21.	0.0490	0.0772	0.5129	0.0502	0.0815	0.5571	5.68
22.	0.0468	0.0749	0.4715	0.0482	0.0793	0.5160	5.44
23.	0.0448	0.0725	0.4311	0.0462	0.0763	0.4709	6.15
24.	0.0439	0.0713	0.4322	0.0453	0.0737	0.4188	5.45
25.	0.0451	0.0729	0.4419	0.0466	0.0768	0.4286	
26.	0.0473	0.0773	0.4440	0.0488	0.0803	0.4162	
27.	0.0496	0.0812	0.4632	0.0511	0.0836	0.4351	
28.	0.0517	0.0853	0.4759	0.0533	0.0874	0.4476	
29.	0.0535	0.0883	0.4767	0.0552	0.0893	0.4504	
30.	0.0550	0.0898	0.5632	0.0568	0.0913	0.5551	
31.	0.0563	0.0905	0.5910	0.0580	0.0930	0.5818	
32.	0.0570	0.0919	0.6082	0.0587	0.0945	0.5987	
33.	0.0574	0.0926	0.6170	0.0591	0.0953	0.6226	
34.	0.0575	0.0925	0.6241	0.0593	0.0967	0.6296	
35.	0.0576	0.0922	0.5687	0.0595	0.0960	0.5739	
36.	0.0579	0.0917	0.5113	0.0599	0.0960	0.4954	
37.	0.0582	0.0923	0.5297	0.0603	0.0958	0.4981	
38.	0.0586	0.0920	0.5259	0.0608	0.0954	0.4966	

39.	0.0591	0.0927	0.5212	0.0614	0.0965	0.4917	
40.	0.0595	0.0945	0.5093	0.0619	0.0985	0.4800	
41.	0.0597	0.0962	0.4856	0.0623	0.0989	0.4936	
42.	0.0597	0.0960	0.4743	0.0623	0.1009	0.5340	
43.	0.0594	0.0952	0.4901	0.0622	0.1006	0.5519	
44.	0.0588	0.0942	0.4990	0.0617	0.0995	0.5609	
45.	0.0579	0.0929	0.4859	0.0607	0.0985	0.5446	
46.	0.0566	0.0915	0.4435	0.0595	0.0976	0.5026	
47.	0.0553	0.0907	0.3991	0.0581	0.0968	0.4506	
48.	0.0547	0.0912	0.3698	0.0574	0.0970	0.3880	

Error plot: (x-axis is forecasting span, from 1 to 48)
with temperature adjusting

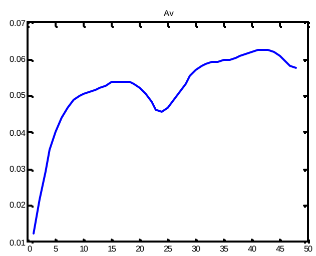


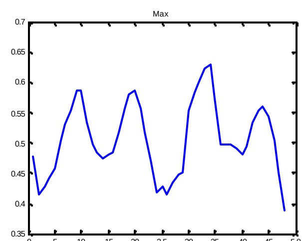


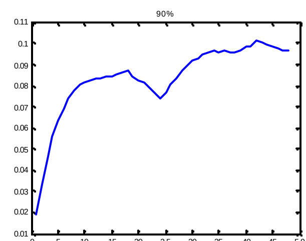


average error maximal error 90% error

With temperature adjusting







4.4 Using forecasted temperature

In this model we use forecasted temperature to modify forecasted load. Test set: Jan 2,2002 – Feb 28, 2002. We have 11 past loads as reference. The result is weighted average load of those reference days. The offset is shown as this list:

day(1) = -7*24; % 1 week
day(2) = -52*7*24; % 1 year
day(3) = -104*7*24 % 2 year
day(4) = -156*7*24; % 3 year

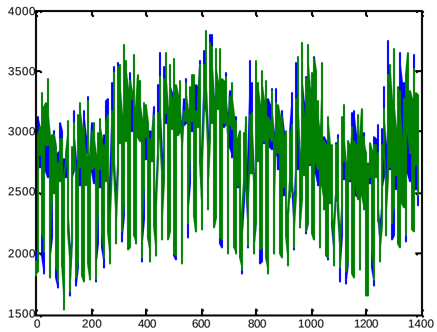
day(5) = -14*24; % 2 week
day(6) = -53*7*24 ; % 1 year
day(7) = -51*7*24; % 1 year
day(8) = -103*7*24; % 2 year

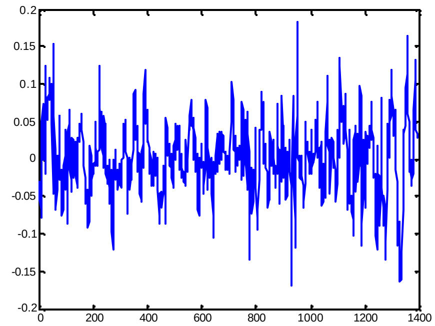
day(9) = -105*7*24; % 2 year
day(10) = -157*7*24; % 3 year
day(11) = -155*7*24; % 3 year

Forecasted load T(i) is modified by forecasted temperature:

T(i) = T(i) - (Tf(k) - SumT)*31;

Where Tf(k) is forecasted temperature and SumT is average temperature over all reference dates.





average error = 3.54% maximal error = 18.32% 90% error = 5.88%
(Temperature forecasting has average error = 5.24%, maximal error = 23.53%)

5. Conclusion

We have used neural network and moving average model in this paper to handle STLF. The best result is

	1-hour	24-hour
Neural network	1.53%	5.45%
Moving average	1.24%	3.54%

The result from MV is better than NN on this dataset. However, it doesn't necessarily mean NN have worse performance than MV on general STLF problem. The MV model uses more expertise and is more specified than NN model.

We can find NN model is a black-box model. When the relationship between various factors is not clear or too complex to use, NN model is a good choice. It needs little expertise and also doesn't generate obvious rule from training data. However, if we already know main dependence between factors, a white-box like MV may be better choice.

And we also tried ensemble neural network and it can reduce error, specially the peak error.

1- The naïve ensemble net reduces both average error and maximal error. Especially, the model is more stable for peak error.
2- The improvement comes from that ensemble network can reduce the variance error
3- However, the average error reduction is not very high, it tells us that the models have similar bias. Basic bias is about 5% and peak error is about 20%, regardless the forecasting span.

The weekly based moving average using forecasted temperature gives a fairly good solution. Its success comes from two sources. The first one is long-range influence of averaging past reference load value, which ensures the stableness of the model, and the second one is short-range influence of temperature which reflects basic instant change by weather.

Further research will be focused on using more weather data in both models. And we will also try to reduce peak error – usually the biggest error—by some rule-based or neural net-based methods.

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