A Heuristic Method in Monitoring Environmental Parameters using a Floating Input Approach in Wireless Sensor Networks

M. Babazadeh, R. Jedermann, W. Lang

***Abstract*—** This work is part of a research activity aiming to improve and to optimize environmental parameters monitoring system. It is essential in order to preserve the quality, safety and shelf life of perishable products.

The present study reports on the investigation a way to both plausibility check and energy management in a wireless sensor network established in a closed space container. It introduces a new technique to decrease the total power consumption due to measuring and transmitting data in a few desired sensor nodes (DSNs). They are either failed or inactive (Sleeping) sensor nodes. They can be deactivated by some of surrounding key sensor nodes (KSNs) due to reduce battery-consumption.

A new technique of the model making to estimate temperature, relative humidity, and air flow as important environmental parameters (EPs) instead of the direct measurement and then assessment the validity of the proposed model using some experiments will be investigated. Introduced estimators use linear models between the KSNs and a DSN. These models can be extended for possible use in different applications such as EP-controllers in air conditioning systems as well as the estimator in fault recognition procedures. We can.

***Keywords*—** Estimation, Relative humidity, Grey-box, Temperature

I. Introduction

In closed space containers equipped with wireless sensor network (WSN), a part of attractive applications in field of control systems can be identification, modeling and control of temperature (T), relative humidity (H), and air flow (F) as the environmental parameters (EPs) and also fault diagnosis in the nodes. According with the present study, to achieve these objectives using model based methods, a simple and applicable model plays an indispensable role. To do that, we are looking for a way to estimate the EPs in some desired sensor nodes (DSNs) instead of the direct measurement.

In addition to [15], [16] and [17] about the energy aware strategies in wireless sensor networks there are a lot of papers which have studied various methods to save or harvest energy for sensor nodes. Our method can be used together with the mentioned methods. Then, in this study we'll only investigate our proposed method. It includes model making, energy saving and fault diagnosis in one approach.

There are some white, grey, and black-box models of T for air-handling units have been addressed in some previous works. It is represented in [1] that, the model of the air handling units (AHU) elements is nonlinear and temperature and relative humidity as controlled variables are coupled. It assumes constant air flow in the AHU as a parameter influence on the other parameters. Also it assumes that temperature and relative humidity change with a constant speed. It uses grey-box approach 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 and humidity and uses separate linear transfer functions for them.

They develop in [2] analytical and numerical models to describe the dynamics of the cryogenic freezing tunnel system. 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. It mentions that heat transfer with phase change is a highly non-linear problem.

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 method 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.

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An online mathematical method (second order model) to model the 3-D spatio-temporal temperature distribution in an imperfectly mixed forced ventilated room for control purposes is presented in [4]. It shows that model based predictive controller (MBPC) using data based mechanistic modeling can be of significant importance in the development of a new generation of climate controllers. 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 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 effect of the ventilation rate on the spatial temperature homogeneity, while keeping the average temperature inside the ventilated chamber constant. It shows 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 in different 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 investigated 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.

Paper [6] using neural network presents an NNARX system for modeling the internal greenhouse temperature as a function of outside air temperature and humidity. Because of slow nature of the mentioned system it doesn't need of frequent retuning the parameters.

Numerical and experimental characterization of air flow within a semi trailer enclosure with pallets has been reported in [7]. 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 shows importance of air ducts in decreasing temperature differences throughout the cargo. It says that prediction using k-ε models are often not accurate. It investigates 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 investigated in [8]. 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 [9], 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.

The transport planning for goods with different temperature requirements form a special case of a vehicle routing problem [14]. The planning can be improved by analysis and prediction of local temperature deviations. The assignment of transport items to different temperature zones and trucks can be done more accurately. The risk for temperature abuse can be evaluated based on the predicted temperature curve for the position of the item inside the truck or container.

All models are obtained between system input so-called 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. Furthermore, 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 some applications. Nonlinear multivariable nature and interconnections between the variables of the EPs in addition to the presence of the load as an unpredictable, immeasurable disturbance, effects of flow dynamic, influence of surfaces and walls inside the container increase complexity of the model which we are looking for.

Some types of acting disturbances in the container are opening the door, changing either direction or rate of F by some freights and thermo dynamical influences of the loads inside the container. When looking at the previous methods with the white-box models, we will see that in addition to encounter some complicate conditions while solving such model identification problem, disturbance may cause a big estimation error.

