Selective Predictors of Environmental Parameters in Wireless Sensor Networks

M. Babazadeh, H.-J Kreowski, W. Lang

Abstract— This paper investigates multiple alternatives to predict environmental parameters (temperature and relative humidity) inside an intelligent container with the aim of the supervision of cool chains. A wireless sensor network will help us to measure those parameters in some distributed points of the closed space.

To achieve the aim of fault detection and also total energy saving in the sensor network, there will be several possibilities. This research deals with prediction of future values of the environment in a few specific sensor nodes by using some of active sensor nodes. It inspects several requirements of the predictors to pick out the most applicable identification styles among ARX, ARMAX, OE, BJ and SS. It employs some key-sensor nodes (KSNs) as predictors of the parameters in a few desired sensor nodes (DSNs). The DSNs either have already been turned to sleeping mode to reduce battery-consumption or deactivated due to energy depletion.

Keywords— Prediction, model, temperature, relative humidity, air flow

I. INTRODUCTION

THERE are lots of research activities in the field of fluid dynamics to make thermo dynamical models for environmental parameters (EPs) in closed spaces. They usually look for a way to improve cooling systems, ventilation or to make homogeneity in the space. They modify either the quality of supply chain or decrease the energy consumed by the cooling systems.

By using a wireless sensor network, online access to the EPs inside of a closed space containers would be possible during transportation. Wireless sensor nodes (WSNs) in these networks are supplied by batteries and they need to be recharged regularly after a while. In some applications there are several ways to recharge them automatically by using energy harvesting methods. Some other applications develop some recipes to save energy for the sensor networks to prolong life time of the batteries. In addition to [14], [15] and [16] there are a lot of studies about various styles to save or harvest energy for the WSNs. Our approach might be used together with the mentioned procedures.

The evaluation framework presented in this paper provides one step towards using predictors to achieve the EPs on slept sensor nodes instead of direct measurement. It deals with different model structures and alternatives to achieve the best prediction results. A Floating Input Approach (FIA) was already presented by the authors via [11], [12], [13]. This approach introduces a linear multi input-single output (MISO) dynamic model to be used between surrounding key- sensor nodes (KSNs) and a desired sensor node (DSN).

There is another work that uses grey-box approach in [1] to combine theoretical modeling, parameter identification of discrete models and partially known models by using optimization techniques. It uses energy balance to achieve to transfer functions of transducers. It makes some models for any device and then identifies unknown parameters by using some separate tests. Under some very special conditions it decouples temperature (*T*) and Relative Humidity (*H*) and uses separate linear transfer functions for them. Analytical and numerical models developments to describe the dynamics of the cryogenic freezing tunnel system have been mentioned in [2]. By a composite model, it uses finite difference methods for sizing the tunnel freezer. It also talks about freezing and freezer dynamics that is useful to have a view of these systems. Reference [3] is a brief review of numerical models of F in refrigerated food applications using (k-ε) model and also a data-base mechanistic modeling technique. They obtain partial differential equations using computational fluid dynamics (CFD) which are without general analytical solution. It is a simulation tool for modeling of fluid flow problems based on the solution of the governing flow equation. Although this technique gives high precision, we can't use it, because this process is necessarily iterative and requires the solution of a huge number of equations at each step.

To model the 3-D spatio-temporal temperature distribution in an imperfectly mixed forced ventilated room for control purposes they use a second order model in [4]. It gives very good definitions of different models (white, grey and black) in a cooling system. It introduces a hybrid between the extremes of mechanistic and data based modeling. This so-called data-based mechanistic (grey box) models provide a physically

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meaningful description of the dominant internal dynamics of heat and mass transfer. It uses model between inlet and outlet.

It uses static experiments to examine the action of the ventilation rate on the spatial temperature homogeneity, while keeping the average temperature inside the ventilated chamber constant. It emphasizes that increasing the ventilation rate decreases the standard deviation of temperature in different places. In a specific rate maximum uniformity is achieved. It fits a curve to temperature of various places. It uses MBPC to optimal control of spatial temperature distribution. It doesn't consider relative humidity.

A combination of CFD and DBM methods is studied in [5]. It outlines a methodology to achieve an accurate model of *T* in a closed space. First of all using k-ε model, turbulence is modeled and then a DBM model was formulated from an energy balance equation. It can reduce complexity of CFD using identification technique. It doesn't consider relative humidity. Some first order models between inlet and individual zones, is considered assuming a constant air flow rate (*F*).

Numerical and experimental characterization of air flow within a semi trailer enclosure with pallets has been reported in [6]. The effect of air flow pattern on *T* is given by this paper. The numerical modeling of air flow is performed using CFD code fluent and second–moment closure, the Reynolds stress model (RSM). It demonstrates importance of air ducts in decreasing temperature differences throughout the cargo. It says that prediction using k-ε models are often not accurate. It looks into numerically and experimentally the air flow pattern throughout a vehicle enclosure loaded with two rows of pallets with and without an air duct system.

Using CFD method flow pattern inside the working area of a pilot scale clean room has been numerically worked over in [7]. Two versions of the k-ε turbulence model have been tested. To solve transport equations the surfaces bounding the domain has been defined clearly during this work. Some comparisons between turbulence models have been done.

