Neural Network based Data Fusion in Food Transportation System

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Abstract - Considering latest improvements, there are different applications for data fusion techniques. In food transportation systems, measuring environmental conditions like temperature and humidity is necessary for monitoring and controlling quality of products. Application of data fusion on measured data increases reliability of food transportation system. This paper introduces application of data fusion on the measurement results from a trading food company in purpose of data approximation and classification. For this purpose, neural network is used for temperature approximation and approximated temperature is being processed for data fusion. Then according to defined fault/failure classes, the temperature records are classified. This leads to increasing reliability of food monitoring system.

Keywords: Data fusion, temperature approximation, neural network, data classification.

1 Introduction

There are numerous applications for data fusion in science and industry. One important application of data fusion is in measurement systems and sensor network which is so called "multi sensor data fusion" [1], [2]. There are two main groups of methodologies for data fusion in measurement systems including model based and model free approaches [3]. In model based approaches, first the whole process is modeled locally/generally and the obtained model is used for inferring information [4].
In second category instead of modeling whole process, data fusion will be knowledge based [5]. One of important techniques for model free data fusion is using neural network [6], [7]. It is used for data prediction and data approximation in different projects [8], [9]. Also by using probabilistic features, neural network is applicable in classification purposes [10]-[13]. Measuring and fusion of environmental conditions like temperature and humidity could increase reliability of transportation system [14]-[15]. For transporting food, these considerations will be important whereas controlling transportation conditions could affect on quality of food. For this purpose all environmental conditions should be checked continuously or periodically for reaching assurance on food quality which is influenced by changes of temperature, humidity, pressure and other conditions. Hence supervision of food has important role in guaranteeing quality of products during transportation.
In this paper, application of data fusion technique for temperature fusion in food transportation system is introduced. Thus, the design of a neural network-based system for temperature approximation is described and an approach for classifying its output on the basis of faults and failure classes is outlined.

2 Neural network design for data approximation in transportation system

There are different methodologies for prediction and classification of data in any system [16], [17]. When the parametric changes in process depend on change of other parameters and establishing invariant situation is not possible or when it's necessary to recover actual signal from existing noise, using parameter estimation methods could be sufficient. Hence first it should be verified whether the parameter is observable or not. The knowledge based techniques are established on learning of events and dynamics in process [18]. In this category, according to the last valid measurement results and using appropriate learning algorithm instead of modeling the process, predicting new values of desired parameters will be possible [19]. Although reminding this fact is necessary that learning procedure and the architecture of applied mechanism have important role in estimation accuracy [20].
For neural network design, two main steps are considered;

- Selection of learning algorithm: In supervised learning, desired target values are known and are given into the neural network by training; according to the training criteria, the weights between different layers of network will be adjusted. During learning process, whole network will map inputs to desired targets based on the learning factors [21]. Basically there are two main approaches in the supervised learning including auto-associate and hetero-associate learning algorithms. In this research, auto-associative approach is used for mapping the input patterns including current/previous valid ambient temperature and some auxiliary values (which are introduced in this paper) into the related valid temperature records.

- Network topology: Next step is decision making on network architecture for application of learning procedure. There are varieties of network architectures including feed forward and feedback topologies. In feed forward topology, there is not any cycle; therefore spreading path for data flow inside the network is completely forward. The most important benefit of using the feed forward topology is response speed instead of feeding the inputs. Also for training the feed forward topology, depending on applications, different algorithms could be used especially "back propagation" which is used in this research (Fig. 1).

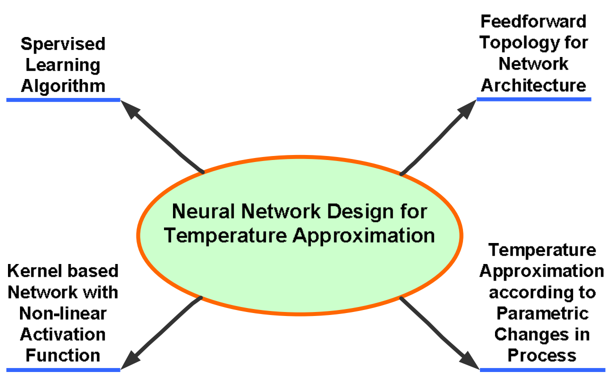

Fig. 1. Neural network design for data fusion in food transportation system

"Multi layer perceptron" (MLP) is a feed-forward neural network which has hidden layer(s) for spreading data. Using nonlinear function for each node in the hidden layer leads to better mapping between the input vectors and targets. Usually there are three main layers in MLP network including input, hidden and output layer [6].

Basically MLP is known as global approximator, but "radial basis function" is used for local approximation purposes when the approximation is considered for limited data range [6]. Fig. 2 shows the applied MLP network for temperature approximation.

