International Journal of Information, Control and Computer Sciences
ISSN: 2517-9942
Vol:1, No:9, 2007

Application of Computational Intelligence for Sensor Fault Detection and Isolation

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***Abstract*—**The new idea of this research is application of a new fault detection and isolation (FDI) technique for supervision of sensor networks in transportation system. In measurement systems, it is necessary to detect all types of faults and failures, based on pre-defined algorithm. Last improvements in artificial neural network studies (ANN) led to using them for some FDI purposes. In this paper, application of new probabilistic neural network features for data approximation and data classification are considered for plausibility check in temperature measurement. For this purpose, two-phase FDI mechanism was considered for residual generation and evaluation.

***Keywords*—**Fault detection and Isolation, Neural network, Temperature measurement, measurement approximation and classification.

I. Introduction

It is necessary to detect and isolate faults and failures by processing measured data in measurement systems. Fault detection and Isolation will increase assurance on quality, reliability and safety of systems. Neural Network is one of the important techniques, which could be applied for plausibility check in measurement systems. Nowadays, different types of ANN application can be found in engineering, military industries, weather forecasting and business. There are lots of architectures for arranging the neural networks, like feed forward and feed back. Also for learning process there are some possibility which could be considered such as supervised, unsupervised and reinforcement learning [2], [7]; so defining and learning all possible events and required decisions, based on type of faults/failures in sensor network should be considered for ANN based plausibility check mechanism. Another possibility is using probabilistic neural network for function approximation and classification purposes [1], [14], [17]; Specht studied on estimation of continuous variables and convergence by memory-based network [5], [6]. Lim and Harrison combined Fuzzy and Probabilistic Neural Network (PNN), for online learning and prediction tasks. They used non-parametric probability estimation procedure during the prediction phase.

During last years, some researchers worked on data fusion techniques [4], [13], [18]; Isermann classified some important techniques for fault detection and isolation purposes [22]. Hall studied mathematical techniques for data fusion in multi sensor system [3]. Betta considered application of fault detection and isolation methods in measurement systems [9], [10], [11]. Kirsch used Bayesian networks for fault diagnosis and O'Reilly studied Local sensor fault detection by applying Bayesian technique [12], [19]. Neural networks could be an important approach for sensor data fusion. Some researchers worked on modeling, signal evaluation and plausibility checking by ANN architectures [27]. Leger and Garland applied combination of statistical control charts and artificial neural networks for FDI purposes [21] and Chen considered a probabilistic model for sensory data evaluation [26].

II. Autonomous Fault Detection and Isolation in Sensor Network

Nowadays, application of autonomy is considered in logistics, industrial, and production processes. These processes can be monitored and controlled using suitable autonomy approaches. Also, using autonomous features play an important role in sensor networks. In fact, adding some autonomous features will increase measurement reliability and accuracy. First, it is necessary to define area of autonomy in a sensor network. Also, selection of a suitable autonomy technique depends on nature and complexity of the system which should become autonomous. One important autonomy feature, which could be applied on measurement systems, is plausibility checking, because it is important to have confident readings. Thus, application of data verification techniques will increase reliability of sensor networks. Also, after fault detection, required considerations could be applied to recover the system from fault/failure conditions, in optimized time with lower risk; thus, plausibility check algorithms will lead to cost efficiency, reliability and safety. The most important subject of this paper is selection and application of suitable fault detection and isolation mechanism for evaluation of temperature readings of a trading food company. Also, classification, evaluation and assessment of measured data, based on an appropriate mechanism are considered.

III. Probabilistic Neural Network Mechanism for Data Approximation and Classification

There are some useful methods for analyzing measurement data, for notification of sensor defection and failure. Some methods are based on the dynamics of the process, like using parameter estimation and observers. It is necessary to consider the capability of modeling and observing process data in this category. These methods are established on estimation of measurement states and variables based on previous and current measured values and observations.

Innovation of new techniques for data classification in artificial neural networks (ANN) and fuzzy logic led to apply them in plausibility checking. In this category, training the plausibility check mechanism with previous measurements should be considered instead of modeling the whole process. Application of Artificial Intelligence to measurement system will cause a nonlinear mapping between measurement results and judgment about reliability of measurements.

