FUZZY NEURAL NETWORKS MODEL FOR BUILDING ENERGY DIAGNOSIS

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ABSTRACT

A comfortable indoor climate environment is necessary for modern buildings and therefore the Heating, Ventilation and Air-Conditioning (HVAC) systems are widely used. Faults or disturbances are normally unavoidable in the systems and they will lead to more energy consumption or degradation of comfort level of indoor climate. Energy consumption is useful to detect the faults. Fuzzy Neural Networks (FNN) model is presented and discussed in this paper. By applying the model on the measured data with fault of an open window in the room, the FNN model is shown to be a good candidate for energy diagnosis. In order to make the fault detection quantitatively, a threshold of a characteristic parameter, derivative of the multiplication of mean value and variance, is applied and shows good results.

INTRODUCTION

Heating, Ventilation and Air-Conditioning systems are widely used to supply suitable conditioned air to the rooms and spaces to maintain an expected temperature and humidity in the buildings.

Buildings, both commercial and residential buildings, consume every year approximately one-third of the total energy consumption (US Department of Energy, 2002). Furthermore, HVAC systems consume every year more than 60% of the building energy consumption in USA (Mull, 1997) and more than 50% in Europe (Hughes, 1998).

After more sensors and automatic control loops are installed in HVAC systems, it is getting more complicated to find the fault by feeling. On the other hand, this makes it possible to realize the fault detection and diagnosis automatically by using the digital information. During long time operation, components or devices in the systems may function improperly (under faulty condition). Faults normally lead to more energy consumption or degradation of comfort level of indoor climate. In USA, faults in HVAC systems can lead to 30% increase of their energy use (Katipamula & Brambley, 1998). Therefore, Fault Detection and Diagnosis (FDD) on the building HVAC systems is a practical and important issue.

Building energy consumption is important information for Fault Detection and Diagnosis on global building level (Yu et al 2002). Dodier and Kreider (1999) present a method by means of belief network, which can be viewed as a probabilistic database containing the knowledge about the system. Energy Consumption Index (ECI) is introduced to do the fault detection in the whole building energy module.

Because of the complexity of the building energy consumption and it comprises so much information and uncertainty, the artificial intelligent method might be a good solution for the diagnosis. In this paper, a Fuzzy Neural Networks approach is studied.

Neural networks are massively parallel and highly distributed computational architectures (Pedrycz, 1998). Learning is an important characteristic of neural networks modelling which allow the weight matrix to be tuned. The goal of learning algorithms is to determine weight matrix in such a way that the networks produce certain output values when certain input values are given.

Fuzzy sets are firstly suggested by Zadeh (1965). In the classical set theory, an object either belongs to one set or not belongs to it. However, most terms of natural language that describe properties of objects do not behave like either 1 or 0. People use vague terms like *warm, high, fast, heavy, approximately zero* etc. It is obvious that each method of representing these terms as a set, as a characteristic function, or as a predicate that can only assume the values true or false, is unsuitable. Establishing an exact limit – like for the property *warm* at 20°C – will always result in undesired behaviour in the transition zone, since almost identical objects – like the temperature of 19.9°C and 20.1°C – are treated as completely different.

There have been a number of ways in which fuzzy sets and neural networks were put together as hybrid structures. These structures are referred to as Fuzzy

Neural Networks. The main reason that makes a successful fusion of fuzzy sets and neural networks is that both technologies are highly complementary.

Neural networks are useful when training data are available. It tends to be efficient when it comes to learning (Pedrycz, 1998) and therefore are naturally inclined to address the behaviour factors of the problems. A mathematical model of the problem and prior knowledge are not necessary. On the other hand, the solution obtained from the learning process cannot be interpreted. The neural network is a black box and the final state cannot be interpreted in terms of rules. This also means a neural network cannot be initialised with prior knowledge even if we have any.

Fuzzy sets are focused on knowledge representation issues including the way in which various factors of vagueness are taken care of. A fuzzy system can be used to solve a problem if the knowledge about the solution is available for instance in the form of linguistic if-then rules. By defining suitable fuzzy sets to represent linguistic (descriptive) terms used within the rules, the fuzzy system can be created from these rules. Both formal model of the problem and training data are not needed.

Fuzzy rule-based systems have the underlying structure of a feedforward multi-layer neural network, with a well-defined functionality for each layer. It has a Radial Basis Function neural networks-like structure. Therefore, Back Propagation algorithms can be adopted to tune both the membership functions and the parameters in the consequent part of the rules, from a set of input-output data.