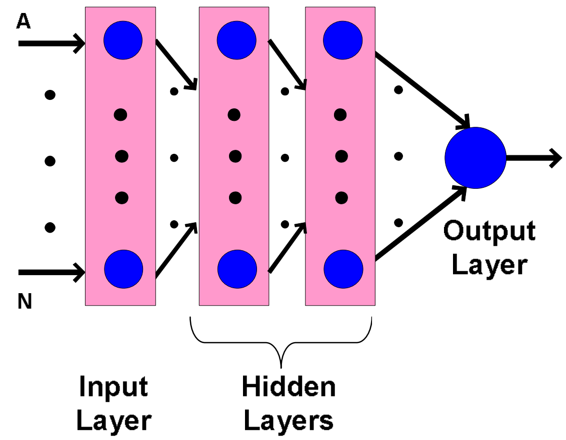

Fig. 2. Architecture of MLP network

For temperature approximation, two main layers including input and output layers are considered. Also 2 hidden layers (respectively including 5 and 3 neurons with sigmoidal activation function) are considered for better mapping.

$$net_j = \sum_{i=1}^{n} w_{ij} x_i \qquad (1)$$

In formula (1), net_j is the weighted input of j-th neuron in second layer, w_{ij} refers to weights between i-th input and j-th neuron in the second layer, x_i is i-th input layer element and n is number of inputs in the input layer. After calculation of net_j, according to (2) the output of each neuron is calculated.

$$\Phi(net_j) = (1 + e^{(-net_j)})^{-1} \qquad (2)$$
$$j = 1, \ldots, m$$

$\Phi(net_j)$ is output of each neuron and m is number of neurons in the second layer [6]. In similar way, all neurons between layers are connected together and data is spread into the network. For training, "gradient descent" algorithm is used.

$$W_{new} = W_c - \alpha_c grad_c \qquad (3)$$

In (3), W_{new} and W_c are respectively new and current weight vectors, $grad_c$ refers to current gradient based on error changes and α_c is training parameter.

3 Temperature approximation in food transportation system

Data approximation mechanism is applied on real temperature records inside compartments containing fresh fish, vegetable and meat inside the trucks. All temperature values are recorded using data loggers in

trucks for transporting food by a trading food company ("Rungis Express") [22]. The accuracy of each data logger is ± 0.5 °C and each truck is split in three compartments. About 40 data loggers are attached in different positions and each data logger could be selected as "under test data logger" for data fusion.
Outside the compartment, two data loggers are considered and each time, average of recorded values by these two loggers is assumed as "ambient temperature" (Parameter A). There is a cooling system which is known as "reefer unit" for cooling the compartment and ventilation purposes and one data logger records continuously the temperature of cooling system which is attached opposite to the cooling system (Parameter B).

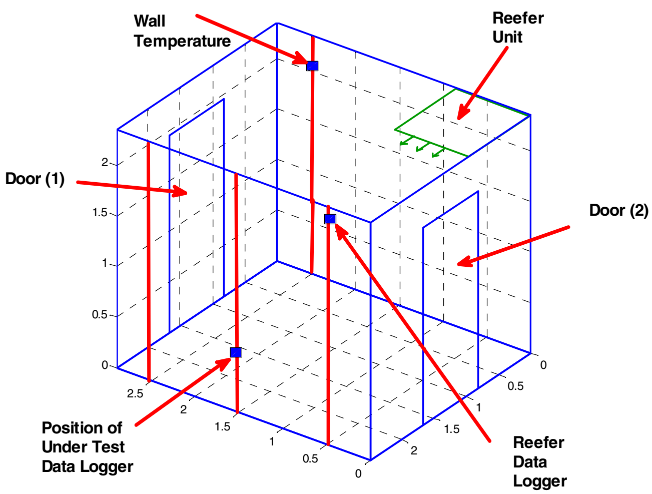

Fig. 3. Compartment and attached data loggers

Fig. 3 shows the compartment and position of attached data loggers for recording temperature. Also position of the "under test data logger" is shown in this figure.