As mentioned in [8], there are two ways to define a grey box model. One way emanates from the black box model frame. A priori knowledge is incorporated as constraints on model parameters or variables. Second way is to begin with a model originating from mathematical relations, which describe the behavior of the system. This means the starting point is a specific model structure based on physical relations.

All models are obtained between system input so-called reefer (inlet) and a point in the corresponding space. With the mentioned models, the EPs in some DSNs can be changed due to variation in the inlet. Some models introduced in the mentioned papers, either linear or nonlinear, do not consider interconnections of the EPs. Particular conditions and limit range of parameter variations of such models are necessary. Despite the high precision, complexity makes some of them impractical and the rest inaccurate in the present application.

Nonlinear multivariable nature and interconnections between the variables of the EPs in addition to the presence of the load as an unpredictable, immeasurable disturbance influence of surfaces inside the container increase complexity of the model.

In the present article a brief introduction of a new grey-box hybrid model of the EPs between the reefer and a DSN will be included. Then, we will use achieved linear multi input-single output (MISO) model to obtain some practical results to find unknown parameters of the proposed linear dynamic model.

II. Problem Formulation

Fig.1 illustrates a container with mounted WSNs. There is a complicate time and place dependent multi variable model between reefer unit (inlet) and each sensor node.

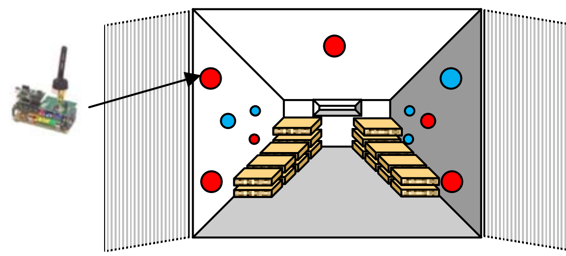

Fig.1. Container with wireless sensor network mounted.

Couplings among the EPs increase difficulties of doing independent experiments and also initial conditions make the measurement results completely different with the previous tests. Any change in *T*, *H* and even *F* in inlet may change both *T* and *H* in all positions of the desired space. Measurements can be affected by disturbances and they might be different even in the same place. In our models, obtained from surrounding key-sensor nodes (KSNs) and a DSN, every non modeled disturbance is modeled as an implicit input change, not as a pure disturbance. It is notice that only some of the KSNs can be among the system estimators. When a disturbance acts on the system, it might excite a few sensor nodes and it can be used to initialize the estimators. Parameters of the mentioned models are obtained using present noise-corrupted data of the KSNs (inputs) and the DSNs (output). This procedure implies some models between the couples of the KSNs_DSN.

According with Fig.2 there will be a network with several KSNs (K1, …, Km) as input nodes and a few DSNs (S1 and S2) as output nodes. KSNs might evaluate measured values and do prediction of the EPs in the DSNs and deactivate them when the conditions are normal and there are no big changes in the environment.

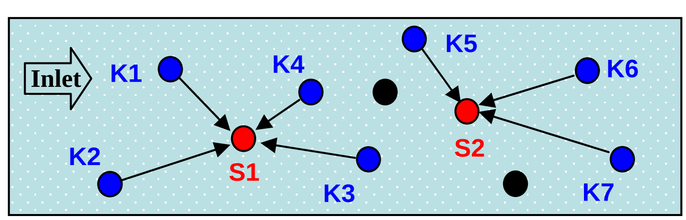

Fig.2. Proposed sensor network.

The KSNs can be located everywhere in to the container, near the door, near to inlet or surrounding the DSNs, but if they are located in some key points, estimation mismatch error due to no considering unpredictable phenomenon would be avoided because while identification based on the proposed technique, most of uncertainties and disturbances are considered indirectly as the input change in the KSNs. Disturbance might be applied to the input, system and or to the output, but in all cases it influences the outputs (KSNs).

Assuming excited KSNs as inputs, the input in defined MISO system will change and output nodes (DSNs) will be influenced of such new inputs. Several MIMO models will be created between the KSNs and a DSN (fig.3).

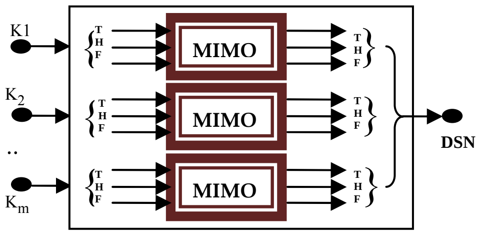

Fig.3. Block diagram of a MISO model of the EPs.

Whereas we would like to increase the accuracy of the predictions and decrease the total power consumption by the wireless sensor network, we are interested in turning more sensors to longer sleeping mode. Due to decrease the calculation, we would like to reduce the number of the KSNs. But, later simulations clarify that the accuracy will be increased with increasing the number of these estimators. The KSNs have separate influences on a DSN. Considering an F direction as a simple example in a three dimensional space, K1 and K2 can be considered more operative than K3. We will obtain a relationship between the KSNs to choose the best estimators.