In this paper, a FNN model is built up by means of ANFIS function of Fuzzy Logic Toolbox of Matlab®. Fault-free data are used to train the networks and get the model. Checking data with a fault introduced are used to validate the model and test the performance of fault detection. Six types of membership functions are used to study the effectiveness. Most of the membership functions except Gaussian can response a big jump in the difference between measurement and model output. Threshold is used to filter out the normal variation which may lead to false alarm. A threshold is derived to make the fault detection. The results show that Fuzzy Neural Networks is a good modelling method for fault detection on the energy consumption of the whole building.

MODELING ANALYSIS

A well-known property attributed to both fuzzy system and neural networks is the fault tolerance regarding small changes in their inputs and parameters. However, it is possible severely to reduce the performance of a fuzzy system by modifying only one membership function slightly (Nauck et al., 1997). Normally this performance is not expected when making the FNN model for simulation but it is a useful characteristic for fault detection.

Fuzzy Neural Networks can be a good solution for the global energy model for fault detection and diagnosis on global building level due to above-mentioned characteristics. In order to find a good FNN structure, an experiment on a real office building in the Netherlands has been carried out.

The office building under test has four floors and with the area about $25x25m^2$. Usually around 50 persons work in this building. A Building Management System (BMS) – InsiteView – is installed to supervise, record and control the HVAC systems of the whole building. Measured data from all the sensors are stored into BMS for every 8 minutes.

Measured data of March 2001 and March 2002 are used for building and validating the FNN model. Two types of energy, natural gas and electricity, are used in the office building during the winter. The gas consumption responds the disturbance and singularity of the energy consumption in HVAC systems more directly than electricity in the wintertime. The electricity consumption shows a more or less normal fluctuation since no large amount of electricity is consumed by HVAC system in wintertime. Therefore, the measured data of gas consumption is used to analyse the FNN structure.

Figure 1 and 2 show the measurement of the gas consumption on March 2001 and March 2002. The data of March 2001, it is supposed as fault-free data, will be used to train the FNN model. The data of March 2002 will be used to check the FNN model and test the performance of fault detection. Two times a fault by an open window in one room, are introduced into the building. One is 9:00 ~ 12:30 on March 14, 2002 and another is 8:30 ~ 16:30 on March 15, 2002. These are 321 ~324.5 hour and 344.5 ~ 352.5 hour in the measurement in Figure 4. In Figure 4, two rectangular indicate these two periods.

The ANFIS function of Fuzzy Logic Toolbox of Matlab® is used to make the FNN models. The acronym ANFIS derives its name from adaptive neuro-fuzzy inference system. Using a given input/output data set, the toolbox function ANFIS constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using either a backpropagation algorithm alone, or in combination with a least squares type of method. ANFIS function combines the learning mechanism of neural networks into fuzzy inference techniques to realize data modelling. When we want to apply fuzzy inference to a system for which we already have a collection of input/output data that we would like to use for modelling, for instance here the gas consumption data. It is not necessary to have a predetermined model structure based on characteristics of variables. Rather than choosing the parameters associated with a given membership function arbitrarily, the parameters could be chosen to tailor the membership functions to the input/output data in order to account for these types of variations in the data values. This is where the so-called neuro-adaptive learning techniques incorporated into ANFIS.

By means of ANFIS, data that used for modelling should be split into two groups. One is so-called training data and another is called checking data. The training data are used to build the FNN model and checking data will be applied on the trained model to validate the training accuracy and to detect strange output that may indicate faults. The training data are supposed to be the representative of the reality and checking data are used to see if the FNN model response as the reality. As we mentioned above, Figure 1 shows the training data and Figure 2 shows the checking data. Part of the checking data is also healthy and two times of fault is introduced at certain periods.

Some common used membership functions are adopted to check which one is suitable for the fault concerning the gas consumption in the building HVAC system. These membership functions are: Triangular, Trapezoidal, Π-, Generalized bell, Gaussian and Product of two sigmoid.

The gas consumption in the building varies in principle periodically every 24 hours. In the night, it reaches the lowest values, sometimes 0, and during the day, it reaches the peak values. Therefore, it is reasonable to trace back the information of one day and take this information as the inputs of the model. From the measurement of one-month hourly data, 744 points can be used as training data. In order to get a useful model of fuzzy neural networks, the amount of inputs and the amount of membership functions are limited. Otherwise, the number of neuron will be bigger than the size of training data.