By adding ANN features, the measurement system will be intelligent because it will be possible to severe evolutionary computing, learning and adaptation features. Therefore, ANN architecture learns from previous measurement results and it could approximate new measurement results based on new conditions. Also, it's possible to judge about unknown events by using probabilistic neural networks, especially for classification purposes. Neural network plausibility check is defined based on comparison of measured data with neural network prediction. Therefore, suitable architectures for arranging the neural networks and the required learning algorithm should be applied and previous measured data will be the input patterns for ANN.

In this research a neural network based FDI mechanism was applied for a set of data loggers; In fact, two separate ANN algorithms were considered for residual generation and residual verification phases, respectively. By comparison of measured data with network prediction, fault residuals were generated and then all residuals were evaluated and analyzed. For temperature readings, previous measured signals were defined and fed to FDI mechanism with separate patterns. In each phase, kernel-based learning method was applied with patterns which were obtained during previous readings.

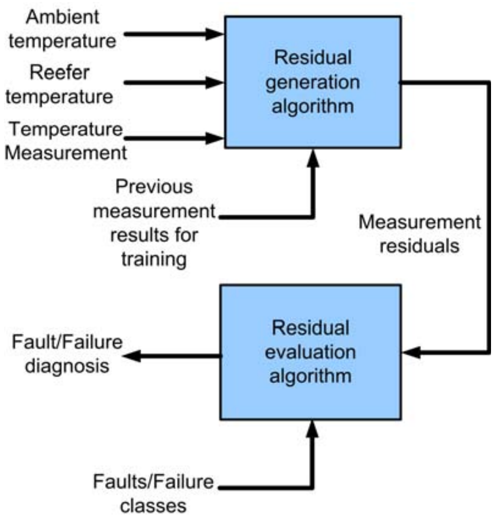

Fig. 1 Fault/Failure detection and isolation diagram

For generating residuals, generalized regression neural network architecture was considered for data approximation. Therefore, in this phase, measurement residuals were generated by comparing measured data with network prediction. In second phase, depending on output of Approximation architecture, probabilistic neural network (PNN) was applied for analyzing probable fault/failure conditions and fault/failure classification. After evaluation of residuals, situation of each measured signal was resulted, by assessment parameters and prediction of ANN.

In Fig. 1, general diagram of two phase FDI mechanism is implemented; for this purpose, both networks should be trained with previous measurement results; then by predicting temperature of data logger, against instantaneous values of other parameters like ambient temperature, approximation will be possible.

After approximation of temperature, measurement residuals will be obtained for feeding second ANN architecture. In this phase, after defining faults/failure classes and some extra conditions (like threshold test), the measurement residuals will be assigned to appropriate measurement classes. Finally, after judgment by evaluation network, all probable faults/failures will be detected.

IV. Sensor Data Fusion for Temperature Measurement in Trucks

In food transportation systems, it is necessary to supervise the quality of food, by measuring environmental conditions, like temperature and humidity. Then, the measured data should be processed based on an appropriate technique for extracting useful information about quality of products. Thus, by tracking measurement results, all possible events in transportation system should be detected and classified according to pre-defined faults/failure classes by analyzing measurement results. In this paper, data fusion mechanism was designed and applied on Temperature measurement results from Rungis Express Company which is a trading food company in Germany (Meckenheim).

There are some trucks which were spilt into three compartments, containing fresh vegetables, fish and meat. Some auxiliary data loggers were attached on different positions of each compartment for recording temperature in compartments, with accuracy of ± 0.5 °C; also there is a reefer in compartment and a fan for ventilation purpose. Because of using the On-Off reefer unit, some fluctuations could be observed during temperature measurement.

Using several data loggers will give possibility of better assessment by FDI mechanism in compartments, despite differences between values, based on position of loggers. Application of temperature approximation techniques will lead cost efficiency in temperature measurements, by using few data loggers. For this purpose, all measured value at the logger positions; reefer air and ambient temperature were considered for temperature approximation for each data logger. Therefore, after approximation all differences between real value of loggers and temperature approximation were considered as measurement residuals. It means that faults evaluation system is sensitive to temperature variations of data loggers over time.