It will be clarify that using data of a KSN_DSN to make single input-single output (SISO) model cannot present surrounding influences completely. It can only interpret variations of the EPs on a DSN from side of the mentioned KSN. Prediction using multi input-single output model (MISO) will cause better accuracy than that using SISO models. As a result, using more effective KSNs is better. Furthermore, whenever sensor failure is occurred in a KSN, other KSNs will be able to continue the prediction. There are also some KSNs which do not have any influences on the DSN, could not help to increase the accuracy.

III. Problem Solution

In [11] we started with a hybrid model consisting of nonlinear interconnections to attain an estimation of the EPs.

$$\begin{pmatrix} T_{SN_i}(t) \\ H_{SN_i}(t) \\ F_{SN_i}(t) \end{pmatrix} = \begin{pmatrix} Z^{-1}(G_{T,F} \bullet T_{inlet}) + g(H_{inlet}, F_{inlet}) + N_T \\ f(T_{inlet}, F_{inlet}) + Z^{-1}(G_{H,F} \bullet H_{inlet}) + N_H \\ Z^{-1}(G_F \bullet F_{inlet}) + N_F \end{pmatrix} \tag{1}$$

(T_{SN}, H_{SN}, and F_{SN}) and (T_{inlet}, H_{inlet}, and F_{inlet}) are respectively the EPs in a SN and inlet. It is noted that, f and g are nonlinear interactions. N_T, N_H, and N_F are measurement Gaussian noise in the WSNs. $G_{T,F}$ and $G_{H,F}$ are transfer functions of *T* and *H*, influenced by *F* and G_F is transfer function of *F* between inlet_SN.

We assumed reefer unit of the container as input and every WSNs as output. Then, we introduced the FIA to simplify it. We applied an argument to solve simplified problem. Above formulation is not a real super position. That is only an assumption.

The influence of variation in F on linear part of the models is considered in the place of poles in linear transfer functions and we assign an exponential function to determine these influences so that their parameters will be determined while operation. According with [11] to perform the nonlinear part we use some basic thermodynamic relations and we have:

$$H = H_0 \bullet 2^{\frac{-(T-T0)}{10.1}}, T = T_0 - \frac{10.1}{\ln 2} \bullet \ln\frac{H}{H_0} \tag{2}$$

$$\Delta T(t) = T_0 - \frac{10.1}{\ln 2} \bullet \ln\frac{Z^{-1}(G_H \bullet H_{in}) + N_H(t)}{Z^{-1}(M_H \bullet H_0)} \tag{3}$$

$$\Delta H(t) = (2^{\frac{-Z^{-1}(G_T \bullet T_{in}) + N_T - Z^{-1}(M_T \bullet T_0)}{10.1}} - 1) \bullet Z^{-1}(M_H \bullet H_0) + N_H \tag{4}$$

$$T_{SN}(t) = Z^{-1}(G_{T,F} \bullet T_{inlet}) + \Delta T(t) \tag{5}$$

$$H_{SN}(t) = Z^{-1}(G_{H,F} \bullet H_{inlet}) + \Delta H(t) \tag{6}$$

(T_0, H_0) are initial conditions of the EPs between inlet and the WSNs, respectively. $G_{T,F}$ and $G_{H,F}$ are identifiable linear transfer functions, (3) and (4) illustrate nonlinear and stochastic parts of *T* and *H*. To simplify the problem we use the advantages of plurality of measuring points in our sensor networks. If the EPs in some KSNs_DSN are close enough, we may obtain approximate linear models. Those can be divided into a set of SISO models and there will be a new multivariable matrix equation in the domain Z to solve:

$$\begin{pmatrix} T_{DSN_i} \\ H_{DSN_i} \end{pmatrix} = \begin{pmatrix} M(G_{T_i} \bullet U_{T_i}) & 0 \\ 0 & P(G_{H_i} \bullet U_{H_i}) \end{pmatrix} \tag{7}$$

(U_{Ti}, U_{Hi}), (G_{Ti}, G_{Hi}), and (T_{DSN}, H_{DSN}) are measured inputs, linear transfer functions of the KSN (Ki)_DSN and values of *T* and *H* in the DSN respectively. M(.) and P(.) are for effects of the KSNs on a DSN.

IV. PREDICTION ALTERNATIVES

During a field test on a truck in the University of Bremen up to 20 data loggers (ibutton) for measuring *T* and *H* were mounted at the walls, top, bottom, inside a closed box and outside the container. Reefer unit (inlet) in the container provides only desired *T*, based on the adjusted set point and *F* and *H* are dependent variables. The variation depends on several factors such as: initial conditions, type and size of freight and so on. There are some obstacles against the natural path of the air flow and different initial conditions in the WSNs because of either positions or corresponding measurement errors. To do some simulation based on the measured data of the WSNs as shown in fig.4 we chose two KSNs and a DSN. We will have different EPs as well as delays in K1, K2, and S1. We look for the prediction of the EPs in S1. As the first step of estimation, while the KSNs and the DSN are active and measure the corresponding EPs, there is a separate MISO system for *T* as well as *H* with inputs K1 and K2 and output S1. All unknown parameters in these models should be determined using an identification technique. In the second step, we can assume KSNs are active and there is a failure on the DSN or it is in sleeping mode (to achieve to energy saving). Depend on our selection of SISO or MISO models, having new inputs, new predictions will be possible in the DSNs.