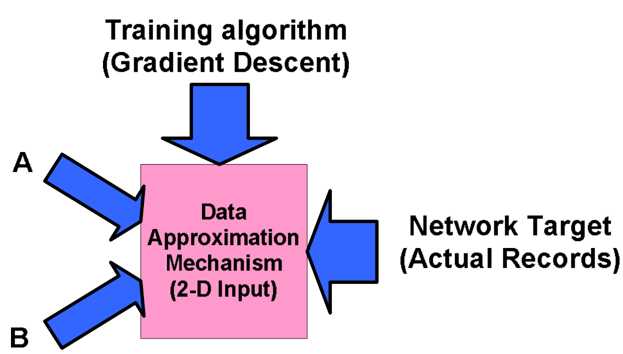

Fig. 4. Training the network using 2-D input

First according to Fig. 4, two-dimensional input (2-D) is entered into the network (including A and B parameters respectively) every 2.5 minutes and actual records of the "under test data logger" are applied into the network as target for being mapped into the input. After training the network using "gradient descent" method, every 15 minutes performance of the training is checked by feeding last input samples. After about 1.5 hour, the network is trained within desired temperature range for data approximation. This time period (1.5 hour) has been considered for reaching the temperature range which will be used during approximation phase.

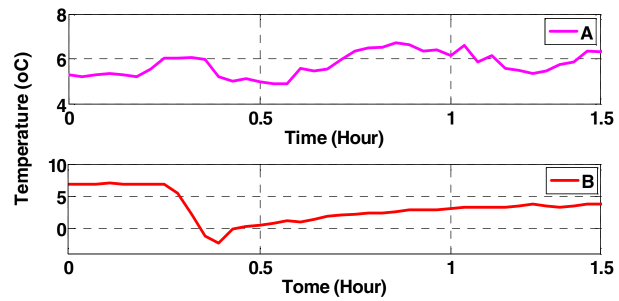

Fig. 5. 2-D input for training the network

Fig. 5 shows two dimensional input including A and B parameters for training the network.

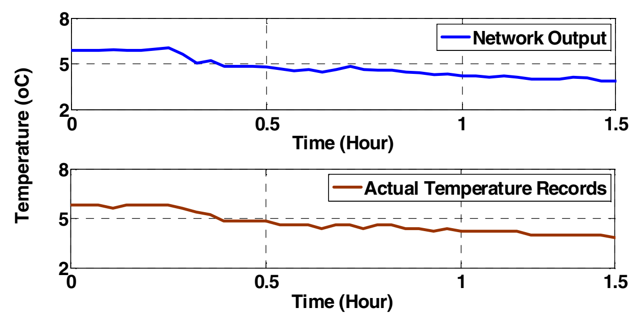

Fig. 6. Network output after training and actual records as target for training

Also according to Fig. 6, performance of training is checked against actual records which have been used as targets for training.

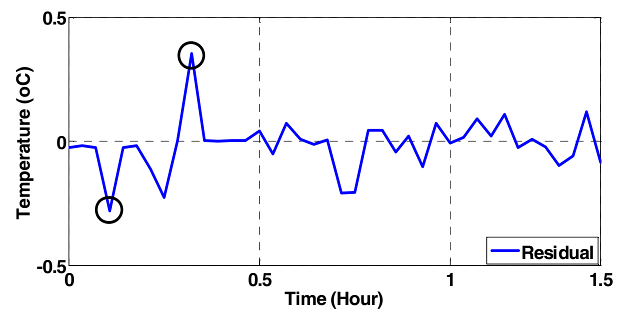

Fig. 7. "Training residual" after mapping 2-D input to actual records

Fig. 7 shows performance of training which is introduced as "training residual" (difference between actual temperature and the network output after training).
After 1.5 hour, the network is ready to start approximation, by reaching desired training performance (-0.2801 °C is the minimum value and 0.3532 °C is the maximum value which are in desired approximation boundary (±0.5 °C)) (Fig. 8). Then new

2-D input values are entered and the network output is calculated.

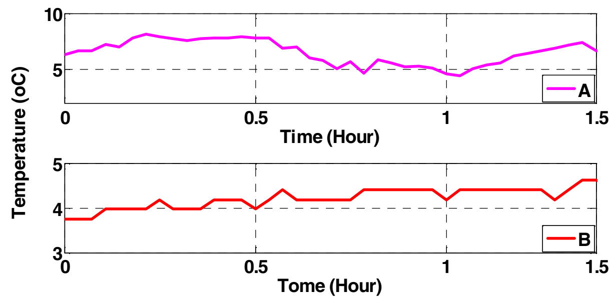

Fig. 8. Feeding new 2-D input for approximation

Therefore after feeding the new values (during next 1.5 hour), temperature approximation could start and it is compared with new actual records (Fig. 9).

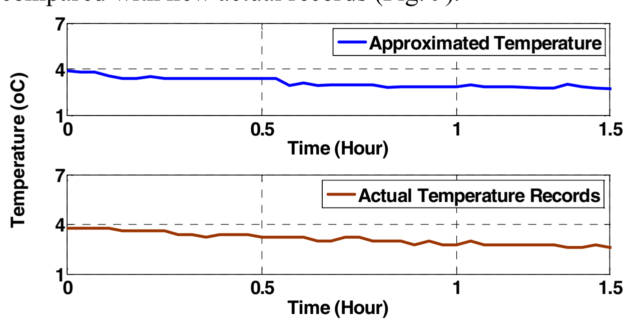

Fig. 9. Temperature approximation after feeding the 2-D input

Fig. 10 shows the approximation residual which is between two limits (±0.5°C).

