Virtual Thermal Sensors for a Spacecraft

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Abstract—Currently there is a lot of satellites in space providing services for us. We are more and more dependent to them. Spacecrafts have the disadvantage that they "live" in the space and whenever a hardware problem occurs on board it is very difficult and very expensive to be fixed. So, a hardware problem means a degradation of loss of functionality in most of the times. In this work we deal with the loss of thermal sensors inside a spacecraft and its recovery by software. We call the recovered sensor *virtual sensor*.

Index Terms—Virtual Sensors, Feed-Forward Neural Networks, Auto-associative Neural Networks

I. INTRODUCTION

Spacecraft are equipped with plenty of sensors. Among them we can find the thermal ones which are useful both for the Flight Control Team to check the status of the spacecraft and for the onboard actuators to regulate the temperature inside the satellite.

Working in space is not an easy task. When something breaks down in space it is very difficult and extremely expensive to be repaired. This is the reason why all spacecraft have to pass a lot of severe tests before going to be launched. Moreover, when hardware problem arise in space it is very likely that they will not be fixed unless a degree of redundancy is available.

In this work we deal with the possible failure of onboard thermal sensors. We are interested, in this special case, to rebuild the values that this sensor would have generated. In the hypothesis that the failed thermal sensor cannot be fixed, we will try to recover its values by means of a virtual thermal sensor, making use of implicit existing redundancy.

How could it be possible? Information about the temperature inside the spacecraft in different locations is correlated somehow. However, this correlation is difficult to find and even to model, taking into account the real physical spacecraft.

In this work we propose to use the Artificial Neural Networks (ANN) to recover the signal of the lost sensor(s). Why neural networks? Because this problem has the two main characteristics that allows to take advantage of this artificial intelligence technique:

– We have a lot of historical data available since no sensor has failed yet, so the neural network can learn by examples.
– We know that there is a relation among the temperatures in different locations of a spacecraft; however it is difficult for us to find it out.

II. APPROACHES

Artificial neural networks can learn the unknown non-linear mapping between inputs and outputs if we have enough representative examples of this mapping. The most interesting capability of ANN is their ability of generalization, that is, the ability to do this mapping for a never seen input. We will take advantage of this interesting capability to create virtual thermal sensors. We will use two kinds of ANN for two different purposes:

1. It may happen that one of the thermal sensors breaks down during in-flight operations while the other thermal sensors are in good conditions. In this case we will be very interested in recovering this sensor. For this purpose we will use a *3 layered feed-forward neural network* with the working sensors as inputs and the virtual sensor as output as described in section IV. A neural network can easily solve this problem, so good predictions are expected. Moreover this technique has the advantage that we could prepare different neural networks, one per each possible sensor failure so we can recover any sensor.
2. It could also happen that after the failure of one sensor another sensor may fail and after it another one and so on. It is difficult to take into account all the possibilities in advance. This is why we will try to train a neural network that is able to recover any of the sensors. This problem is much more difficult to be resolved than the previous one, so we can expect that the prediction will be not so good as when recovering just one sensor. For this purpose we will use an *auto-associative neural network* as described in section V.

In both approaches we will run all experiment regarding neural networks using the MatLab® Neural Network Toolbox [2].

The following statistical function have been used to measure the performance of each network:

– Mean Square Error in Training (SET). It will give us and idea on how good the neural network is learning this mapping. It is the standard value to measure the performance in training of ANNs.
– Average value of the error in the training set, in absolute value (meanTrain). It is a complementary value to the SET. It will also inform about the average error done in training. It will be shown in the outputs units.
– Standard deviation of the errors in the training set (stdTrain). This performance measurement will inform

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about the dispersion of the training error. It is important not only to have a small error average but also that the dispersion of the error is small. A small value of this parameter will indicate that the error in almost the same for most of the patterns, so we can rely in the average values.

– Average value of the error in the testing set, in absolute value (meanTest). It is the same thing as meanTrain but considering the testing dataset.
– Standard deviation of the errors in the testing set (stdTest). It is the same thing as stdTrain but considering the testing dataset.
– Mean Square Error in predicting the testing set (SEP). It is the same thing as SET but considering the testing dataset.

We will give a special attention to all the testing performance measurements.