After manually adaptation, data with 6 hours step are chosen. This means the FNN model use gas(t-24), gas(t-18), gas(t-12), gas(t-6) as the input and gas(t) as the output. The model shows some qualitative clue for the fault of opening window. Figure 3 and Figure 4 are the example training and checking results with the generalized bell membership function. For the rest type of membership function, the training results are similar but the checking results are a bit different. These results can be seen from Figure 5-9.

The training results of the FNN are fluctuated within a band (Figure 3). However, the prediction of the absolute value is bad. Therefore, the FNN model is not suitable for predicting the absolute values. The reason is that the measured data is the hourly gas consumption; any disturbance can quickly influence the simultaneous value. The dynamic result may get better or worse even if small phase change. On the other hand, it is shown to be able to detect the fault. A peak can be found in the faulty period and this shows strong correlation. The peak dominates the system so strongly that it can be used for fault detection. The fluctuation of the difference between measurement and model output is within a band when the data are healthy. As soon as the fault happens, most membership functions reflect this in the checking results. This can be seen from Figure 4 to Figure 9 (except Figure 8 of gaussian membership function). Different membership function responds different amplitude for the fault. Interesting thing is that the FNN model react a negative value during the faulty period. This is possible because the real historical measured data will play as the input of the model. When the fault has happened, the model accumulates the faulty effect and then expects less energy consumption. Few hours later, this accumulation leads to a negative value. The failure of Gaussian membership function may be due to its relative smooth and symmetric shape. All the other membership functions are asymmetric and have inflexion.

Qualitatively, after the faulty conditions are introduced, the checking result shows a relatively high difference between measurement and model output. Only gaussian membership function has strong tolerance to the fault and no sharp difference can be found.

The linear output with combination of different type of membership function has been tried. However, because linear output asks more neurons in the FNN structure, the model cannot represent the reality completely.

Qualitatively we can conclude that it is possible to use FNN model to make the fault detection. In order to use this possibility, the phenomenon should be quantified. A method will be developed more detailed in the following section.

THRESHOLD DEFINITION

In order to detect the fault quantitatively, the threshold of the residuals is necessary. It is very important that the generation of residuals' threshold is independent of disturbances. The disturbances come from the unknown input noise signals, modelling errors, etc. Because of the presence of noise disturbances and other unknown signals acting upon the monitored variable (gas consumption), the residuals are usually stochastic variables $S_i(t)$ with mean value and variance (Willsky, 1976)

$$\bar{S}_i = E\{S_i(t)\};\ s_i^2 = E\{[S_i(t) - \bar{S}_i]^2\} \qquad (1)$$

as normal values for the fault-free process. Analytic symptoms are then obtained as changes

$$\Delta S_i = E\{S_i(t) - \bar{S}_i\};\ \Delta s_i = E\{s_i(t) - \bar{s}_i\} \qquad (2)$$

with reference to the normal values and $t > t_f$ where t_f is the time instant of fault occurrence.

To separate normal from faulty behaviour, usually a fixed threshold

$$\Delta S_{threshold} = e \cdot \bar{s} \cdot S \qquad e \geq 2 \qquad (3)$$

has to be selected. By this means, a compromise has to be made between the detection of small faults and false alarms.

In this study, the maximum $\bar{s}_i S_i$ for the training data is chosen for the threshold $\Delta S_{threshold}$. After analysing all six types of membership results, these maximum $\bar{s}_i S_i$ are shown in the follow table.

Table 1 maximum $\bar{s}_i S_i$ for different membership functions

	$\max(\bar{s}_i S_i)$		$\max(\bar{s}_i S_i)$
Triangular	29.7	Generalized bell	37.4
Trapezoidal	40.9	Gaussian	37.35
Π-	41.4	Product of two sigmoid	44.5

Figure 10 and Figure 11 show the results of the mean value and variance on the residuals of FNN model with generalized bell membership function.

The same analysis has been done on the other types of membership function and they show the similar result as generalized bell membership function.

Take some tolerance from the value in Table 1, $\bar{s}_i S_i$ is chosen as 45. Considering the equation (3) and choose å=2, a threshold can be obtained

$$\Delta S_{threshold} \approx 2 \times 45 = 90 \qquad (4)$$

Meanwhile, the derivative of the variable $\bar{s}_i S_i$ helps the fault detection as well. Figure 12 shows a summary of the results on $\bar{s}_i S_i$. The start of the fault can be easily detected by the positive peak and the end of the fault can be detected by the negative peak.

