Impact of Weather Inputs on Heating Plant – Agglomeration Modeling

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Abstract: This article describes performance of artificial neural network (ANN) on modeling interface between a heating plant and an agglomeration. ANN perform one step ahead prediction of water temperature returned from agglomeration based on input water temperature, flow and atmospheric temperature in past 24 hours. Usage of ANN in two factual heating plant in Komorany and Detmarovice, Czech Republic. Main concern of the article is to explore possibility of tuning ANN accuracy by additional inputs for humidity and wind speed.

Key-Words: artificial neural network, modeling, heting plant, weather, humidity, wind speed

1 Introduction

An interface between a heating plant and an agglomeration is a highly complex system. The heating plant send heat in a form of hot water with variable temperate and flow into the agglomeration and receive back cooled water with variable transfer delay.

As the flow and the temperature are independent variables set up by a heating plant staff or an automatic regulator the one and only unknown variable for the interface modeling is a value of returned water temperature.

However a process of prediction of the returned temperature is affected not only by past values of the input temperature and the flow but also by a set of various external factors. The most important external factors are without questions past values of atmospheric temperature nevertheless other weather factors as humidity or wind speed should be also considered. In addition different sociological factors as people common wake up time can also play its part.

In the heating plant located in Komorany Czech Republic and owned by United Energy [1] the returned temperature can be predicted by artificial neural network (ANN) based on the input temperature, the flow and the atmospheric temperature only as the humidity and wind speed are not measured or are unavailable.

This article explore possibilities of tuning Komorany ANN prediction precision by employing additional information about the humidity or the wind speed past values. The very same ANN as in Komorany is put at work in similar heating plant in Detmarovice [2] where information about the humidity and the wind are at disposal. This new inputs are later added into ANN and impacts on ANN prediction are measured to answer the question whether or not are the humidity and the wind speeds are important factors for ANN prediction in Komorany.

2 Problem Formulation

This chapter describes available data for ANN training and evaluating in Komorany and Detmarovice as well as performance and structure of base ANN used in both.

2.1 Komorany data

For the heating plant in Komorany which is the main concern of the article. The data between October 2005 and December 2007 are available. However winter heating period is much more interesting for a heating plant than summer period and heating plant-agglomeration interface behavior in summer time significantly differ from heating time so only months in the heating period between October and March have been considered. Maximum and minimum values of the input temperature (Tin), the flow (F), the atmospheric temperature (Ta) and the returned temperature (Tout) in this scope can be seen in next table. In the heating plant all this values are measured in periods less than one minute but for ANN concerns one hour period means were created. Hence after removal of invalid values 10897 hours values are at disposal.

Table 1, Komorany Data Borders

Variable	Border	Value	Unit	Sense
Tin	Max	137.6	°C	Independent Variable
	Min	77.4		
F	Max	2583.2	tons per hour	Independent Variable
	Min	44.6		
Ta	Max	20.4	°C	Inner

	Min	-13.9		Variable
Tout	Max	71.7	°C	Dependent Variable
	Min	48.1		

For the usage in ANN all values were interpolated into 0-1 interval in accordance with their borders.

2.2 Komorany ANN

The main task for ANN in Komorany is to predict Tou one (hour) step ahead from Tin, F and Ta inputs. ANN has to deal with variable transfer delay which affected Tout. Transfer delay is a function of F and differs in various parts of heating transfer system. An example of transfer delay from heating plan to one of the most far points of agglomeration as provided by heating plan can be seen in this table.

Table 2, Transfer Delay to Aglomeration

F [kg per seconds]	Transfer delay [hours]
876,0	4:44:16
739,8	5:43:20
554,8	7:48:49
385,5	14:16:49

To approximate this variable transfer delay function ANN is provided by inputs for past 0 to 23 hours. For Tin, F, Ta values it means 72 inputs. Table below describe ANN structure.