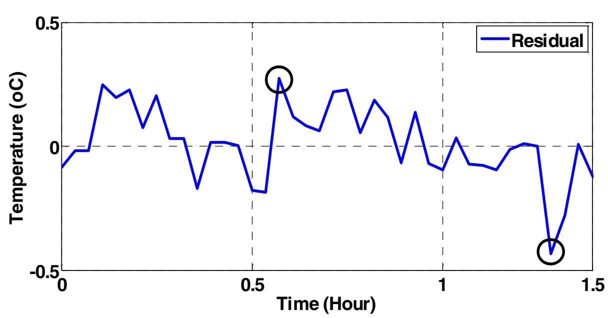

Fig. 10. Approximation residual after training with 2-D input

Also according to Fig. 10, the value of minimum approximation residual is -0.4341 °C and the maximum value is 0.2729 °C. For improving performance of approximation mechanism, third parameter is used. Influence of temperature changes on the wall of compartment is assumed as "wall temperature" (Parameter C) which generates third dimension of input vector. For this purpose, similar 2-D input pattern in addition to third parameter are entered into the network; then it could be possible to compare the performance of both approximation architecture. Therefore according to Fig. 11, 3-D input pattern (A, B and C parameters) is used for training the approximation network for 1.5 hour.

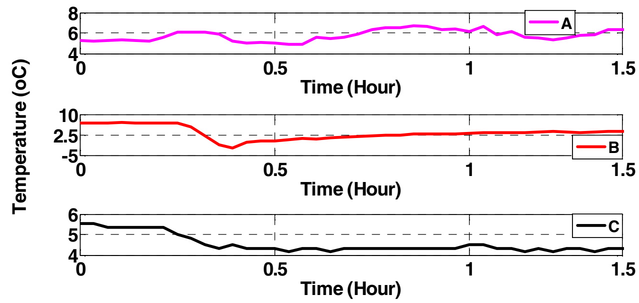

Fig. 11. 3-D input for training the network

According to Fig. 12 and 13, performance of training and the obtained training residual are shown.

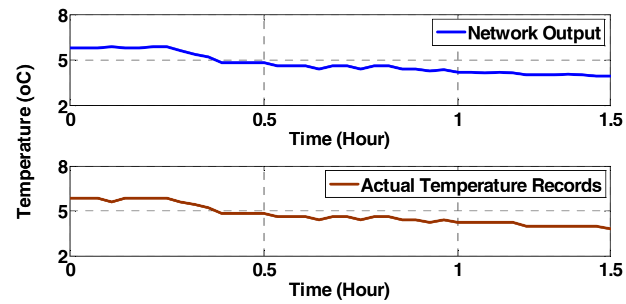

Fig. 12. Network output after training and actual records as target for training

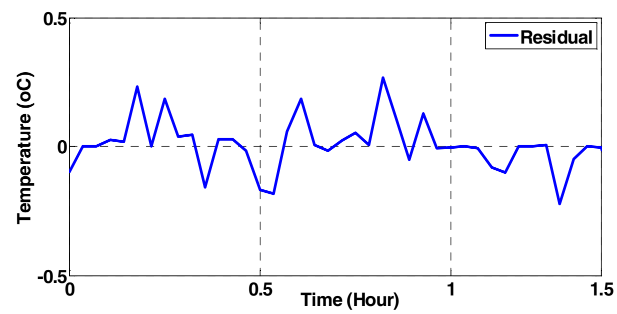

Fig. 13. "Training residual" after mapping the 3-D input to actual records

Fig. 14 shows new values of 3-D input for starting approximation and according to Fig 15, the approximated temperature is compared with the actual records.