Thus, our proposed technique considers the influence of disturbance on the EPs estimation using a grey-box model in a wireless sensor network. Furthermore, the proposed techniques are independent from the type of the ventilation. Our method acquires a minimum power consumption of the batteries in the DSNs.

We include a brief introduction of a new grey-box hybrid model of the EPs between the inlet and a DSN in the present article. Then, we use advantages of a sensor network to achieve an independent multi input-single output (MISO) simple linear model. Obtained results will be supported with the real experiments. At the end, some practical rules to attain a near optimal EP-estimation will be introduced. This paper will introduce a new method to achieve the best estimation of the EPs and it might be helpful in fault diagnosis and energy management as well. The work is currently being done and the results of this kind of applications will be published later.

II. Problem Formulation

Fig. 1 shows a symbolic scheme of the container. There is a complicate time and place dependent multi variable model between the inlet and a spatial position. Coupling among the parameters of environment arise difficulties of doing independent experiments and the measurement results completely depend on the initial conditions.

Any change in *T*, *H*, and even *F* in the source (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. We will use an optimal combination of several models obtained from surrounding key sensor nodes (KSNs) and a DSN so that every non modeled disturbance is modeled as an implicit input change, not as a pure disturbance.

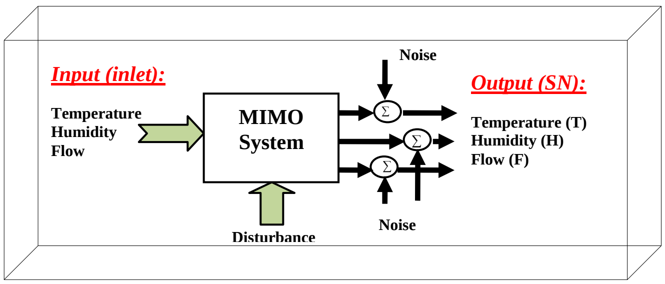

Fig. 1 Container as an input-output model

The KSNs will be the system estimators. When a disturbance acts on the system, it might excite a few sensor nodes. After initializing at least one of the estimators with a disturbance, parameters of several models are obtained using present noise corrupted data of the KSNs and the DSNs and also previous data from the DSNs.

Those models are identified only between some couples of a DSN and the selected KSNs. According with Fig. 2 there will be a network with several nodes and branches, several KSNs (K1, …, Km) as input nodes and a few DSNs (S1 and S2) as output nodes. It is noted that in addition to characteristics like an ordinary sensor node (SN), KSNs have three major tasks:

1. They measure EPs in a defined period.
2. They might evaluate measured values and do estimation of the EPs in a few DSNs in some clusters and update previous models, based on the new measurements (depending on using autonomous or non autonomous strategy, main computations can be done by main processor or KSNs).
3. They deactivate the DSNs when all conditions are normal and there are no big changes in the EPs.

The DSNs can be considered in sleeping mode or even failed. 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 avoidable because while identification based on the proposed method, most of uncertainties and disturbances are considered indirectly as the input change in the KSNs surrounding the DSNs. When speaking about a loaded closed space container, with a variation in the inlet or even any variation of the environment inside the container, signals measured by the DSNs and the KSNs will be different with those during a specific off-line identification stage. Several MIMO models will be established between the KSNs and a DSN (fig. 3). To reduce the estimation error a few questions should be answered:

i. How long the achieved models are valid?
ii. How many KSNs are adequate to do estimation?

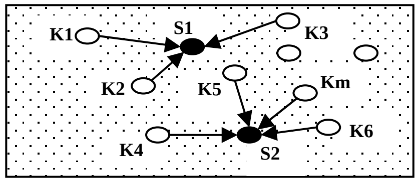

Fig. 2 Proposed sensor network

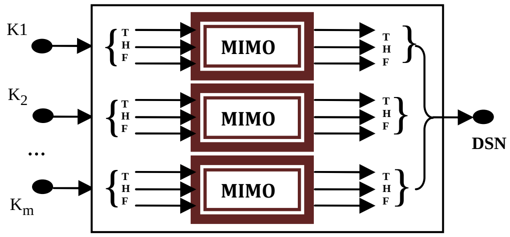

Fig. 3 Block diagram of a MISO model of the EPs

Whereas we would like to increase the accuracy of the estimations 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 contributed in the estimation. But, simulations show that the accuracy will be increased with increasing the number of these estimators. According with fig. 4, depending on the conditions of the EPs, different KSNs have different influences on a DSN. Considering an *F* direction as a simple example in a three dimensional space, K1 and K2 can be considered more effective than K3. We will obtain a relationship between different KSNs to choose the best estimators.