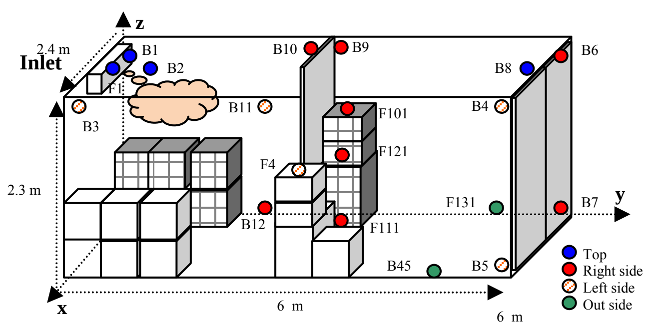

Fig.4. A container with mounted data loggers to measure *T* and *H*.

According with [9], using model identification schemes with the general form of input-output data in (8), we will have separate sets of linear transfer functions of *T* and *H* both for K1_S1 and K2_S1:

$$y(t) = \frac{B(q)}{A(q)} \bullet u(t - nk) + \frac{C(q)}{D(q)} \bullet e(t) \qquad (8)$$

A, B, C, and D are polynomials of operator (q) and nk is delay time of input signal u(t). Also, y(t) and e(t) are output and estimation error respectively. As represented in fig.5, during the measurement test we opened the door for different durations (one minute at t=150, 330, and two minutes at t=220). The curve with the less variation is related to a node far from the inlet or inside a box, reduces the F rate. The first part of the curves is related to loading and turning-on the ventilation system and the last part is permanent turning off, opening the door to unload the freights out of the container.

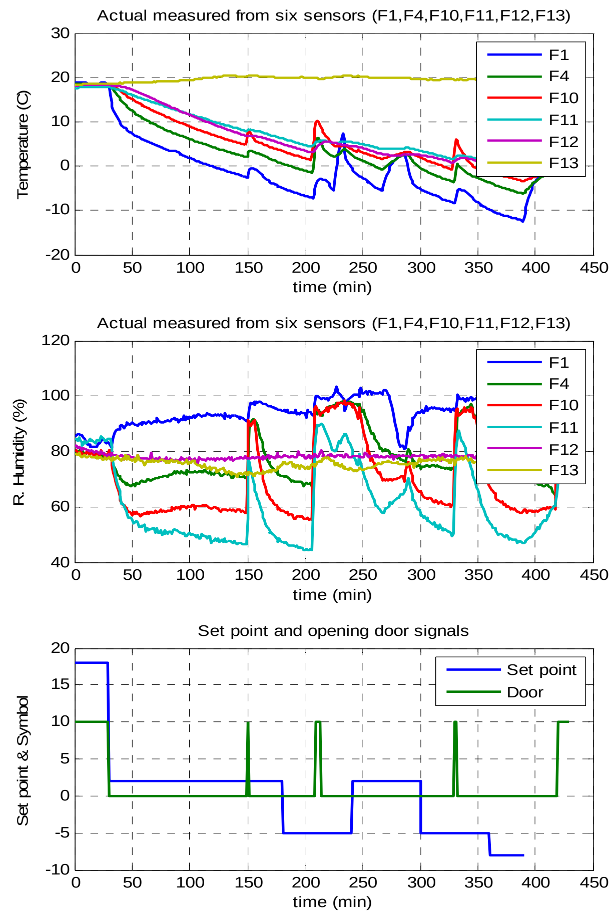

Fig.5. Actual *T* and *H* inside and outside the container (Ts= 1 min).

Some parameters, influenced on the quality of estimation:

1. Different estimation methods such as ARX, ARMAX, OE, BJ and SS to see the corresponding differences.
2. Difference of accuracy of the estimation using other number of data-samples in learning stage.
3. Investigation of different adaptation indexes
4. Observing the influence of the number of KSNs and model order on the estimators.
5. Using either online or offline predictions.
6. Using suitable sensor nodes.

V. COMPARING DIFFERENT ALGORITHMS

Assuming only one KSN as estimator and one DSN (S1) as the object of estimation, and having its actual measurement, we will attain different results using ARX, ARMAX, OE, BJ and State Space methods in another experiment.

Whereas order one can't cause a good performance, a third order linear model was chosen and unknown parameters was obtained via the mentioned approaches. At the first step we studied the effect of model structure on the performance of prediction. The black curve represents actual measurement of temperature on S1 and the others show different predictions.

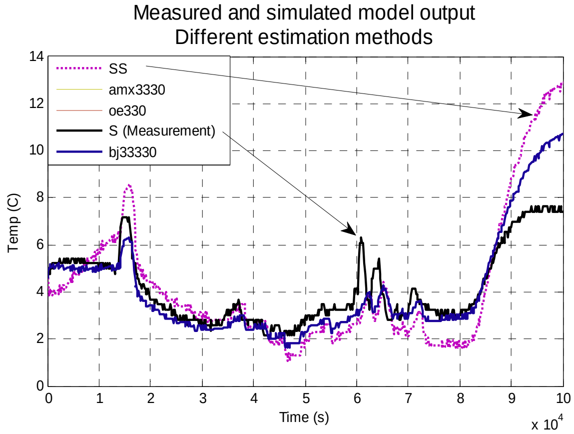

Fig.6. Prediction using different off-line methods.