CONCLUSION

FNN modelling is studied to fulfil the task of the Fault Detection and Diagnosis on the energy consumption of the whole building. Fault-free measured data are used to build up the model and another measured data with a fault are used to validate the model and test the performance of fault detection. Difference FNN structures with six types of membership functions are analysed. By applying the model on the measured data with fault of an open window in the room, the FNN model shows for the healthy period, the model output responds normally and during the faulty period, a big jump appears. Threshold for the fault detection is derived from the moving mean value and variance in a certain period (24 hours). The derivative of the multiplication of mean value and variance shows a good possibility on detecting the faults.

Five membership functions can detect the fault by finding the overshoot of the threshold. Gaussian membership function has strong tolerance for the fault and cannot find the fault. This may be due to its smoothness and symmetric shape.

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NOMENCLATURE

S	residual signal (gas consumption) [$m^3 h^{-1}$]
t	time [h]
E	mean value
s	variance
e	threshold constant

Subscript

i	signal index
f	faulty moment

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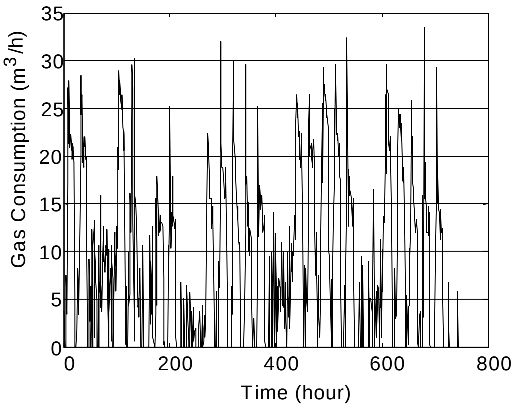