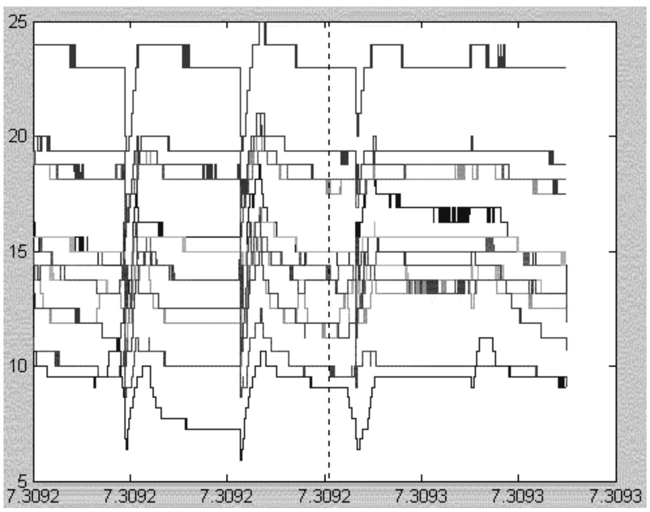

Figure 1. All 14 internal thermal sensors temperature values are shown. The training set data is on the left hand side (before the dotted line). It contains two ecplises. The testing set data is on the right hand side (after the dotted line). It contains 1 eclipse.

III. DATA

The data used to validate these approaches are the thermal sensors readings from the spacecraft 4 of Cluster II constellation [4].

Cluster II was launched on summer 2000. This mission is an in-situ investigation of the Earth's magnetosphere using four identical spacecraft simultaneously. They do simultaneous measurements and sometimes fly in a lopsided pyramid or tetrahedron formation. They are able to make a detailed, three-dimensional study of the electrical and magnetic fields changes and processes taking place in near-Earth space. Their mission is to complete the most detailed investigation yet made into the ways in which the Sun and Earth interact.

Each Cluster II spacecraft has 14 internal thermal sensors [3] in the main equipment platform: 8 in the upper side and 6 in the lower side. The investigation is focused on the values of the selected thermal sensors registered from 8/March/2001 00:00:00 to 18/March/2001 23:59:59 in 1 minute step. This data are interesting because in the selected period 3 eclipses took place[1]. The total number of samples is 15338. We have divided this data into two different dataset:

– Training set: from the 1^{st} to the 8500^{th} sample, contains 2 eclipses.
– Testing set: form the 8500^{th} sample to the 15338^{th} sample, contains 1 eclipse.

So we can evaluate the performance of the neural networks on data never seen by the neural network. Figure 1 shows these two data sets graphically.

IV. FEED-FORWARD NEURAL NETWORK FOR A VIRTUAL SENSOR

In this section we will explain how a sensor can be recovered making use of the existing correlation with other thermal sensors ignoring a priori the analytical complex relationship. The ANN will find it out for us.

We will use for this case a typical feed-forward neural network made of an input layer, a hidden layer and an output layer. The input layer will have 13 input neurons corresponding to the 13 thermal sensors that are working properly. The output layer will have just 1 output neuron corresponding with the thermal sensor we want to recover (the first sensor on the upper side of spacecraft named *MEPU_T1*). This output itself is the virtual sensor.

The hidden layer will be made of several neurons with sigmoid transference functions.

Choosing the topology of a neural network is a difficult time-consuming task that most of the times is solved by the designer's experience. This approach has the inconvenience that some possibilities may be discarded, and therefore, some good neural network candidates are not even taken into account. The advantage is that the designer may find a good artificial neural network at the beginning of his investigation saving time; however, he/she will not be sure that the guessed topology is the very best.

We try to overcome this problem by training and testing systematically all the possible topologies ranging from 1 to 40 neurons[2] in the hidden layer. This procedure has the advantage that every topology is tried, so, at the end, we know what is the best performing neural network with much more confidence. This procedure, however, takes a bit more of time in training and testing but this process can be automated.

The performance analyses made use of the statistical parameters introduced in section II.

We have 40 different ANN. To select the best ones in a systematical way the following procedure was used: the

[1] It is interesting to include eclipse periods in the datasets because while in eclipses the temperature outside the spacecraft quickly drops, affecting therefore to the internal sensor measurements. We can improve the model accuracy in extreme conditions by taking into account the eclipse periods. The reader may identify the 3 eclipses considered in the dataset looking at Figure 1.