We will make a group of some effective KSNs with a definite priority. Although K3 is not among the impressive KSNs, it may have two properties: it has good correlation with related DSN. Then, it will improve the accuracy of the estimation. Otherwise, it won't be among the prior estimators.

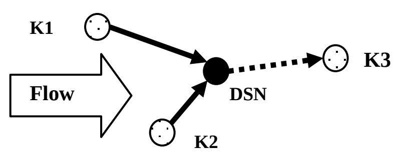

Fig. 4 Impression of the KSNs on a DSN

Because of chaotic direction of the *F* in the real applications and regard to the limitation in number of *F* sensors, predicting the direction and then verifying the effective KSNs is impossible. Therefore, there will be a mismatch error due to considering non effective KSNs in the estimation process. It will be shown that using data of a KSN_DSN to make single input-single output (SISO) model cannot present surrounding influences completely.

It can only show the EPs variations in a DSN from side of the mentioned KSN. Estimation 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 estimation. There are also some KSNs which do not have any influences on the DSN. Far from the DSN, they could not help to increase the accuracy.

III. Problem Solution (Hybrid Model)

We start with a simple mathematical model to attain an estimation of the EPs in a desired place inside the container. We will apply then our view points to introduce a more precise nonlinear model. We use an argument to solve simplified problem. According with fig. 1, beginning with the linear transfer function matrix between input (inlet) and outputs (SNs), we will have several independent MIMO systems for inlet_SN. The arrays of matrix in (1) show the effects of variation in inlet on the SN in the domain of Z-transform.

$$\begin{pmatrix} T_{SN_i} \\ H_{SN_i} \\ F_{SN_i} \end{pmatrix} = \begin{pmatrix} G_{T_i} & -G_{HT_i} & 0 \\ -G_{TH_i} & G_{H_i} & 0 \\ 0 & 0 & G_{F_i} \end{pmatrix} \bullet \begin{pmatrix} T_{inlet} \\ H_{inlet} \\ F_{inlet} \end{pmatrix} \tag{1}$$

For the sake of simplicity we omitted the operator Z in the above matrix relation. (T_{SN}, H_{SN}, and F_{SN}) and (T_{inlet}, H_{inlet}, and F_{inlet}) are the EPs in a SN and inlet respectively.

In [12], insufficiency of (1) because of no considering nonlinearities has been proven. Omitting index (i) because of simplicity, we complete (1) using f and g as nonlinear interactions. N_T, N_H, and N_F are measurement Gaussian noise in the SN. $G_{T,F}$ 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. Following formulation is not a real super position. That is only an assumption.

$$\begin{pmatrix} T_{SN_i}(t) \\ H_{SN_i}(t) \\ F_{SN_i}(t) \end{pmatrix} = \begin{pmatrix} Z^{-1}(G_{T,F} \bullet T_{inlet}) + g(H_{inlet}, F_{inlet}) + N_T \\ f(T_{inlet}, F_{inlet}) + Z^{-1}(G_{H,F} \bullet H_{inlet}) + N_H \\ Z^{-1}(G_F \bullet F_{inlet}) + N_F \end{pmatrix} \tag{2}$$

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 for determining these influences so that their parameters will be determined while operation. References [1], [5] suggest the first order dynamic model for the mentioned transfer functions. Then we can use a general form in the below for the linear part of the hybrid model:

$$G_{T,F} = K_T \bullet \frac{\prod_{i=1}^{mT}(Z - Z_i)}{\prod_{j=1}^{nT}(Z - P_j)} \tag{3}$$

$$G_{H,F} = K_H \bullet \frac{\prod_{i=1}^{mH}(Z - Z_i)}{\prod_{j=1}^{nH}(Z - P_j)} \tag{4}$$

We derfine the poles and zeros (P_j and Z_i) as functions of *F* so that higher *F* causes faster response of *T* and *H*. According with [12] and with Z^{-1} as unit delay in domain of Z-transform, to perform the nonlinear part we use some basic thermodynamic relations and we have:

$$H = H_0 \bullet 2^{\frac{-(T-T0)}{10.1}}, T = T_0 - \frac{10.1}{\ln 2} \bullet \ln \frac{H}{H_0} \tag{5}$$