V. Measurement Approximation for Residual Generation

The known methodologies for residual generation are basically divided in signal-based (input-output) and model-based techniques. In this application, signal-based methodology was considered for residual generation. For application of neural networks in residual evaluation, all residuals should be generated, whether by another neural network architecture or by other methods. As mentioned, in this research the FDI algorithm was defined by two ANN architectures for residual generation and residual evaluation. Two-phase FDI architecture led to better performance and higher flexibility in system design. In first step, ANN approximation architecture was applied to generate residuals by comparing current measurements with previous trained patterns. This architecture is a feed forward neural network, which is generally used for function approximations in system modeling and prediction.

Approximation module copies the training patterns for mapping into related target patterns, to be used for estimation of responses in comparison with new measurement inputs. The output is estimated using a weighted average of the outputs of the training patterns, which the weights are related to the distance of the point, from the point being estimated.

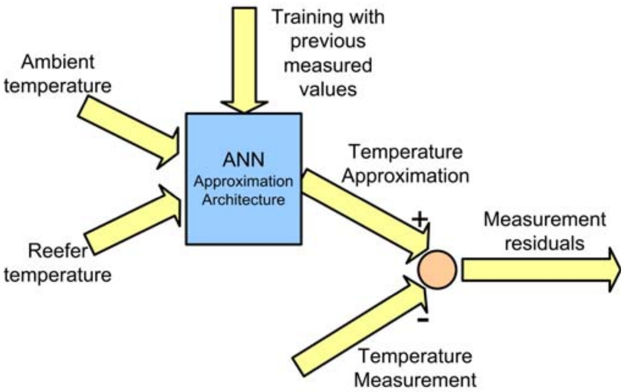

Fig. 2 Residual generation in measurement system

For approximation of temperature measurement, reefer and ambient temperature were entered to the network as input patterns. Against input patterns, readings of each data logger were considered as target patterns. By this way, each reading for ambient temperature and reefer air were mapped to reading of data logger; therefore, after spreading the data to network, approximation mechanism could be able to predict next temperature values of data logger based on new values of ambient and reefer temperature. Then, differences between temperature measurement and approximation could be calculated and observed as measurement residuals.

VI. measurement Residual Evaluation with Probabilistic Neural Network

Residual evaluation techniques can be established by threshold decisions, statistical methods, and classification mechanisms; in this paper, Residual evaluation for measurement system was established for classification of residuals, according to faults/failures classes and extra conditions for improving evaluation results. Fig. 3 shows the criteria which was considered for residual evaluation.

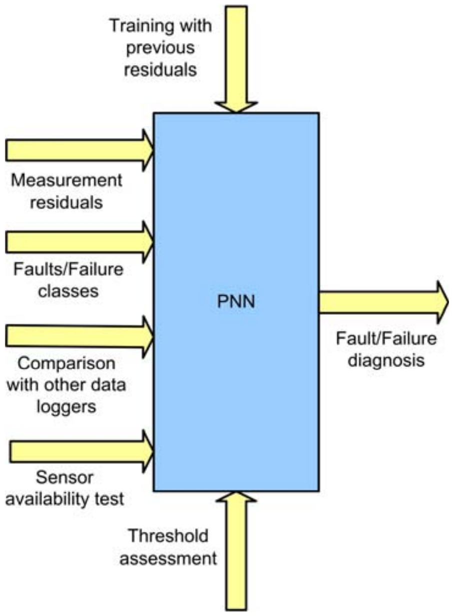

Fig. 3 Residual evaluation in measurement system

By replacing the sigmoid activation function, which is often used in neural networks with an exponential function, probabilistic neural network (PNN) for defining nonlinear decision boundaries will be obtained. This architecture can map input patterns to all classification targets; so the task of this network is estimation of the probability for classification purposes. Also the architecture requires less training rather than the linear neural networks, but a higher number of hidden nodes. Training was limited to a reduced number of known residual patterns with mapping into assigned faults/failures classes for description of all possible problems in measurement system. Before applying the neural network for evaluation of these residuals, the network has to be trained based on the mentioned classes.