[2] We consider that 40 neurons in the hidden layer will be enough as an upper limit.

neural network topologies are sorted by their different performance values and the three first neural networks of each sorting are taken into account. Table 1 shows these results:

SET	13:39:1	13:36:1	13:31:1
MeanTrain	13:18:1	13:8:1	13:9:1
StdTrain	13:39:1	13:36:1	13:31:1
MeanTest	13:22:1	13:32:1	13:34:1
StdTest	13:32:1	13:34:1	13:31:1
SEP	13:32:1	13:34:1	13:22:1

Table 1. Best neural networks topologies for the different performance measurements for 1 virtual sensor.

We can now focus on those ANN that appear at least to times in Table 1:

- Networks 13:22:1, 13:36:1 and 13:39:1 appear 2 times.
- Networks 13:31:1, 13:32:1 and 13:34:1 appear 3 times.

Let's concentrate on the neural networks that appear 3 times. Their performance values are shown in Table 2.

In this case the neural network 13:32:1 is preferred because it is the one with better performance in testing. Figure 2 shows the values generated by the virtual sensor using the neural network 13:32:1 and it is compared with the real sensor reading. The match is very good even when an eclipse has occurred (at the beginning when the temperature goes down to 13°C).

Topology	SET	MTrain	StdTrain	MTest	StdTest	SEP
13:31:1	0.04309	0.01058	0.20731	0.32113	0.37668	0.03074
13:32:1	0.05479	0.01131	0.23381	0.13379	0.32236	0.02168
13:34:1	0.04354	0.0014	0.20867	0.18362	0.32603	0.02324

Table 2. Performance values of the best neural networks when recovering the sensor MEPU_T1.

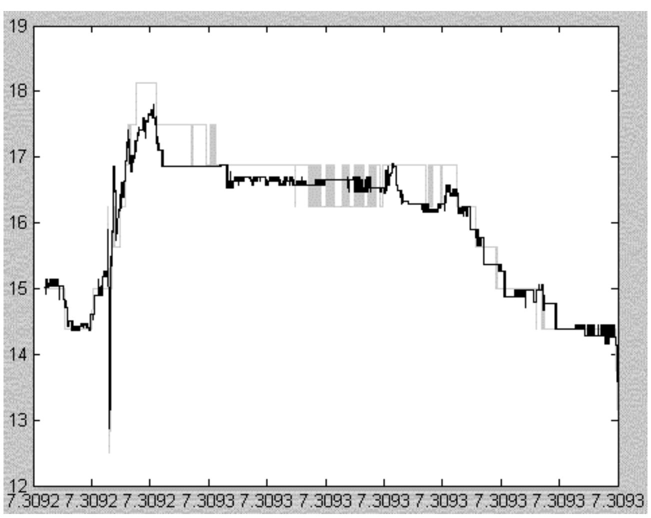

Figure 2. Virtual sensor temperature values (in black) versus real sensor temperature values (in grey) using the feed-forward neural network 13:32:1

The virtual sensor seems to behave accurately. Figure 3 shows the errors of this virtual sensor. We have computed some statistics measurements from the errors values:

- The maximum of the errors' absolute values is 0.8713 degrees. This means that the error done in the prediction is 6.08% at most with respect to the actual values.
- The average of the errors' absolute values is 0.2774 degrees. This means that the error done in the prediction is about 1.68% in average with respect to the actual values.

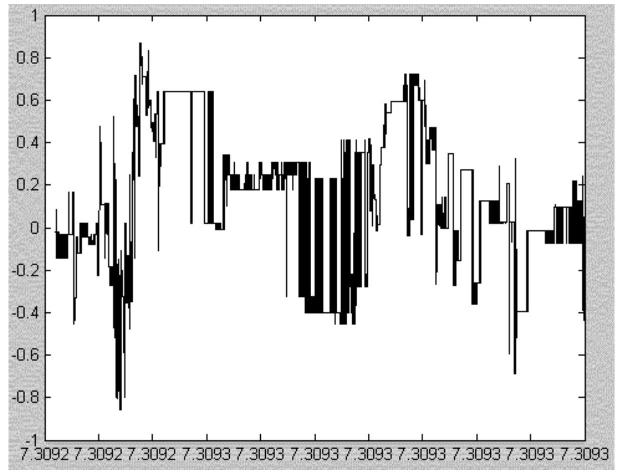

Figure 3. Errors (in degrees) of the Virtual Sensor for the testing data.