Interconnections can be obtained in the following:

$$\Delta T(t) = T_0 - \frac{10.1}{\ln 2} \bullet \ln \frac{Z^{-1}(G_H \bullet H_{in}) + N_H(t)}{Z^{-1}(M_H \bullet H_0)} \tag{6}$$

$$\Delta H(t) = (2^{\frac{-Z^{-1}(G_T \bullet T_{in}) + N_T - Z^{-1}(M_T \bullet T_0)}{10.1}} - 1) \bullet Z^{-1}(M_H \bullet H_0) + N_H \tag{7}$$

As an example showed in fig. 5, assuming that there are two KSNs, one DSN and an inlet (which provides F, T, and H), we are looking for the estimation of the EPs in S1. There are a few obstacles against the natural path of *F* and different initial conditions in the SNs because of either positions or corresponding measurement errors. With variations of *T*, *H*, and *F* in inlet at different times, we can see the EPs in K1, K2, and S1 including different delays.

The EPs in K1, K2, and S1 with the initial conditions in table I has been illustrated in fig. 6. As the first step in the estimation, while the KSNs and the DSN are active and measure the corresponding EPs, there are two MISO systems for *T* as well as *H* with inputs K1, K2, and output S1. All unknown parameters in these models should be determined using an identification technique.

Actually, we can assume that KSNs are active and either there is a failure on the DSN or it is in sleeping mode. Having new inputs we will have the new estimations in the DSNs using existing MISO models. The important note is that this hybrid model can give a view of system and we will use it for the next steps only for making a mathematical model.

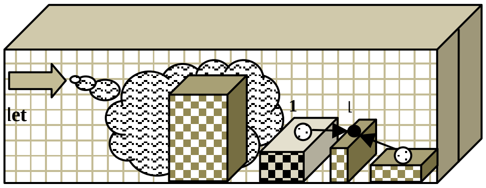

Fig. 5. A container with inlet, KSNs (K1, K2), and one DSN (S1)

Using the relation in matrix equation (2) and with the initial conditions in Table I, one can observe the simulation results in fig. 6. It shows the EPs in a SN when changing *T*, *H* and *F* in inlet (Reefer).

Table I. INITIAL CONDITIONS AND DELAYS

	T_0 (°C)	T_{delay}	H_0 (%)	H_{delay}	F_0 (m/s)	F_{delay}
Inlet	10	---	30	---	15	---
K1	9	5	28.5	7	13.5	2
K2	8.5	3	27	4	3	5
S1	8	8	25.5	2	10	8

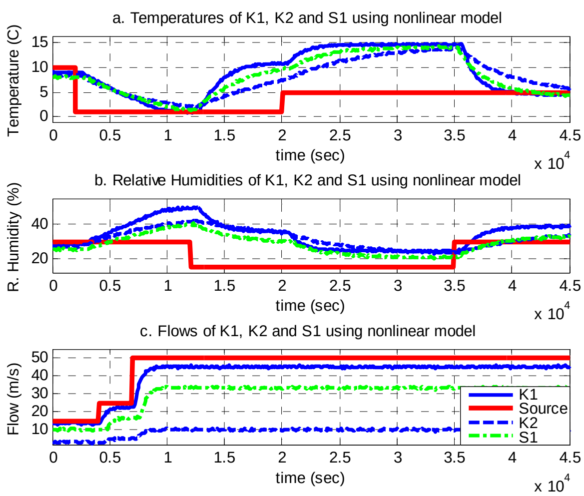

Fig. 6 Outputs when T, H, and F in inlet change in different times (Sample time: Ts= 90 s)

(T_0, H_0, and F_0) and (T_{delay}, H_{delay}, and F_{delay}) are initial conditions and delay time of the EPs between inlet and SNs, respectively. Accordant with Fig. 6, while reducing *T* in reefer, *T* in the SNs decreases and because of its reverse effect on *H*, relative humidity increases as well.