Both types of applied neural network architectures are kernel-based methods for Temperature approximation and evaluation [14], [17]. For PNN architecture, three layers were considered including input, output and a hidden layer including radial units. The radial units used for extracting trained data with Gaussian function. The greatest advantage of using PNN is using probabilistic features for classification of measurement results by nonlinear mapping.

VII. Measurement Simulation Results

For residual generation and evaluation phases, measurement readings of first day were fed into the networks for training approximation and evaluation mechanism, for two trucks, respectively. As mentioned before, ambient, reefer and

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data logger temperature were measured for first 24 hours for training the networks. For next 12 hours, based on measurement of ambient and reefer temperature, data logger temperature could be approximated instantaneously. Then, by comparison between temperature readings and approximation, measurement residuals were obtained for feeding into second ANN architecture. Also measurement threshold test and measurement results of other data loggers, near the "under test logger", are auxiliary tests for decision making by residual evaluation network. For designing approximation architecture, radial basis network was used for function approximation including two layers. In first layer, radial basis function was considered for calculating weighted inputs with distances. Two input patterns including ambient temperature ($T_{Ambient1}$) and reefer ($T_{reefer1}$) were applied for spreading into radial basis functions of network;

$$P_{in1} = \lfloor T_{reefer\ 1}; T_{Ambient\ 1} \rfloor \quad (1)$$

In fact, for training neural network, P_{in1} was applied for residual generation mechanism. The readings could be obtained every 10 minutes, so for one day (24 hours), totally 144 readings are available. Therefore, depend on measurement ranges and number of readings, P_{in1} contains 144 rows and 2 columns for mapping into 144 elements in Target (T_t). Therefore in second layer, linear network was considered for calculation of weighted input against temperature readings as target (T_t).

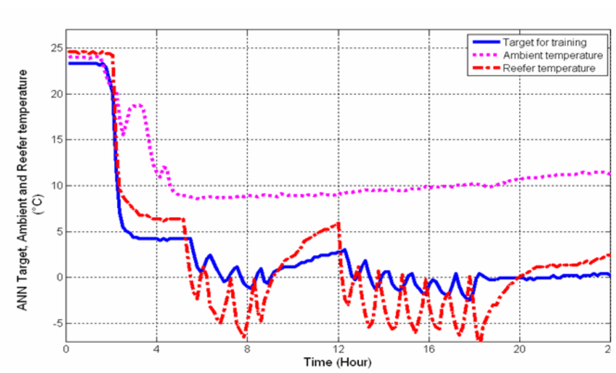

Fig. 4 Training network for temperature approximation in first truck

For better fitting of measurement data, the spread parameter was considered smaller than the typical distance between input patterns. Although for fitting measurement data more smoothly, larger spreading parameter should be considered. Fig. 4 shows the training procedure of network, based on ambient and reefer temperature for first truck. After training the network by readings for first day, mechanism started to predict temperature for next 12 hours. For this purpose, by instantaneous values of ambient and reefer temperature, mechanism started to predict temperature of data logger. Thus, after application of new input patterns (P_{in2}), approximation of measurement could be observed for comparison with data logger readings (T_m). Input pattern (P_{in2}) contains new ambient temperature ($T_{Ambient2}$) and instantaneous reefer temperature ($T_{reefer\ 2}$) for data approximation;

$$P_{in2} = \lfloor T_{reefer\ 2}; T_{Ambient\ 2} \rfloor \quad (2)$$

In Fig. 5, new temperature approximation is simulated, based on instantaneous readings of ambient and reefer temperature. In Fig. 6, temperature readings and approximation could be compared with reefer air. Also, the same procedure was applied for second truck for temperature approximation, by ambient and reefer temperature as input patterns.