These positive results demonstrate that a virtual sensor can be used instead of the real one when a problem in one of the sensors arises in space.

V. AUTO ASSOCIATIVE NEURAL NETWORK FOR ALL VIRTUAL SENSORS

To recover the signal from any lost internal thermal sensor we are supposing the availability of implicit redundant information; we are assuming that the temperatures in the different parts of the spacecraft are somehow correlated. A method to recover the signal of all sensors could be the following:

- First we summarize all the inputs so we have the same information in a reduced representation. We can do it because the information from the sensors is redundant in some way.
- Then, once we have this summary containing only the information that is not correlated, we can reconstruct all the sensors values because they depend on this summarized information.

This process can be done by an auto-associative neural network where the output values should be the same as input values after the summarization process. It consists of 5 layers as shown in Figure 4:

- The first layer contains the actual inputs from the thermal sensors.
- The second layer compresses the information from the first layer (input layer) into the third layer (summary layer). It acts as a compressor because it maps the 14 inputs neurons into a fewer number of neurons in next hidden layer.
- The third layer contains the summary of the information from the thermal sensors without redundancy. This layer

tries to keep uncorrelated information about the thermal sensors.
- The fourth layer decompresses the information from the third layer (summary layer) to the fifth layer (output layer). It acts as a decompressor because it maps into 14 output neurons fewer neurons that contains compressed information from the previous hidden layer.
- The fifth layer is the output layer and will contain the recovered sensors values (virtual sensors).

The auto-associative neural network is trained to learn to do compression, summary and decompression. In the training phase we provide the training set as input as well as output, so it has to learn how to summarize the information in the inputs. In the testing phase we provide the testing set with errors as inputs and we expect to get the same data recovered, behaving as 14 virtual sensors.

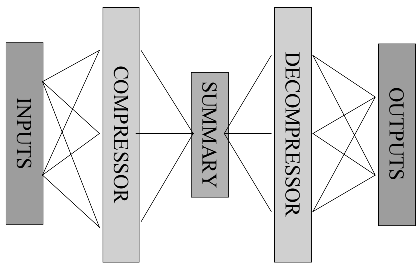

Figure 4. An associative neural network. The layers *input* and *output* have k neurons, the layers *compressor* and de*compressor* have m neurons and the *summary* layer has n neurons. $m \geq k$ and $n < k$.

We will examine a lot of different auto-associative neural network topologies with the structure *14:M:N:M:14* where $M \geq 14$ and $N < 14$[3]. We will try all the possibilities of $M=14..30$ and $N=4..10$ resulting in 119 different auto-associative neural networks.

The training algorithm will try to minimize not only the mean square error of the outputs but also the number of connections[4]. It is known that the fewer connections a neural network has the better is its ability to generalize. We take advantage of this fact to get neural networks with good generalization capabilities.

In the case of the auto-associative ANN we have modified a bit the way in which the testing performance measurements are computed. The *meanTest*, *stdTest* and *SEP* will be computed as the average of 15 values of *meanTest*, *stdTest* and *SEP*. These 15 values are:

- *meanTest*, *stdTest* and *SEP* of testing the ANN with all the sensors working properly.
- *meanTest*, *stdTest* and *SEP* of testing the ANN with the sensor $i=1..14$ cancelled and all other sensors working properly.

The cancellation of a sensor consists of replacing it by a constant value. At first we thought this value could be 0 but the problem was 0 does not belong to the range of temperatures of the ANN inputs and produced a biased output. For this reason, we will use the average of the inputs values for the sensor i as the constant value. From the practical point of view it is not a big inconvenience since all these 14 values can be computed from the training set off-line. So, when a thermal sensor onboard is lost we will use this average value as input for the neural network.