There is the same reverse behavior when reducing *H* in reefer. Changing the rate of *F* changes the speed of the responses of *T* and *H* in the SNs. As an alternative state to achieve to floating input approach (FIA) as shown in [12], we can write (6) and (7) in the new following forms:

$$T_{SN}(t) = Z^{-1}(G_{T,F} \bullet T_{inlet}) + \Delta T(t) \tag{8}$$

$$H_{SN}(t) = Z^{-1}(G_{H,F} \bullet H_{inlet}) + \Delta H(t) \tag{9}$$

$$\Delta T(t) = g(.) + N_T, \Delta H(t) = f(.) + N_H \tag{10}$$

$$T_{SN}(t) = T_{linear(fromT_{inlet})} + T_{nonlinear(fromH_{inlet})} \tag{11}$$

$$H_{SN}(t) = H_{linear(fromH_{inlet})} + H_{nonlinear(fromT_{inlet})} \tag{12}$$

$G_{T,F}$ and $G_{H,F}$ are identifiable linear transfer functions and $\Delta T, \Delta H$ are nonlinear parts of *T* and *H* plus Gaussian white noise. We use (5) when obtaining nonlinear parts of (11) and (12). To simplify the problem we use the advantages of plurality of measuring points in our sensor networks. Disturbance might be applied to the input, system and or to the output, but in all cases it influences the outputs (KSNs).

Now, assuming excited KSNs as input nodes, the input in defined MISO system will be changed and output nodes (DSNs) will be influenced of such new inputs. If the EPs in the KSNs and a DSN are close, we can have some approximate linear models written for KSN_DSN.

We will see later some of the KSNs have this property more than the others and can be considered as the estimators so that we can assign identifiable linear models for KSN-DSN. Models of KSNs_DSN can be split into a set of SISO transfer functions and there will be a new multivariable matrix equation to solve:

$$T_{DSN}(t) = G_T \bullet T_{KSN}), H_{DSN}(t) = G_H \bullet H_{KSN}) \tag{13}$$

$$\begin{pmatrix} T_{DSN_i} \\ H_{DSN_i} \end{pmatrix} = \begin{pmatrix} M(G_{T_i} \bullet U_{T_i}) & 0 \\ 0 & P(G_{H_i} \bullet U_{H_i}) \end{pmatrix} \tag{14}$$

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

One of the advantages of the new formulation of the problem is capability to diagnose disturbances. To show this, we used ARMAX model identification method according with [10], written in (14).

As shown in Fig. 7, when there is a variation of *T* near to K1 as disturbance at the time 25000 s. We suppose that because of vicinity, it influences only on K1 and S1 not K2. To compare output estimation of the regular model achieved from inlet_S1 with our model using KSNs_S1, we have plotted both estimations in S1.

Despite of the model obtained from inlet_S1, suggested method detects its influence on S1. We do not use models with order more than three, whereas those models arises some difficulties in the application.

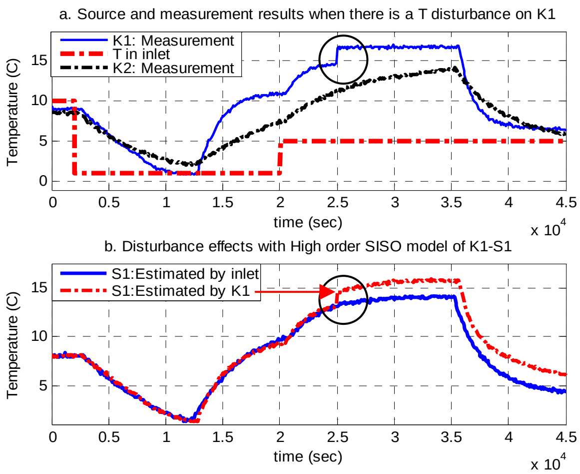

Fig. 7 (a) T, measured in inlet, K1 and K2; (b) estimation using inlet and K1with a disturbance at 25000 s with sample time: Ts= 150 s

IV. Estimation Based on Measurements

We used ARMAX model instead of ARX and output error method (OE) to include flexibilities to define colored-noise in the model. Fig. 8 shows the difference, when applying ARX and ARMAX model identification methods. With the OE method, some time the same performance as ARMAX method is obtained, but ARMAX is better for our system.

In the mentioned test we used 300/ 400 samples of data for estimating unknown parameters of the model in (15) and the rest data samples for validation.

We will identify a linear transfer function for *T* and *H* for any pair of KSN-DSN. It is noted that q in the following formula is the same operator as Z-transformation method. A, B and C are unknown polynomials and nk shows the number of delays included in input signal u(t). Signal e(t) represents white-noise disturbance value.