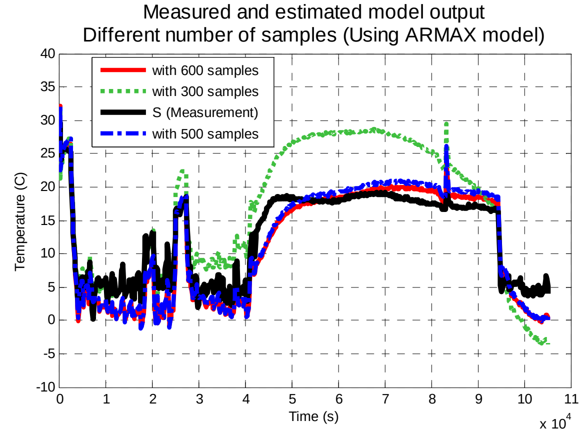

Fig.7. Comparison of different data number used for model making

According with fig.6, using previous results of measured temperature we used 500 samples out of 691 to make a model and then used the remained samples to validate that model. It represents that the methods BJ, ARMAX and OE provide a better adaptation to actual measurement with the same quality, better than state space (SS) method. Due to good flexibility of ARMAX method as well as less amount of calculations in compare with the other schemes such as Box-Jenkins in addition to achieving to the same quality of estimation leads us to choose this routine among the other ways.

VI. Results with Different Data Number

A very common question is that how many samples are enough to a good estimation?

In our thermo dynamical system, answer to this question is influenced of a few parameters such as the situation of measured inputs (measured temperature in the estimator KSNs). If they don't have any big change, prediction is not too sensitive to the number of data-samples to create the model. This means, we may use less number of measured data to make the model and then use that model to predict output accurately. However, when we have big variations in inputs, we should consider them in the obtained model. Because, it makes clear we have much variation around the desired sensor node so that we should be cautious. In this case we need more samples to make more accurate model to have better prediction.

We changed the number of data-samples for estimating and then we applied complete range of measured-data and assessed validity of models. Obviously, when the number of data is reduced, some methods can't be converged and the performance of prediction is relatively weak.

Achieved model can be used for predicting the EPs in the new situations provided that it already consists of relatively similar variations in the learning section. Having ARMAX method, fig.7 shows increasing data number up to 500 out of 691 provides better performance and increasing the samples more than 500 changes the quality little. Then we can say that in most cases 70 % of whole range of data horizon is enough to have an acceptable prediction in 30 % of the rest. Increasing the order more than three causes no big improvement.

VII. Different Indexes of Fitting

We want to find the best estimators in the stage of learning, before using the achieved models as predictors in the rest of procedure. There are several indexes:

$$Fit\ \% = \left[\frac{1-\|y-\hat{y}\|}{1-\|y-\bar{y}\|}\right] * 100 \tag{9}$$

$$AIC = \log(V) + 2\frac{d}{N} \tag{10}$$

$$FPE = V * \frac{1+\frac{d}{N}}{1-\frac{d}{N}}, \qquad SSE = \sum_{1}^{n}(error)^2 \tag{11}$$

$$Covariance(K1,S1) = C = \begin{pmatrix} C_{ii} & C_{ij} \\ C_{ji} & C_{jj} \end{pmatrix} \tag{12}$$

$$NC = Normalized\ \ Covariance = \frac{C_{ij}}{\sqrt{C_{ii} \bullet C_{jj}}} \tag{13}$$

Table 1 represents the result of a comparative study in case various conditions applied to estimators. Above indexes candidate separate estimators having different samples of data, orders, and indexes. As a general note, bigger NC and %FIT or smaller SSE cause more careful estimation.

The bold numbers in the rows emphasize the best estimators. Usually In case enough number of data, high order MISO model causes the best estimation. Then we recommend using either the MISO models or SISO model by using sensor nodes with more fitting index with output data. Those KSNs have more correlation with the DSN. Two columns in the left side of the table represent measured values and the others assign to the estimation results. The column so-called selected results, represents the amount of parameters such as NC, %FIT and SSE for different kinds of estimation. For instance with 100 samples out of 429, measured value of K2 has more NC than K1 (two columns in the left side) and High order MISO model with NC= 0.936 has the most NC among the other orders of K1-S1 or K2-S1. Also this estimation has the most %FIT and SSE among the other estimations. Only for used sample= 200 the best estimation is obtained by low order MISO. Because, with less number of data, model is not containing the whole conditions and therefore cannot be used to predict the rest of data having all input data. To have a good model we need to have enough data.