We have 119 different ANN to examine. To select the best ANN the following procedure has been used: the neural network topologies are sorted by their different performance values and the three first neural networks of each sorting are taken into account. Table 3 shows these results:

SET	14:28:9:28:14	14:30:9:30:14	14:29:8:29:14
MeanTrain	14:28:10:28:14	14:17:7:17:14	14:26:8:26:14
StdTrain	14:23:5:23:14	14:30:9:30:14	14:28:9:28:14
MeanTest	14:26:8:26:14	14:23:9:23:14	14:15:9:15:14
StdTest	14:30:9:30:14	14:29:4:29:14	14:19:10:19:14
SEP	14:30:9:30:14	14:19:10:19:14	14:15:9:15:14

Table 3. Best neural networks topologies for the different performance measurements for all virtual sensor.

Now we focus on those ANN that appear at least to times in Table 3:

- Networks 14:15:9:15:14, 14:19:10:19:14, 14:26:8:26:14, and 14:28:9:28:14 appear 2 times.
- Network 14:30:9:30:14 appears 4 times.

Let's concentrate in the ANN that appears 4 times. Its performance values are shown in Table 4.

Topology	SET	MTrain	StdTrain	MTest	StdTest	SEP
14:30:9:30:14	0.1792	0.0604	0.2883	0.0980	0.5550	0.0355

Table 4. Performance values of the best neural network when recovering all the sensors.

This artificial neural network is the best found when the recovery of all sensors is considered. Figure 5 and Figure 6 show the virtual and actual sensors for testing data where the corresponding input sensor has been cancelled and all the others are working properly. The caption of each subfigure shows the maximum error done and also the average error.

These results show that the selected ANN provides accurate predictions for some of the sensors but it is performing not so good recovering some others:

- The most accurate virtual sensors are: 1, 2, 5, 6, 7, 8, 13
- The less accurate virtual sensors are: 3, 8, 12, 14.

VI. CONCLUSIONS

We have used two kinds of artificial neural networks to construct virtual thermal sensors for a CLUSTER II spacecraft. The first ANN consists of a feed-forward ANN for the recovery of just one sensor. This ANN performs very well and can be used in an operational environment or even onboard. This success encouraged us to try to build an ANN that can reconstruct all the sensors. For this purpose we have used an auto-associative ANN. The performance of this ANN is good for some thermal sensors but not for all

[3] N should be smaller than the number of sensors because it is going to summarize them and M should be greater or equal to the number of sensors, otherwise the summarizing process will be done in this layer.

[4] This process is called regularization.

of them; so, it cannot be used operationally, at the moment, and improvement of its performance is required.

VII. FUTURE WORK

The future work in this area will focus on these fields:

- Try new topologies, kind of neural networks or training algorithm to improve the performance of the virtual sensors.
- Design a black-box system to recover all the thermal sensors. It may have several ANN inside instead of just one. Anyway, the user will use it as a single tool to recover the signal of any failed sensor.
- Investigate what is the minimum number of working sensors we need to be able to do accurate predictions for any sensor.
- Inclusion of additional sensors apart from the ones inside the main equipment platform (attitude, power consumption, devices working status (on/off), etc…).
- Design an architecture for a possible onboard implementation.

VIII. REFERENCES

[1] G. Waterworth, “The Use of Neural Networks in Sensor Failure Detection and Signal Reconstruction”, ESM 2002 (189-193).

[2] MathWorks, “Neural Network Toolbox User’s Guide”, March 2001

[3] W. Pitz, “CLUSTER Thermal Control Subsystem User’s Manual”, European Space Agency.