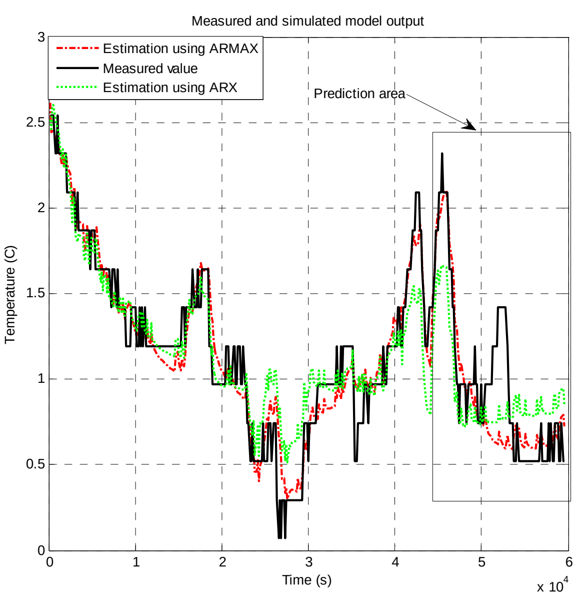

Fig. 8 Performance of the outputs of ARX and ARMAX models in compare with actual measurement (Sampling time: Ts= 150 s).

$$A(q) \bullet y(t) = B(q) \bullet u(t - nk) + C(q) \bullet e(t) \qquad (15)$$

This approach was applied to *T*, measured during field tests in cooperation with a German food retailer [11]. Up to 40 data loggers were mounted at the walls of the compartment for fish and meat. A 2-point control turned on the ventilation if *T* below the refrigeration unit rose above a given set point. As said before, models of T, H, and F can be independent if we use proper KSNs as estimators. Fig. 8 shows the measurement results in three SNs (700 points). The curve with the less variation is related to a node far from the inlet or behind a fruit 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 related to its permanent turning-off, opening the door and unloading the freight. Although we could omit the first and last part of the data, we consider them to show capability of the proposed techniques.

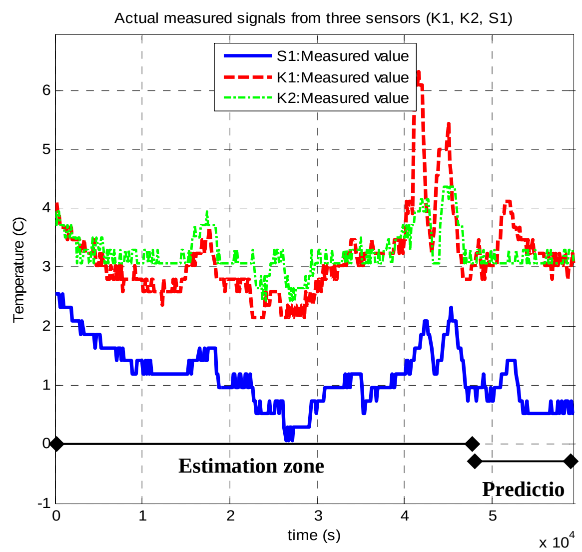

Fig. 9 Actual *T* inside the container in three points (Ts= 150 s)

Refer to fig. 9 as the measured signals in three points (three SNs) we got some important points:

1. In the portion of estimation, we have some correlations and in some points we don't have that. It means that some input-output data of KSNs-DSN which is correlated can help the model to be completely fit with the related data, but in some periods of time we have no correlation. These data will make the ultimate model weaker. This behavior comes from nonlinearities that we didn't considered while model making. This kind of nonlinearities showed in fig. 13 may be produced by some SNs which either are:
    1. Far from each other
    2. Some of them are inside the closed space boxes and etc.
    3. Failed sensors.
2. In prediction stage, if the new input data have good correlation with the obtained linear model from

previous stage, we will have accurate prediction, else we'll achieve to some incorrect predictions.

3. It would be better if we can sort the best KSNs (estimators) to use as predictors in the next steps.
4. As shown in fig. 12, if we use several KSNs instead of one, we will be sure that we catch the effects of the EPs from different sides around the DSN.
5. One may wants to predict a DSN using average of two or many KSNs. Fig. 12 represents that when data of KSNs are close and different with the DSN, average method doesn't give good results.