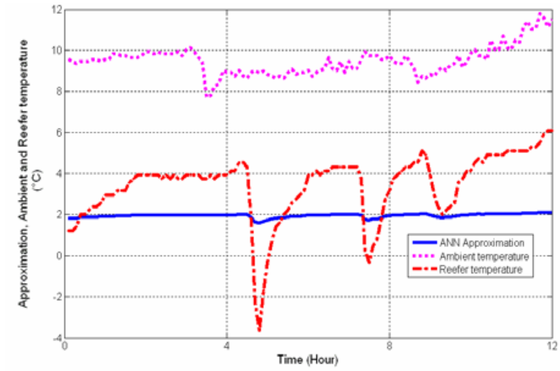

Fig. 5 Temperature approximation results with ANN in first truck

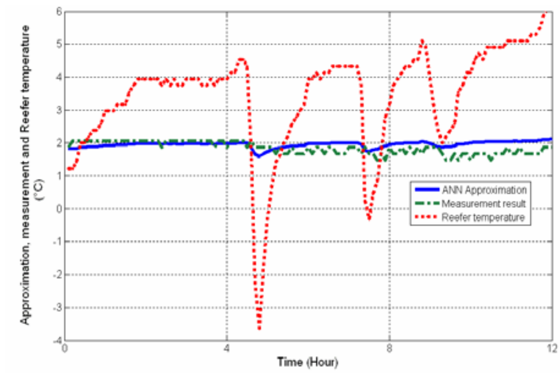

Fig. 6 Temperature readings and approximation results in first truck

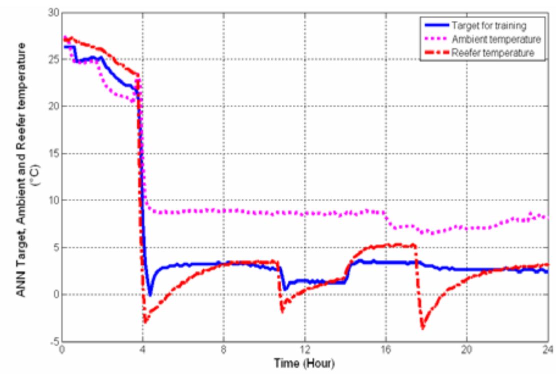

Fig. 7 Training network for temperature approximation in second truck

In Fig. 7, training of network is shown for second truck in 24 hours and in Fig. 8, 9, approximation of data logger temperature is simulated for next 12 hours, by feeding instantaneous ambient and reefer temperature into the network.

According to Fig. 6, 9, the accuracy of approximation results depends on precision of training for approximation network. In fact, another important feature which should be considered for residual evaluation is training error. For this purpose minimum, maximum and average values of training error were considered for improving residual evaluation performance. These values were used to extend boundaries of faultless signal values for decision making. After preparing the measurement residuals, second mechanism will start evaluation phase with another ANN architecture including probabilistic features.

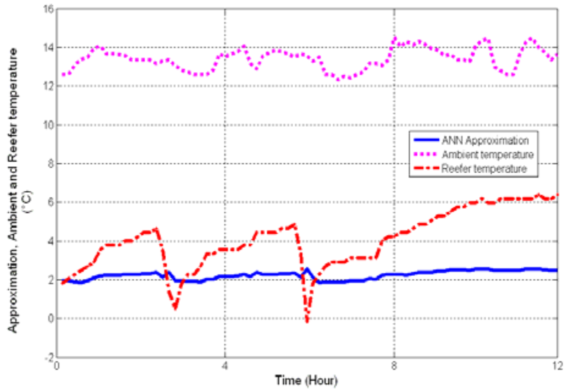

Fig. 8 Temperature approximation results with ANN in first truck

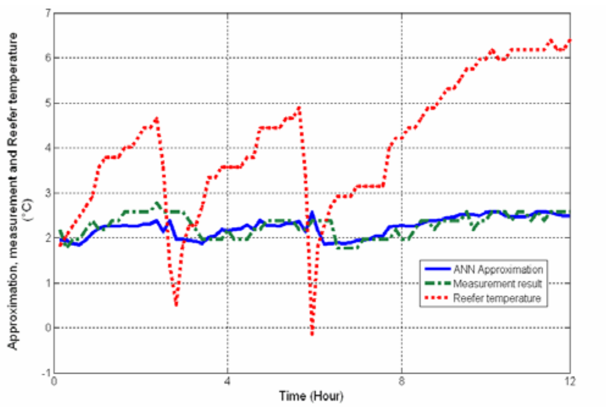

Fig. 9 Temperature readings and approximation results in second truck

Goal of designing residual evaluation architecture is describing fault/failure classes for pattern classification. In fact, in second neural network, by using probabilistic features, measurement results are classified in different fault/failure classes. Probabilistic features are used for decision making on measurement residuals, especially which located in borders of class boundaries. Fig. 8 shows one faultless measurement residual after temperature approximation in first truck for 12 hours. Also, some extra tests routines including threshold test and comparison of measured data with other data loggers improved precision of pattern classification mechanism. Ü