[4] CLUSTER II Internet Home Page: http://sci.esa.int/cluster/

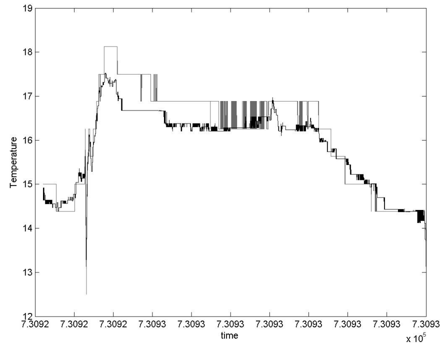

Figure 5.1. S1. MaxE = 1.087678, AvgE = 0.358769

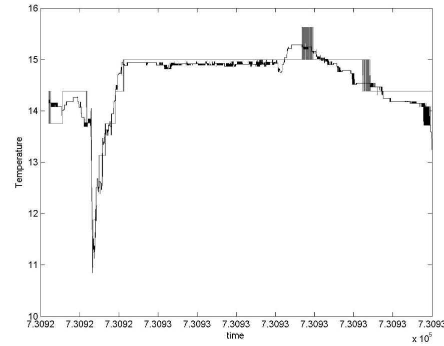

Figure 5.2 S2. MaxE = 1.133641, AvgE = 0.180796

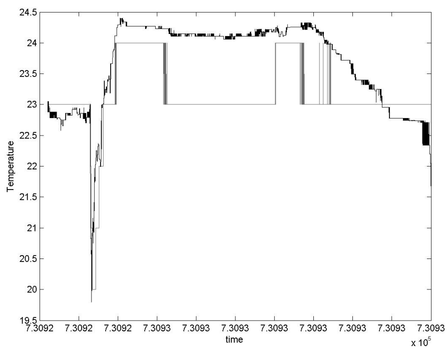

Figure 5.3 S3. MaxE = 2.026057, AvgE = 0.632747

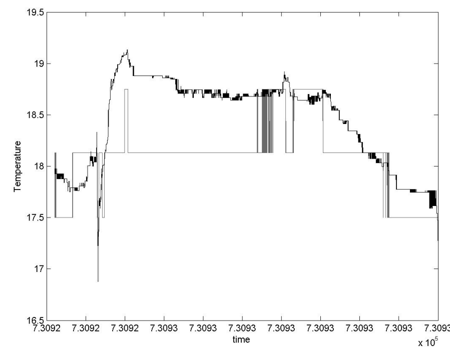

Figure 5.4 S4. MaxE = 0.974826, AvgE = 0.400444

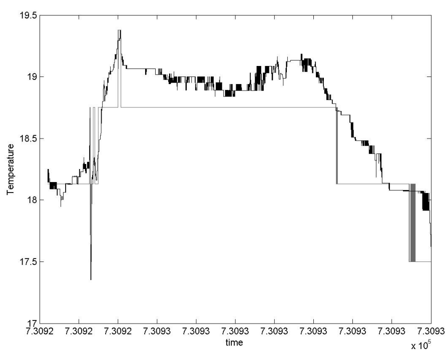

Figure 5.5 S5. MaxE = 0.641505, AvgE = 0.239218

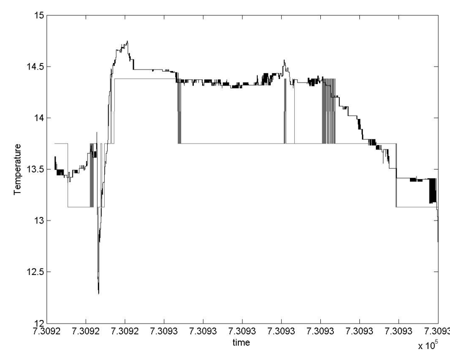

Figure 5.6 S6. MaxE = 0.844385, AvgE = 0.363155

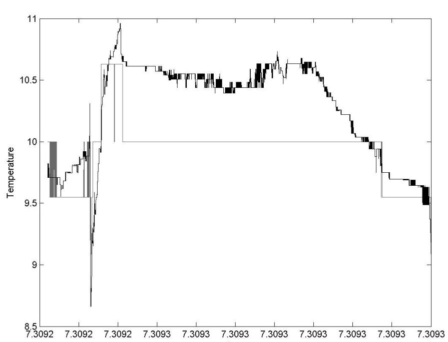

Figure 5.7 S7. MaxE = 0.848365, AvgE = 0.374647

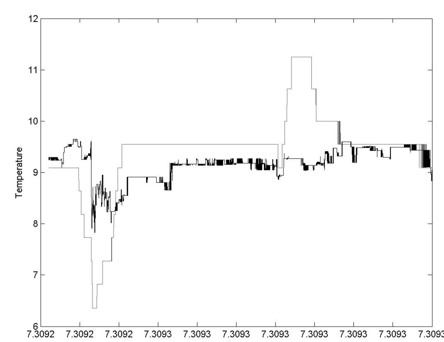

Figure 5.8 S8. MaxE = 2.409701, AvgE = 0.584554

Figure 5. Virtual sensors (in black) versus real sensors (in grey) from the upper side of the main equipment platform. All the virtual sensors use the same auto-associative neural network 14:30:9:30:14. Please note that the vertical axis of every subfigure is different to improve the view detail. Legend: SN means recovery of Sensor N, MaxE means maximum error in the predictions (in degrees), AvgE means average error in the predictions (in degrees).