Table 1. An example of choosing the best estimators in case different number of data, indexes, orders, SISO and MISO For Estimating *H*

Measured K1	Measured K2	Ave(K1,K2)	Low order (K1-S1)	High order (K1-S1)	Low order (K2-S1)	High order (K2-S1)	Low order MISO	High order MISO	Index	Selected Results:	Used Samples	Total Samples
-0,929	**0,956**	0,361	0,309	0,488	0,442	0,884	0,837	**0,936**	N.C.	0,936	100	429
			-12,8	7,6	-13,6	-15,1	15,9	**17,9**	Fit (%)	17,9		
255,7	**92,3**	476,5	317,7	260,3	320,0	324,1	236,8	**231,4**	SSE	231,4		
0,363	**0,560**	0,501	0,232	0,389	-0,073	0,328	**0,562**	0,331	N.C.	0,562	200	429
			-9,5	-76,0	-135,1	-195,5	**0,2**	-93,2	Fit (%)	0,2		
92,9	229,7	248,9	20,2	32,4	43,3	54,4	**18,4**	35,6	SSE	18,4		
0,290	**0,426**	0,375	0,298	0,250	0,162	0,357	0,610	**0,664**	N.C.	0,664	300	429
			4,3	-2,2	0,7	1,1	19,0	**23,7**	Fit (%)	23,7		
156,0	267,1	248,9	17,6	18,8	18,3	18,2	14,9	**14,1**	SSE	14,1		
0,233	**0,344**	0,303	0,121	0,359	0,190	0,426	0,611	**0,728**	N.C.	0,728	400	429
			0,1	6,4	1,0	9,3	19,5	**31,0**	Fit (%)	31,0		
178,3	312,4	248,9	18,4	17,2	18,2	16,7	14,8	**12,7**	SSE	12,7		
0,227	**0,348**	0,303	0,300	0,612	0,148	0,545	0,625	**0,764**	N.C.	0,764	429	429
			3,3	18,1	0,9	16,2	18,7	**35,2**	Fit (%)	35,2		
192,3	327,8	248,9	17,8	15,1	18,3	15,4	15,0	**11,9**	SSE	11,9		

VIII. MODEL ORDER AND NUMBER OF KSNS

Because of being time consume and causing over fitting problems, model orders more than three are not suitable in this application. Although measured K1_S1 has less covariance than K2_S1, using both K1 and K2 has more covariance than using each of them individually, because a MISO model can consider the effect of environment around of a DSN in different directions. To select either one or more KSNs provided that there are no additional conditions, these steps should be followed:

(1) Large number of data of (KSNs) and the DSN, enough to estimate is necessary.

(2) Covariance matrix for KSNs_DSN should be computed.

(3) After sorting the normalized covariance the best estimators are those with bigger NC.

(4) Picking up the number of the estimators for each DSN depends on the number of all KSNs and the DSNs and capability of the processor and required accuracy.

Using the experiments by ARMAX method we will compare the results through fig.8 and fig.9, when we use both one and two KSNs as the estimator. MISO model is more robust than SISO model. However, with proper KSNs, SISO model needs less calculation and gives reasonable prediction.

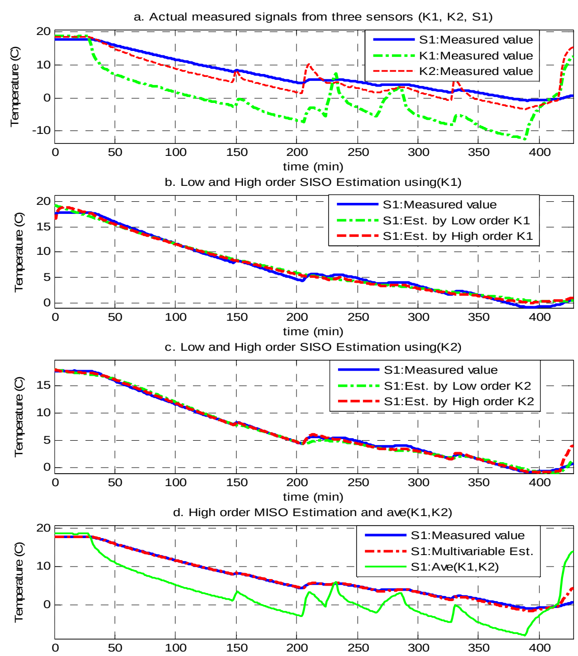

Fig.8. Comparing the result of prediction of Temperature (*T*).

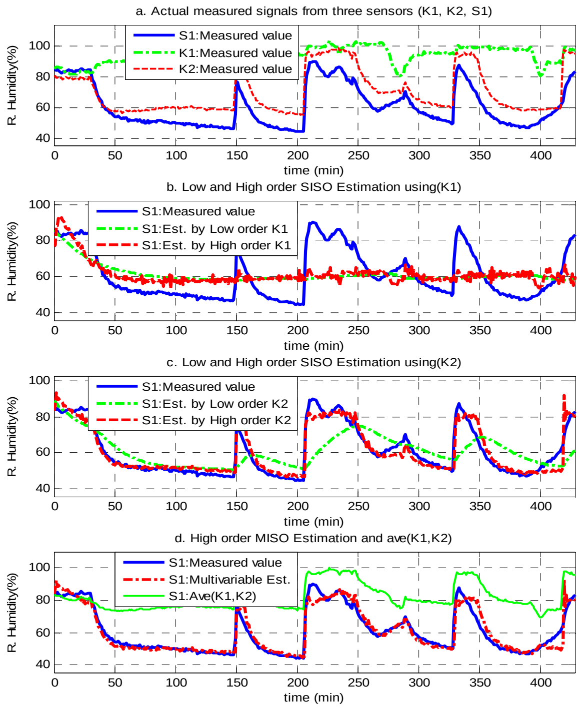

Fig.9. Comparing the result of prediction of R. Humidity (*H*).