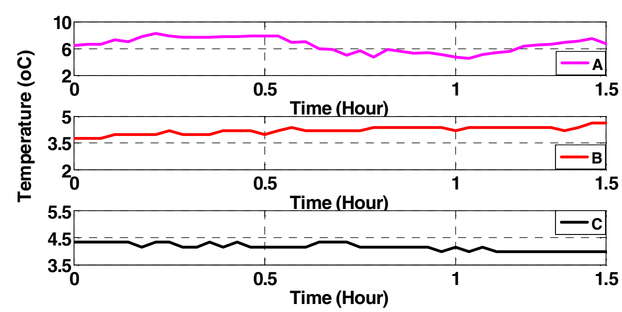

Fig. 14. Feeding new 3-D input for approximation

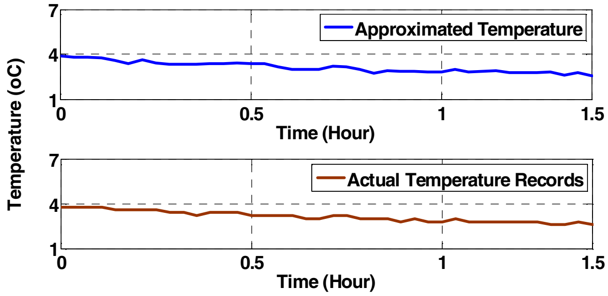

Fig. 15. Temperature approximation after feeding the 3-D input

Also Fig. 16 shows that the minimum value of approximation residual is -0.2243 °C and the maximum value is 0.2673 °C. It means that by using the wall temperature as third dimension of input pattern, the accuracy of temperature approximation is improved (Fig. 10).

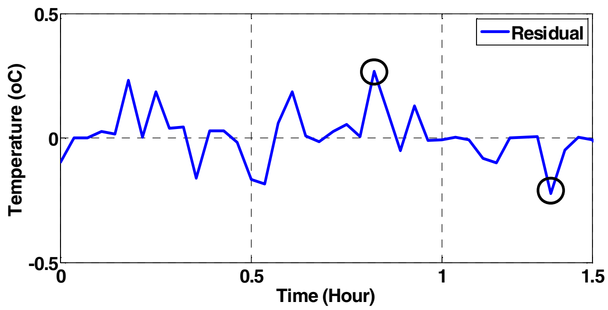

Fig. 16. Approximation residual after training with 3-D input

4 Data classification in transportation system

Next step is "data classification" which is included in data fusion mechanism. For this purpose according to approximation residual (ΔT) and pre-defined fault/failure classes, the temperature records of the "under test data logger" are classified (Fig. 17).

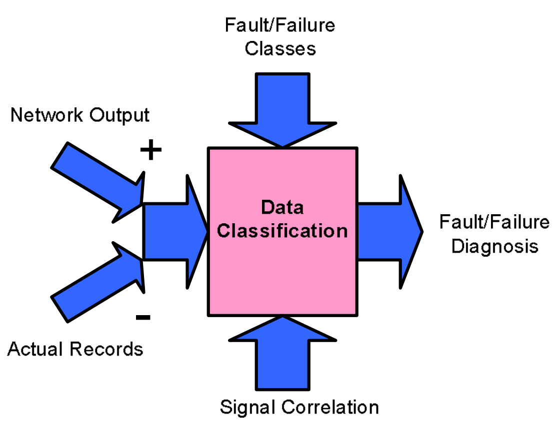

Fig. 17. Data classification mechanism

$$\Delta T = T_{Actual} - T_{Network} \qquad (4)$$

In (4), T_{Actual} is actual records of the under test data logger and $T_{Network}$ is the approximated temperature.

For data classification, 4 classes are defined including:

- Class (1): The approximation residual is in desired range ($-0.5 < \Delta T < +0.5$) and there is not any fault/failure (Fig. 15 and 16).
- Class (2): The approximation residual is not accurate enough for judgment ($0.5 < |\Delta T| < 1.5$). In this case, correlation between the approximated temperature and actual records is assessed.

$$Corr(A1, A2) = \frac{Cov(A1, A2)}{\sigma_{A1}\sigma_{A2}} \qquad (5)$$

For this purpose covariance of the approximated temperature (A1) and actual record (A2) is calculated and then is divided to standard deviation of each signal; it shows correlation factor between two signals. In class (2), when the correlation factor is more than 0.5, it is classified as subclass (2.1) which means the temperature records are reliable; otherwise it is classified as subclass (2.2) and it is evaluated like class (3)/class (4).

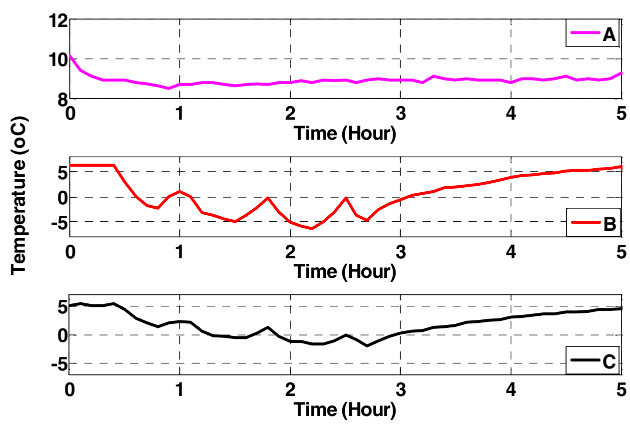

Fig. 18. Feeding 3-D input for approximation (Class (2))