Fig. 10 and fig. 11 show the prediction using only one KSN. The measured signals were chose such that there are approximately linear relations between KSNs-DSN. In both cases, third order transfer functions show better performance than first order. To show our goals, the first part which we removed from original measurement, was about the starting time that sensors had different temperature (between the steady state). Also we deleted the last part that was the measured values in opening the door mode. We'd like to have good conditions to present the behavior of the approach in normal situation and later we will see various situations.

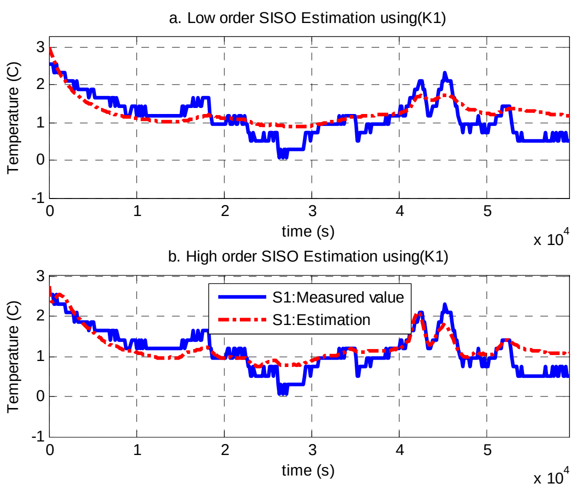

Fig. 10 Estimation using K1 compare with actual measurements.

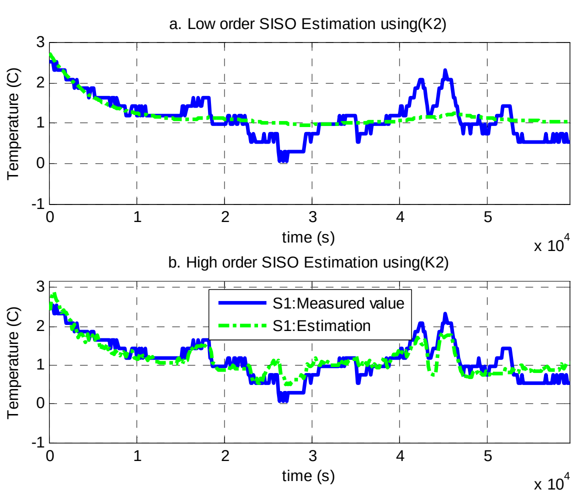

Fig. 11 Estimation using K2 compare with actual measurements.

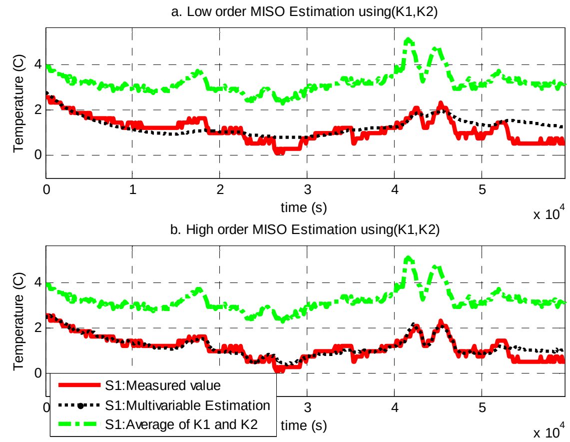

Fig. 12 Estimation using MISO system containing K1, K2 compare with actual measurements (sampling time: Ts= 150 s).

As the first step, covariance matrix (C) of the measured values of K1, K2, …, Km, with S1 should be determined and to compare the covariance of the different signals, they should be normalized (NC) as shown in the following as an example:

$$Covariance(K1,S1) = C = \begin{pmatrix} 0.472 & 0.185 \\ 0.185 & 0.265 \end{pmatrix} \qquad (16)$$

$$NC(K1,S1) = \frac{C_{ij}}{\sqrt{C_{ii} \bullet C_{jj}}} = \begin{pmatrix} 1 & 0.52 \\ 0.52 & 1 \end{pmatrix} \qquad (17)$$

Table II. Normalized Covariance in Different Situation

models	NC compare with S1	
	Order (1)	Order (3)
Estimation using K1	0.739	0.834
Estimation using K2	0.72	0.735
K1	0.52	
Average of K1 and K2	0.625	
K2	0.699	
MISO Estimation using K1, K2	0.749	**0.922**

Table 2 shows that different estimations in S1 using different KSNs have different correlations with the actual measurements.