Table 3, Komorany Base ANN

Output	Tout h+1
Hidden layer	10 neurons
72 Inputs	Tin h-23 … Tin h-0
	F h-23 … F h-0
	Ta h-23 … Ta h-0

ANN is standard feedforward artificial neural network [3] with sigmoid transfer function in hidden layer and linear input and input layers. As training method Levenberg-Marquardt has been chosen [4]. From prepared data set (see 2.1) values from 2005 and 2006 years were chosen as training set – 6529 samples and values from 2007 years were chosen as testing set – 4320 total.

The ANN was trained 10 times for 20 epochs and prediction accuracy was measured on testing set as RMSD [5].

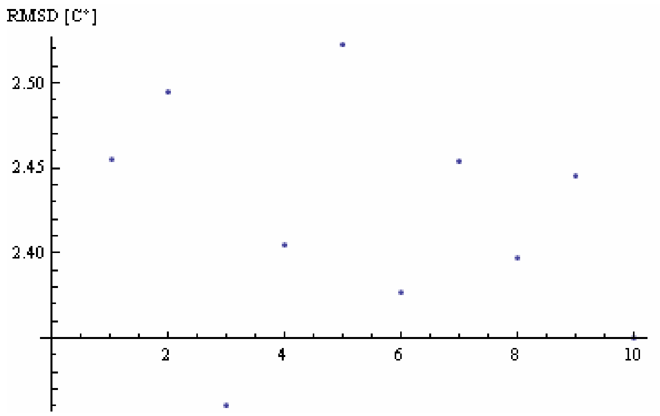

Figure 1, RMSD of Komorany base ANN

Average RMSD of ANN is 2,421 °C.
Average NRMSD is 10,3 %.

2.3 Detmarovice data

For evaluating of impacts of the humidity (H) and the winter speed (WS) inputs which miss in Komorany ANN data from similar Detmarovice heating plant are used. Detamarocive heating plant store per hour data sample from year 2003 until 2008 so the same intervals as in Komorany were picked up.

Table 4, Detmarovice Data Borders

Variable	Border	Value	Unit	Sense
Tin	Max	150.62	°C	Independent Variable
	Min	17.76		
F	Max	846.9	tons per hour	Independent Variable
	Min	0.46		
Ta	Max	35.92	°C	Inner Variable
	Min	-25.39		
H	Max	101.81	relative %	Inner Variable
	Min	17.55		
WS	Max	9.43	m/s	Inner Variable
	Min	0.		
Tout	Max	61.18	°C	Dependent Variable
	Min	19.38		

2.4 Detmarovice ANN

Same ANN as in Komorany was applied on Detmarovice data in same pattern as in Komorany. The ANN was trained 10 times for 20 epochs and prediction accuracy was measured on testing set as RMSD as can be seen on next figure.

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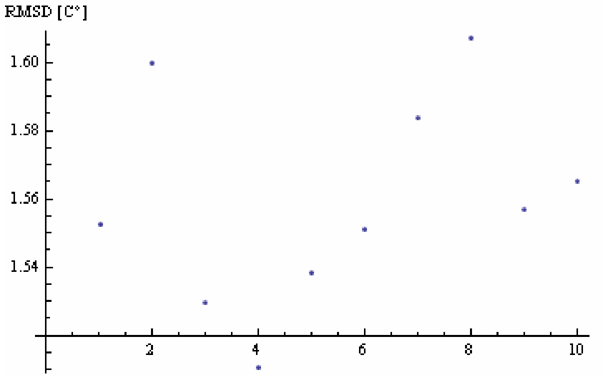

Figure 2, RMSD of Detmarovice base ANN

Average RMSD of ANN is 1,560 °C.
Average NRMSD is 3,7 %.

3 Problem Solution

To evaluate impact of added inputs of H or WS on base ANN prediction accuracy two expanded ANN on for H and another for WS have been created and tested.