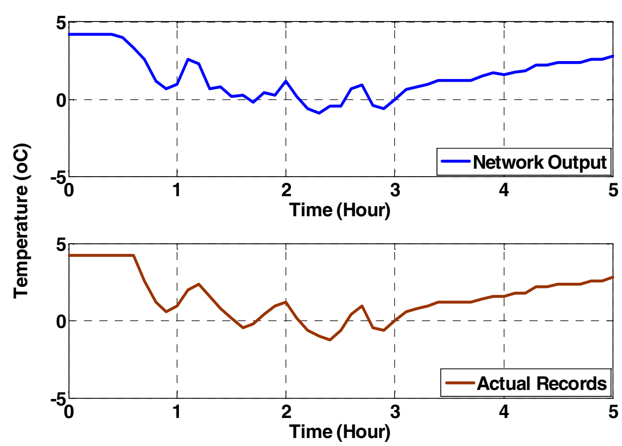

Fig. 19. Temperature approximation after feeding the input (Class (2))

According to Fig. 18 and 19, the 3-D input is fed into the network and the approximated and actual records are compared and situation of class (2) occurs where the approximation residual is in unknown area ($0.5 < | \Delta T | < 1.5$)(Fig. 20).

Although the approximation residual is not in desired area but correlation factor is 0.748. It's more than 0.5 and the record is classified in class 2.1.

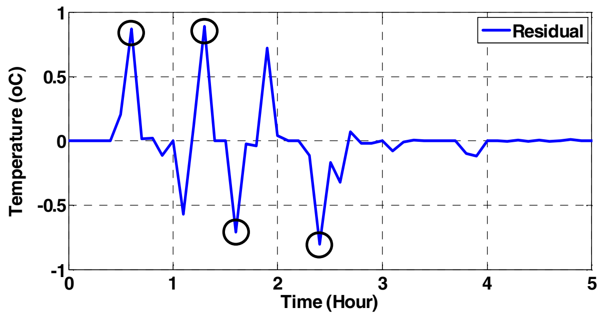

Fig. 20. Approximation residual (Class (2))

- Class (3): The values in class (3) could be classified in three subclasses including door opening, sealing problem and data logger defection. Sometimes there is a reason for penetrating ambient air into the compartment. Actual record (T_{Actual}) changes toward the ambient temperature (T_{amb}) and situation of the data logger next to the door of compartment is checked for finding the reason (whether the door is open incidentally or there is sealing problem in compartment). Also it is possible to detect probable deviation in performance of data logger.

Fig. 21 shows an example in class (3), where the logger record increases toward the ambient temperature. Also amplitude of residual in this class is shown in Fig. 22.

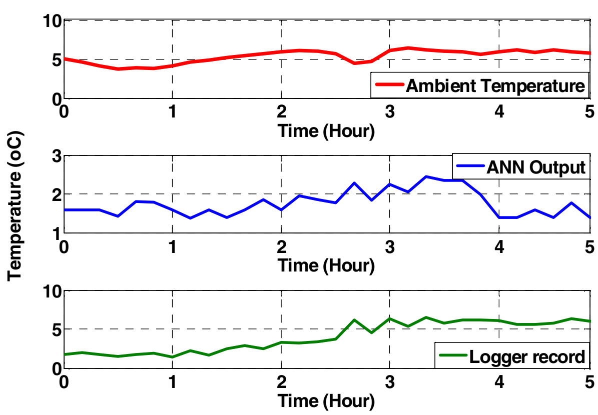

Fig. 21. Temperature approximation (Class (3))

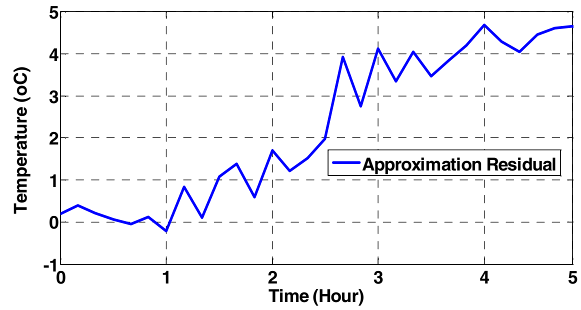

Fig. 22. Approximation residual (Class (3))

- Class (4): The logger record doesn't change and the approximated temperature is completely equal to approximation residual. It means that according to changes in values of the input parameters, the temperature record of data logger is expected to change continuously but lack of battery charge causes significant change in approximation residual.