Figure 1 dynamic gas consumption of March 2001

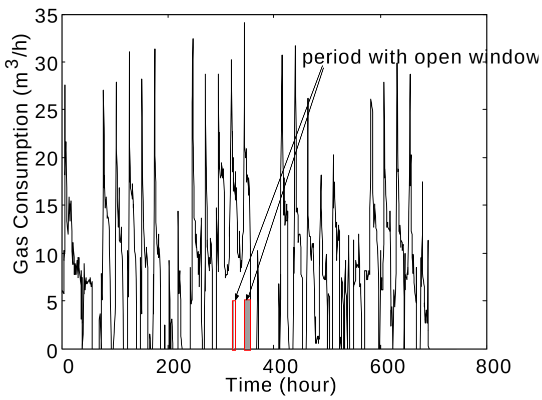

Figure 2 Dynamic gas consumption of March 2002

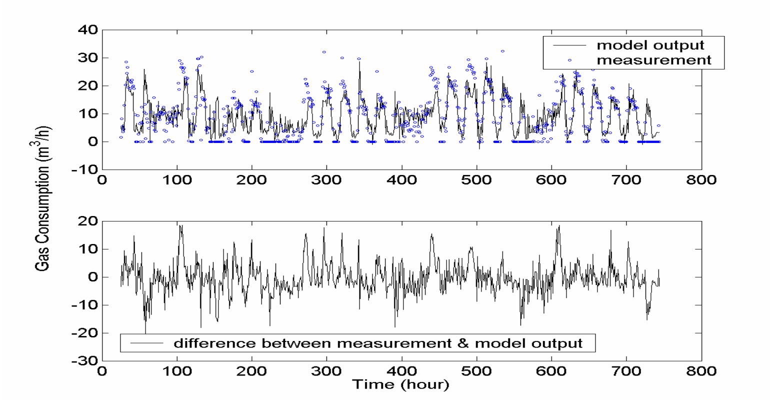

Figure 3 Training result by generalized bell membership function

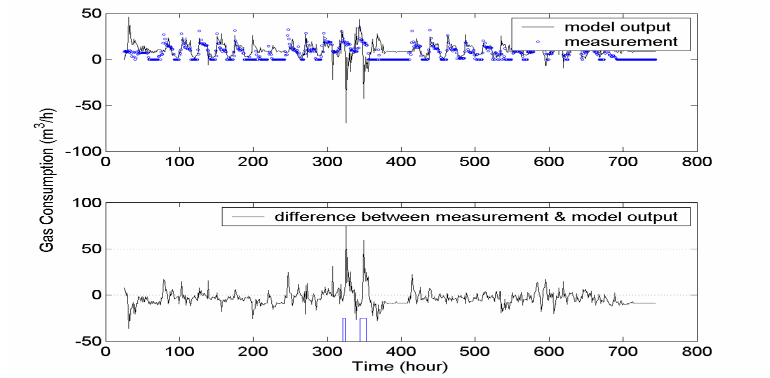

Figure 4 Checking result by generalized bell membership function

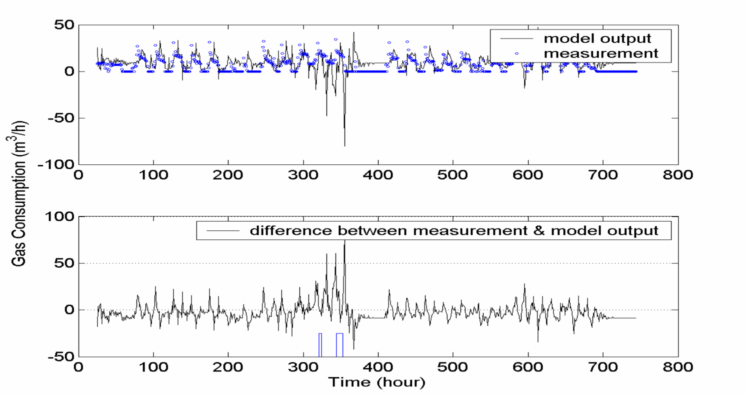

Figure 5 Checking result by triangular membership function

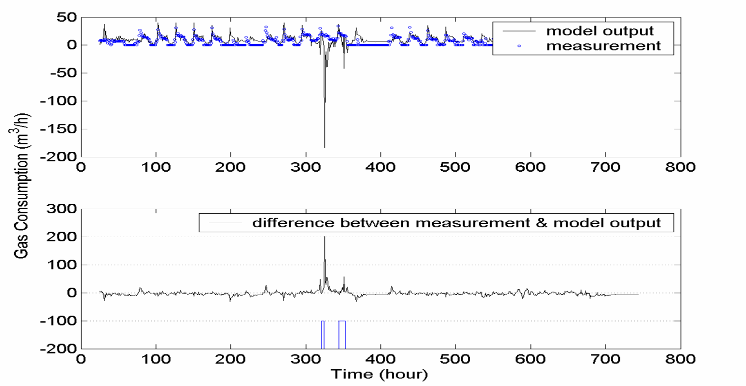

Figure 6 Checking result by trapezoidal membership function

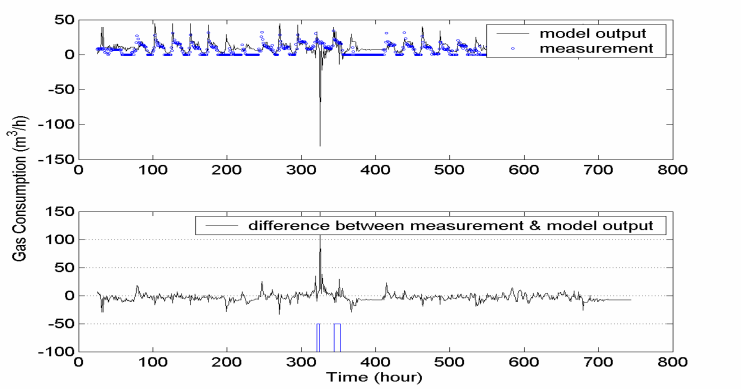

Figure 7 Checking result by ***P****- membership function*

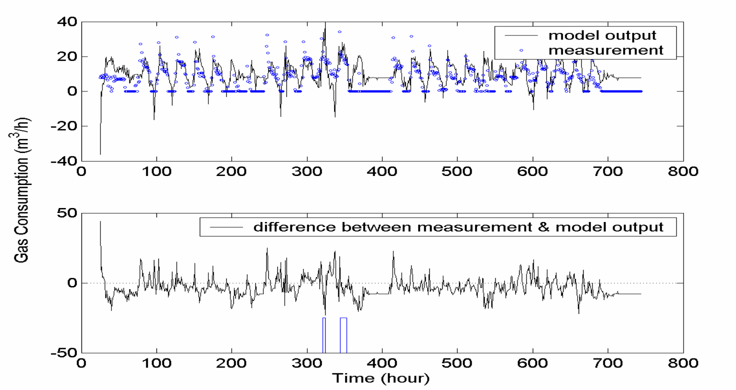