3.1 ANN with H inputs added

24 more inputs for H are added into Detmarovic base ANN

Table 5, Detmarovice ANN with H inputs

Output	Tout h+1
Hidden layer	10 neurons
96 Inputs	Tin h-23 … Tin h-0
	F h-23 … F h-0
	Ta h-23 … Ta h-0
	H h-23 … H h-0

ANN with H inputs performance is described bellow.

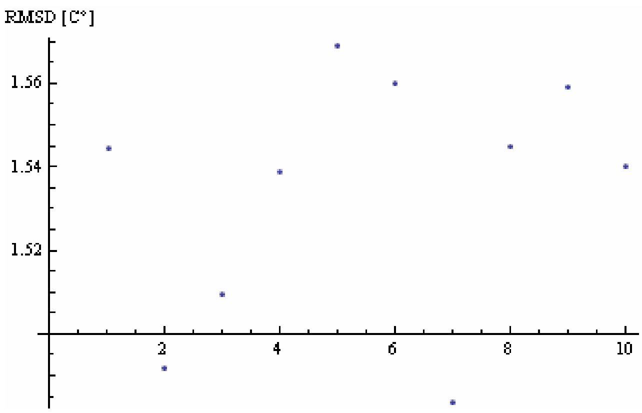

Figure 3, RMSD of Detmarovice base ANN

Average RMSD of ANN is 1,534 °C.
Average NRMSD is 3,6 %.

3.2 ANN with WS inputs added

24 more inputs for WS are added into Detmarovic base ANN

Table 6, Detmarovice ANN with WS inputs

Output	Tout h+1
Hidden layer	10 neurons
96 Inputs	Tin h-23 … Tin h-0
	F h-23 … F h-0
	Ta h-23 … Ta h-0
	WS h-23 … WS h-0

ANN with WS inputs performance is described bellow.

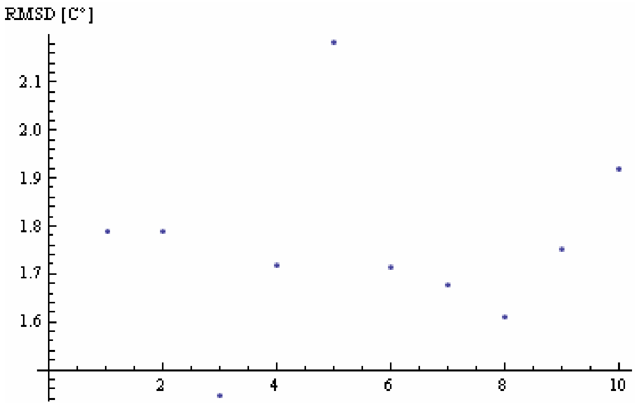

Figure 4, RMSD of Detmarovice base ANN

Average RMSD of ANN is 1,759 °C.
Average NRMSD is 4,2%.

4 Conclusion

Experimental results shown that appending H inputs into ANN with use only Tin, F and Ta inputs can perform small improvement of ANN prediction accuracy. Actual improvement of RMSD was 0,026 °C and NRMSD 0,1%.
However employment of WS inputs into base ANN perform expressive fall of accuracy. RMSD grow up for 0,199 °C and NRMSD grow up for 0,5%.
Hence usage of WS inputs in base ANN seems to be defiantly unproductive. For usage of H inputs further tuning of ANN and more statistic experiments should be done to make this improvement work economically in Komorany heating plant.

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References:

[1] http://www.ue.cz/
[2] http://www.cez.cz/cs/uvod.html
[3]BOSE, B.K., LIANG, P. 1996. *Neural Network Fundamentals with Graphs, Algorithms, and Aplications*. McGraw-Hill Series in Electrical and Computer Engineering, 478 p. ISBN 0-07 006618-3.
[4]http://mathworld.wolfram.com/Levenberg-MarquardtMethod.html
[5] http://en.wikipedia.org/wiki/RMSD