When the logger doesn't have battery charge it doesn't show any value (an example is shown in Fig. 24) and according to Fig. 25 approximation residual changes dramatically, therefore this is included in class (4).

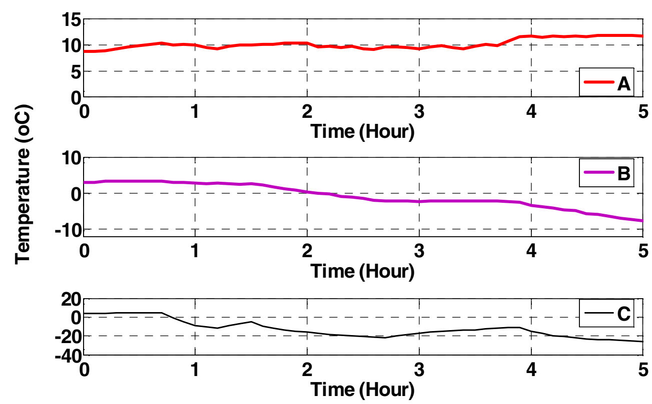

Fig. 23. Feeding 3-D input for approximation (Class (4))

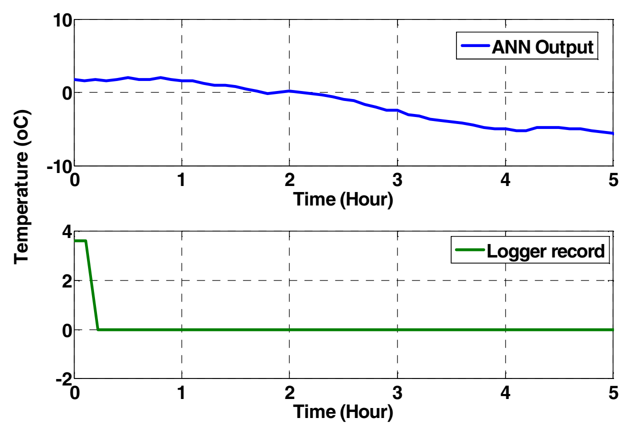

Fig. 24. Temperature approximation results (Class (4))

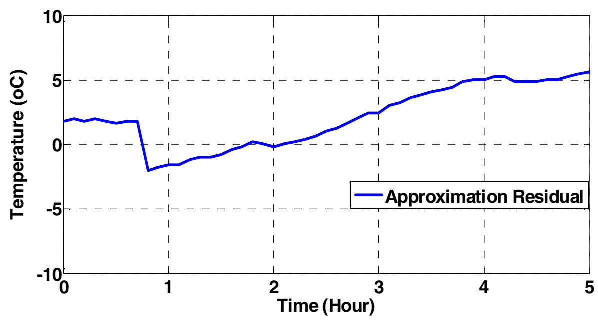

Fig. 25. Approximation residual Class (4)

Table (1) describes the applied procedure for data classification based on predefined fault/failure classes. Therefore after temperature approximation, according to applied algorithm, all temperature records are classified.

Class	Specification	Situation
1	$-0.5 < \Delta T < +0.5$	Normal
2	$0.5 < \lvert \Delta T \rvert < 1.5$ $\lvert Correlation \rvert > 0.5$	Subclass 2.1 (Normal)
	$0.5 < \lvert \Delta T \rvert < 1.5$ $\lvert Correlation \rvert < 0.5$	Subclass 2.2 (Class(3)/(4))
3	$\lvert \Delta T \rvert \geq 1.5$ $T_{Ambient} \approx T_{Actual}$ $T_{Ambient} \approx T_{Door}$	Door opening
	$\lvert \Delta T \rvert \geq 1.5$ $T_{Ambient} \approx T_{Actual}$ $T_{Ambient} \neq T_{Door}$	Sealing problem
	$\lvert \Delta T \rvert \geq 1.5$ $T_{Ambient} \neq T_{Actual}$	Data logger Defection
4	$\Delta T = T_{Network}$	Low Battery

Table 1. Data classes (1-4)

5 Conclusion

New algorithm for data fusion is introduced and applied on real temperature records from a trading food company. Data fusion algorithm is established on application of neural network for data approximation. For this purpose, multi layer perceptron is used for temperature approximation. Also by using an auxiliary parameter, improvements in temperature approximation is outlined. Finally according to defined fault/failure classes, temperature classification algorithm is applied.

Acknowledgment

This research was supported by the German Research Foundation (DFG), as part of the Collaborative Research Centre 637 on "Autonomous Cooperating Logistic Processes". We especially thank the CCG Cool Chain Group Holding AG, CCG FRA and Rungis Express AG for provision of the test facilities.