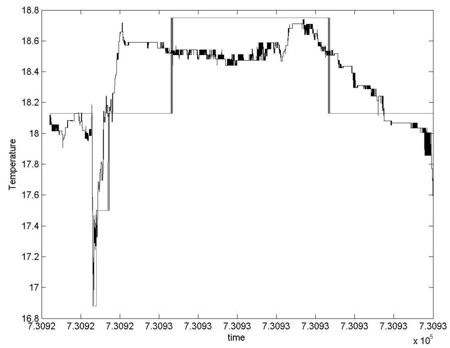

Figure 6.1. S9. MaxE = 0.743328, AvgE = 0.220086

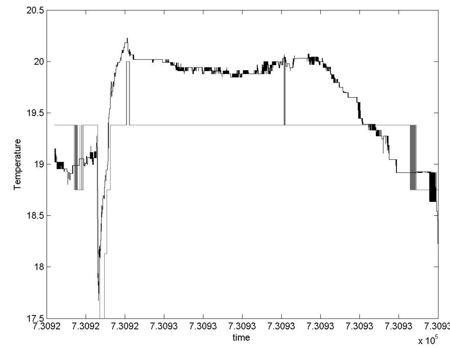

Figure 6.2 S10. MaxE = 1.195032, AvgE = 0.459327

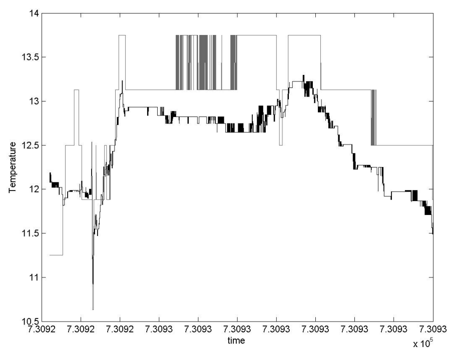

Figure 6.3 S11. MaxE = 1.155648, AvgE = 0.551520

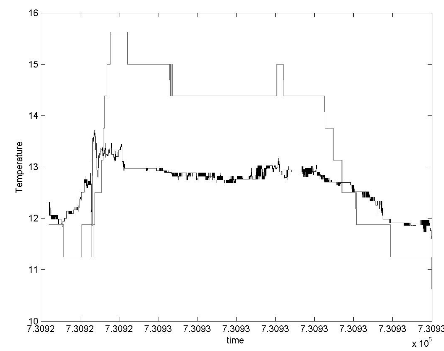

Figure 6.4 S12. MaxE = 2.695336, AvgE = 1.228437

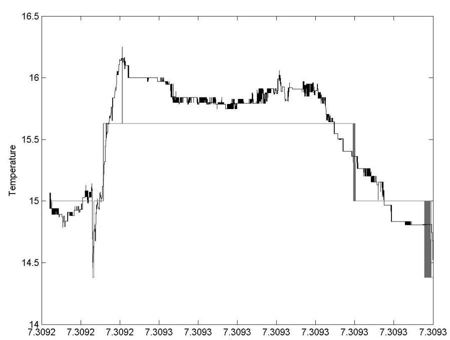

Figure 6.5 S13. MaxE = 0.535689, AvgE = 0.209220

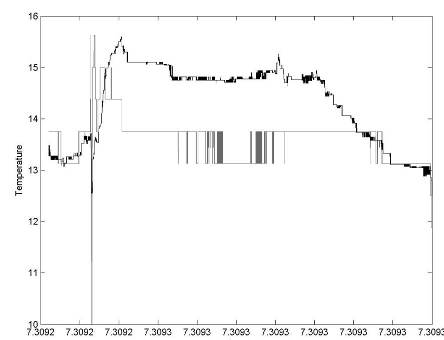

Figure 6.6 S14. MaxE = 2.541744, AvgE = 0.837727

Figure 6. Virtual sensors (in black) versus real sensors (in grey) from the lower side of the main equipment platform. All the virtual sensors use the same auto-associative neural network 14:30:9:30:14. Please note that the vertical axis of every subfigure is different to improve the view detail. Legend: SN means recovery of Sensor N, MaxE means maximum error in the predictions (in degrees), AvgE means average error in the predictions (in degrees).