Figure 8 Checking result by Gaussian membership function

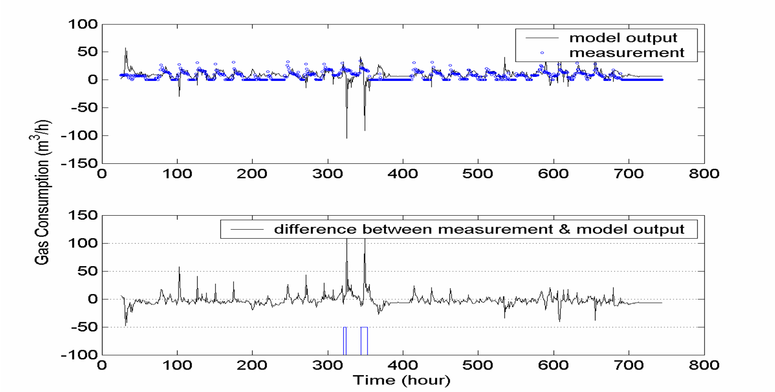

Figure 9 Checking result by product of two sigmoid membership function

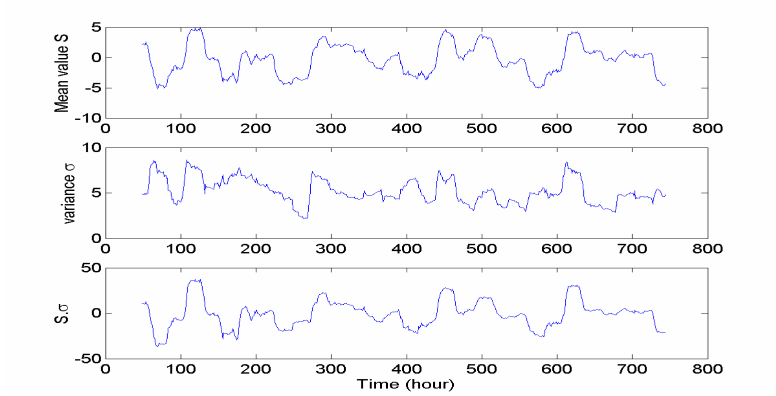

Figure 10 mean value, variance and their multiplication for the residuals of training result of generalized bell membership function

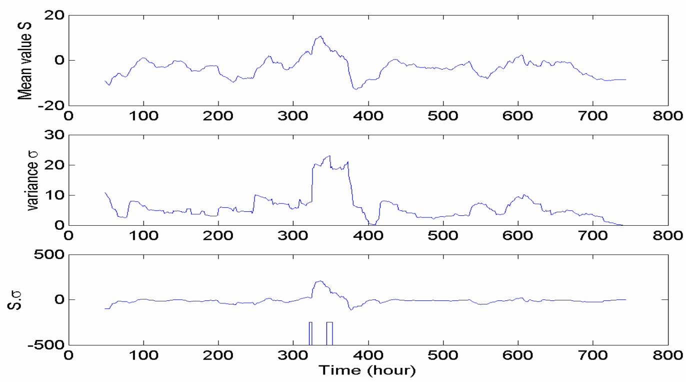

Figure 11 mean value, variance and their multiplication for the residuals of checking result of generalized bell membership function

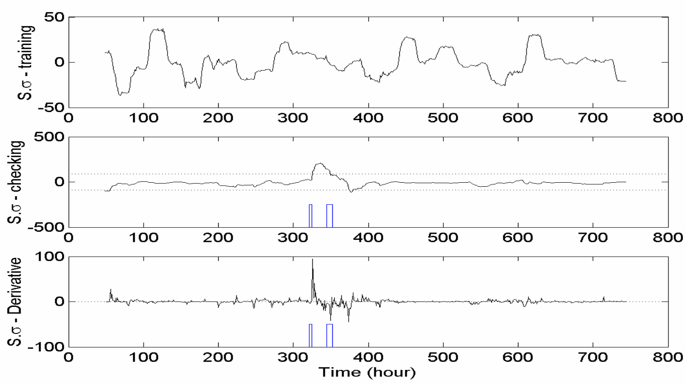

Figure 12 Summary of training, checking and derivative of the multiplication of mean value and variance $S \cdot s$