References

[1] D. L. Hall and J. Llinas, “An introduction to multisensor data fusion,” Proc. IEEE, vol. 85, pp. 6–23, Jan. 1997.

[2] P. K. Varshney, “Multisensor data fusion,” Electron. Comm. Eng. J., vol. 9, no. 6, pp. 245–253, 1997.

[3] G. Betta, and A. Pietrosanto, ‘‘Instrument Fault Detection and Isolation: State of the Art and New Research Trends,’’ IEEE Transactions of Instrumentation and Measurement, 2000.

[4] P. Balle, D. Fussel, and O. Hecker, “Detection and isolation of sensor faults on nonlinear processes based on local linear models,” in Proc. Amer. Control Conf., Albuquerque, NM, June 1997, pp. 468–472.

[5] G. Betta, M. Dell’Isola, C. Liguori, and A. Pietrosanto, “Expert systems for the detection and isolation of faults on low-accuracy sensor systems,” in Proc. IEEE Workshop ET&VS-IM/97, Niagara Falls, Ont., Canada, pp. 39–48, May 1997.

[6] S. Haykin, “Neural Networks”, Englewood Cliffs, NJ: Prentice-Hall, 1998.

[7] L. C. Jain and V. R. Venuri, “Industrial Applications of Neural Networks”, Boca Raton, FL: CRC Press, 1999.

[8] Y. M. Chen and M. L. Lee, “Neural networks-based scheme for system failure detection and diagnosis”, Mathematics and Computers in Simulation 58, 2002, 101–109.

[9] G. Betta, M. Dell’Isola, C. Liguori, and A. Pietrosanto, “An artificial intelligence-based instrument

fault detection and isolation scheme for air conditioning systems," in Proc. XIV IMEKO World Congr., vol. VII, Tampere, Finland, pp. 88–95, June 1997.

[10] D. F. Specht and H. Romsdahl, "Experience with Adaptive Probabilistic Neural Networks and Adaptive General Regression Neural Networks", Proceedings of the IEEE World Congress on Computational Intelligence, 2, 1203-1208, 1994.

[11] P. G. O'Reilly, "Local sensor fault detection using Bayesian decision theory," in UKACC Int. Conf. Control '98, Sept. 1–4, 1998, pp. 247–251.

[12] C.P Lim, R. F. Harrison, "Probabilistic Fuzzy ARTMAP: an autonomous neural network architecture for Bayesian probability estimation" Artificial Neural Networks, Fourth International Conference on Volume, Issue, 26-28 Jun 1995.

[13] Y.-J. Oyang, S.-C. Hwang, Y.-Y. Ou, C.-Y. Chen and Z.-W. Chen, "Data classification with radial basis function networks based on a novel kernel density estimation algorithm," IEEE Trans. Neural Netw., vol. 16, no. 1, pp. 225–236, Jan. 2005.

[14] Hueter, G.J., Diamond, A.L., Platt, C., and Quandt, S.C., "Neural Network-Based Automated Food Inspection", Food Processing Automation II, 1992, p 291.

[15] Ibarra, J. G. and Tao, Y., "Estimation of Internal Temperature in Chicken Meat by Means of Mid-Infrared Imaging and Neural Networks", Proc. of SPIE - The International Society for Optical Engineering, vol. 3543, 1999, p 24-31

[16] A. Jain, "Frost prediction using artificial neural networks: A temperature prediction approach," M.Sc. thesis, Artificial Intelligence Center, University of Georgia, Athens, GA, 2003.

[17] J. L. Crassidis and J. L. Junkins, "Optimal Estimation Of Dynamical Systems", Applied Mathematics and Nonlinear Science. Boca Raton, FL: CRC Press, Mar. 2004, vol. 2.

[18] N. Cristianini and J. Shawe-Taylor, "An introduction to support vector machines and other kernel-based learning methods", Cambridge University Press, 2000.

[19] R. P. Leger, Wm. J. Garland and W. F. S. Poehlman, "Fault detection and diagnosis using statistical control charts and artificial neural networks", Artificial Intelligence in Engineering 12, 1998, pp. 35-41.

[20] E. Vonk, L. C. Jain, and R. P., Johnson, "Automatic Generation of Neural Network Architecture using Evolutionary Computing", World Scientific Publishing Company, Singapore, 1997.

[21] R. Caruana and A. Niculescu-Mizil, "Predicting good probabilities with supervised learning," in Proc. Amer. Meteorology Conf. (AMS 2005), San Diego, CA, 2005, vol. 1.6.

[22] R. Jedermann, W. Lang, "Semi-passive RFID and beyond: steps towards automated quality tracing in the food chain", in: International Journal of Radio Frequency Identification Technology and Applications (IJRFITA), 1(2007)3, pp. 247 – 259.