IX. ON-LINE OR OFF-LINE AND AVERAGE TECHNIQUE

Based on fig.10 and fig.11, using on-line estimation we obtain very good accuracy, but to use for energy management system that we need large number of prediction points, it can't be a good choice. In this case off-line estimation which uses all previous data of system gives better performance. However, it is suitable to use in short horizon predictions. Then, it is applicable in fault diagnosis.

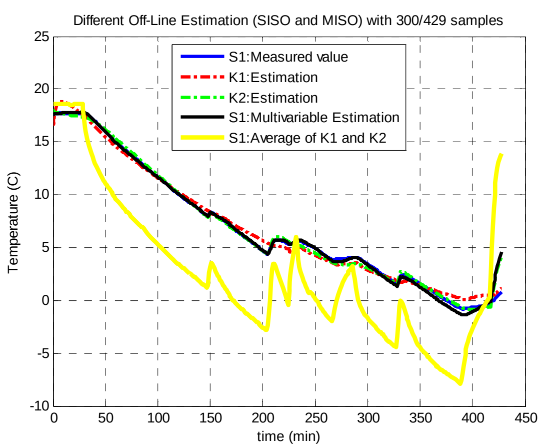

Fig.10. Off-Line estimation using 300/429 samples

The simplest way to estimate the EPs in a sensor node is finding the average of the EPs from the surrounding WSNs. Fig.11 states that it can't be a good estimation, but it is a reliable amount not far from the others. This value can be used when we lose all estimation in the real application.

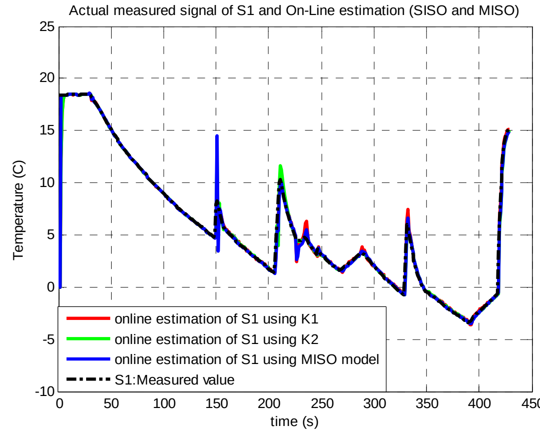

Fig.11. Off-Line estimation using 300/429 samples

X. PREDICTION IMPROVEMENT

There will be several periods of learning and predicting working the implemented approach. In the first learning stage we make a model and latter, in the first prediction stage, having the present inputs, we use the model to predict output.

Although we would like to have a continuous curve consisting of learning (model making) and prediction stages, always value of prediction is not fit with the measurements. It means that when we start second stage of measuring, the first measured data is different with the last predicted data of former prediction stage. We are not interested in to have such difference in the first part of each measurement stage.

Fig.12 is an actual prediction based on the achieved model from a part of whole data. There are some differences between actual measurement and prediction. Particularly when using SISO model either K1 or K2 don't make very good prediction where the MIMO model causes better fitted prediction.

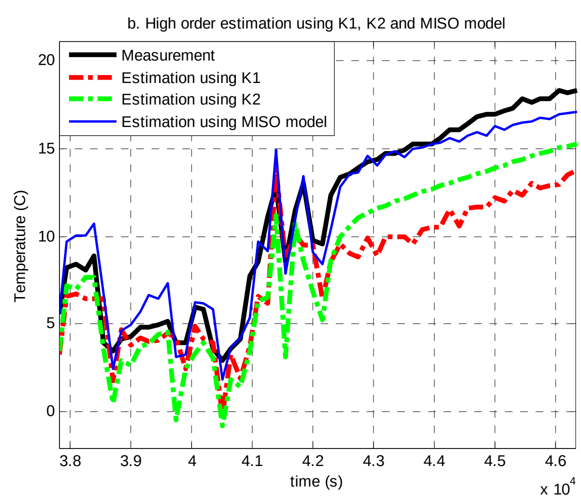

Fig.12. Estimation using K1 (%FIT= 40.78).

To explain whole procedure, fig.13 shows an example of separate learning and Prediction stages. Obviously it clarify the differences mentioned before. Input is the measured values by a KSN which is always available.