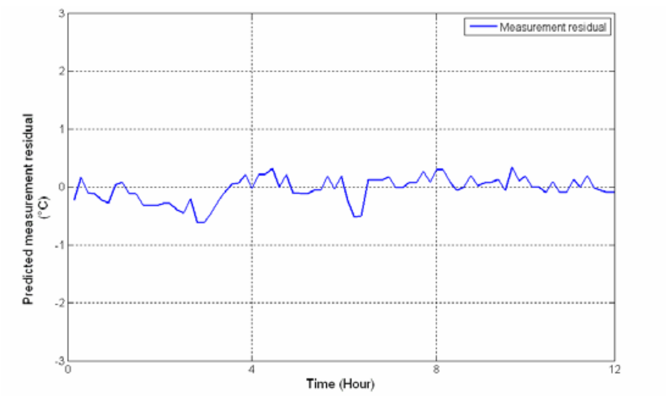

Fig. 10 Measurement residual after approximation

For evaluation of residuals, following classes were considered for faults and failures:

1. Data logger defection: for this purpose, measurement values from data loggers should be compared and rate of temperature oscillation should be unique between different data loggers. Big differences between values of one data logger with the others and also with approximated value will be detected as data logger defection (Class 1).
2. Disconnection in communication linkage: when the temperature readings remain for a long period on zero, it means that the communication linkage is disconnected from data loggers and it is not available. For this purpose duration of 30 minutes was considered in evaluation mechanism. Thus, 4 continuous readings will be compared and if all were equal to zero, it means that communication linkage should be assessed and class 2 should be assigned.
3. Putting warm box: After putting warm box in compartment (A box with at least 5 °C more than data logger temperature is assumed warm box), neighbor loggers will show different values. It means that temperature change won’t be unique between data loggers and rate of temperature changes will vary in some positions. Therefore, more than 5 °C temperature rise in curve is implemented as class 3.
4. Removing warm box: After removing warm box, some loggers will show temperature changes by decreasing temperature in some positions. Temperature fall more than 5 °C temperature is categorized in class 4.
5. Opening the door: sometimes opening the door will cause a big change in data logger readings, although it depends on ambient conditions. Thus temperature variation of data loggers, near the door should be observed carefully for detecting this case (Class 5).

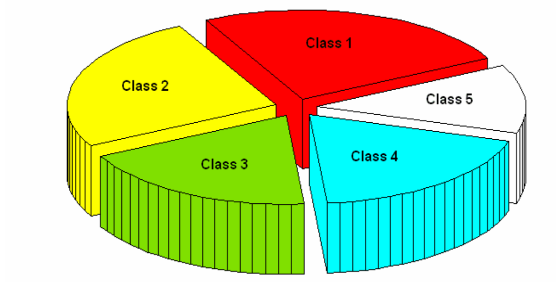

Fig. 9 Probabilistic distribution of faults/failures in residual evaluation mechanism with neural network

The fault/failures classes were used in designing probabilistic neural network, for decision making on measurement residuals. Distribution of fault/failure classes is very important which could have significant influences on fault diagnosis performance. Fig. 9 shows distribution of faults/failures probability in residual evaluation module.

After application of residual evaluation algorithm, whole mechanism could diagnose all probable fault/failures. Therefore, the fault/failure mechanism could distinguish faulty and faultless measurements and related classes, for improving reliability in measurement system.

VIII. Conclusion

In this paper, application of neural network was implemented for autonomous fault detection and isolation in temperature measurement system. Two separate ANN architectures were considered for measurement residual generation and residual evaluation. In first phase, ANN approximation architecture was applied to generate residuals by comparing measurements with temperature approximation. In second phase, based on output of first ANN architecture, probabilistic neural network (PNN) was applied for analyzing probable fault/failure conditions and fault/failure classification. After evaluation of residuals, situation of each measured signal was resulted, based on assessment parameters and approximation of ANN.

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 test facilities.

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