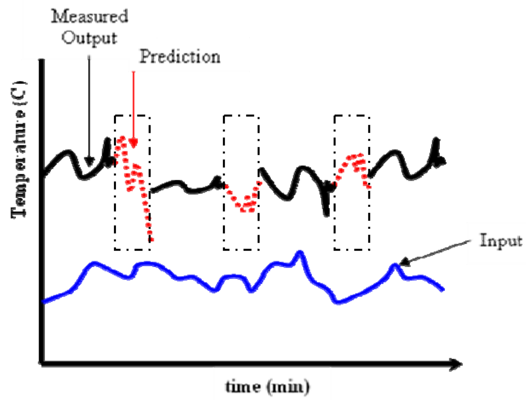

Fig.13. Whole stage of estimation and prediction

To move the green curve, obtained by predictors to blue curve in fig.14 we use a formula in the following:

$$\hat{y}_{new}(t)=\hat{y}_{old}(t)+\frac{\hat{y}_{last}}{y_{first}}*\frac{(t-t_0)}{(t_1-t_0)} \tag{14}$$

(t_0 and t_1) are respectively starting time of the first and second measurements. ($y^\wedge_{last}(t)$ and $y_{first}(t)$) are the last point of prediction and first point of second measurement. and $y_{new}(t)$ is the new improved prediction. In this way we will be able to move the last point of prediction to the first point of the next stage of measurement. Other points of prediction will also be moved linearly and the first point of prediction won't change.

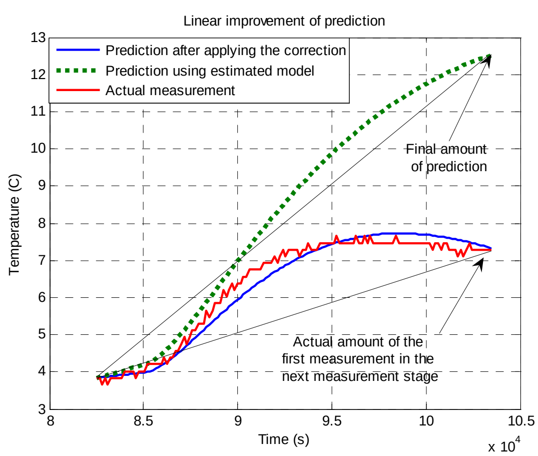

Fig.14. Primary prediction and its improvement.

XI. Choosing Improper Sensor Nodes as Estimator

Models of *T*, *H*, and *F* can be independent if we use appropriate KSNs as estimators. Fig.15 exhibits the measurements of three SNs. After using these KSNs to predict parameters in the DSN, fig.16 shows less accuracy with K1 (near to reefer unit), far from the DSN and another one (K2) near to the DSN. Using both K1 and K2 in a MISO model also gives acceptable prediction.

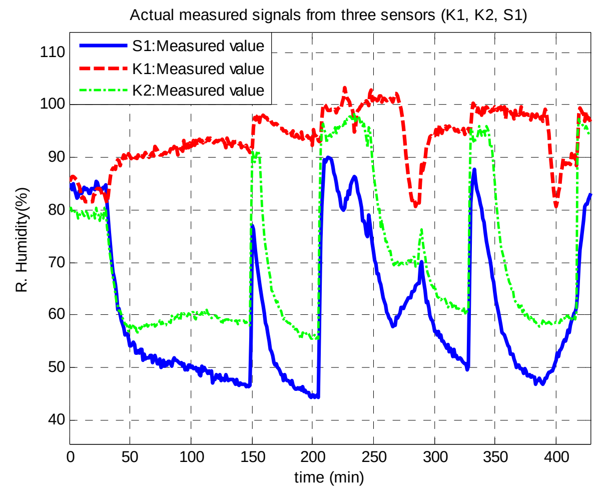

Fig.15. Comparing the result of prediction of R. Humidity (*H*) when a far sensor node is chose as predictor.

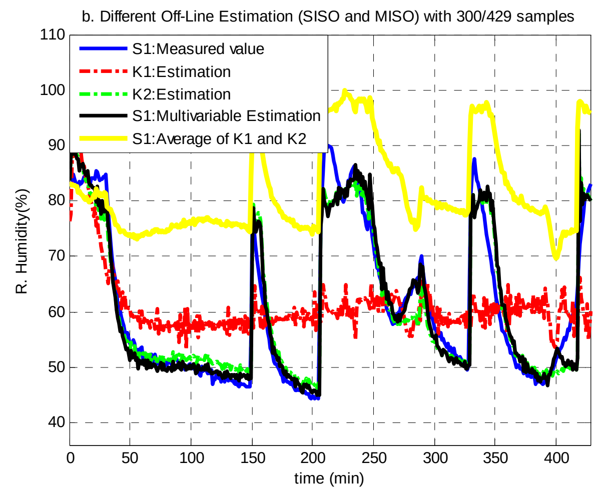

Fig.16. Comparing the result of prediction of R. Humidity (*H*).

XII. Conclusion

Different identification schemes to achieve more applicable one to implement a new method of estimation of environmental parameters inside a closed space container was evaluated. We used system identification tool-box of Matlab in addition to several programs to simulate different situations.

This work used actual measurements to evaluate the properties of different wireless sensor nodes as estimator and predictor with regard to lately introduced Floating Input Approach (FIA). The effects of different numbers of data-samples, various performance indexes as well as different numbers of employed WSNs on the accuracy of predictions were studied. Furthermore, a way to improve the accuracy of procedure was introduced. Implementing the represented approaches and calculating the amount of energy saving when applying the FIA can be an interesting issue for future works. Combining the proposed recipe with the existing battery management techniques to achieve a better performance might also be of interest to those who are working on energy management of Wireless sensor networks.

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