Fig. 12 and table II illustrate that K2_S1 has more correlation than K1_S1 both in measurement and estimations of S1. Estimation using SISO model of K2_S1 is better than it by K1_S1. The obtained results show that higher order models cause better estimation (higher covariance).

Therefore, using K2 is prior to using K1. Because of the time consuming processes and causing over fitting problems the model orders more than three are not suitable in this application. Although K1_S1 has less covariance than K2_S1, covariance of MISO system using both K1 and K2 is more than each of them lonely and then MISO estimation using K1 and K2 to estimate S1 is more accurate than SISO models.

Increasing the number of estimators will increase covariance of the response. Another important result is that using average method has less covariance than both proper

KSN (K2) and MISO estimation using K1, K2. It is better than estimation using only one KSN.

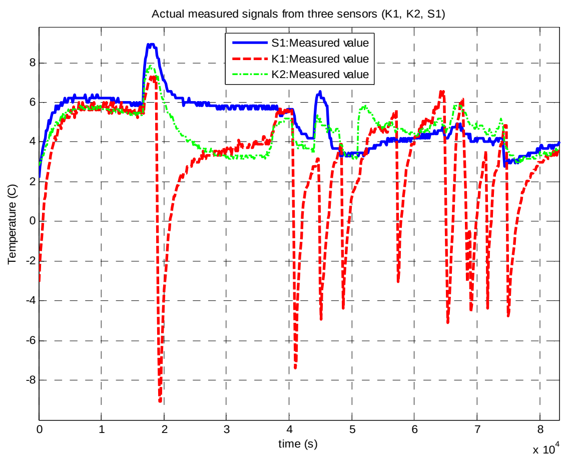

Fig. 13 Measured temperatures by three sensor nodes far away.

Fig. 13 shows the experimental results in three points, one near to inlet which has big and fast variations (K1). Second (K2) and third (S1) are located far from each other and far from K1. Although K1 and S1 differ from each other with respect to variations, K1 can make better fit in prediction than K2. It comes from this fact that our model is a linear dynamic model, a low pass filter, and then it damps the variations of K1-S1. However, model of K2-S1 is actually a nonlinear model (with lower covariance and lower sum of squared error) and we force to fit a linear model to it. As an example, we use 500 samples of data for model making and 50 remained data to validate the model. It illustrates, although K2 is better than K1 with respect to the normalized covariance, in prediction stage a high order model of K1-S1 acts better. This result is supported with the sum of squared-error method (SSE). The more normalized covariance, the better fit,the less SSE.

Used Nr. of Samples= 500 , **Total Samples=** 550

Normalized covariance:

Measured K1= 0.217
Measured K2= **0.431**
……………………..
Ave (K1, K2)= 0.323
Lo w order (K1-S1)= 0.870
High order (K1-S1)= **0.896**
Low order (K2-S1)= 0.695
High order (K2-S1)= 0.745
Low order MISO= 0.866
High order MISO= 0.848

Sum of squared error:

Measured K1=78.9
Measured K2=**28.6**
……………………..
Ave (K1, K2)= 48.2
Low order (K1-S1)= 15.2
High order (K1-S1)= **13.2**
Low order (K2-S1)= 22.2
High order (K2-S1)= 20.5
Low order MISO=14.8
High order MISO=15.7

As a result, it would be better we choose some sensor nodes in vicinity as a group. When we don't choose proper KSNs, we can not introduce an index to determine the best KSN. In this case we can choose all KSNs as estimators. But if we choose the KSNs near to each other, we will have linear dynamic relation between KSNs and a DSN, we can sort them based on an index like sum of squared error or covariance. Then we can choose one or several with respect to their priorities. We may use electromagnetic waves power measured by the SNs to make groups of KSNs and a DSN. If one of the KSNs is failed, it must be considered as a new DSN in addition to the previous DSN in the related group. Whereas the calculation is being done after ending a period of time, if diagnosing any fail in the KSNs, failed sensor nodes will be removed from the list of the KSNs and move to the DSNs' list.

In case of enough previous data of the failed sensor, they should be considered as output data in the new identification procedure between the rest KSNs and the failed KSN as a new DSN. If the number of data is not sufficient, it can be made by average method. It needs some if –then –else protocol to program the identifier applicable in different situations.

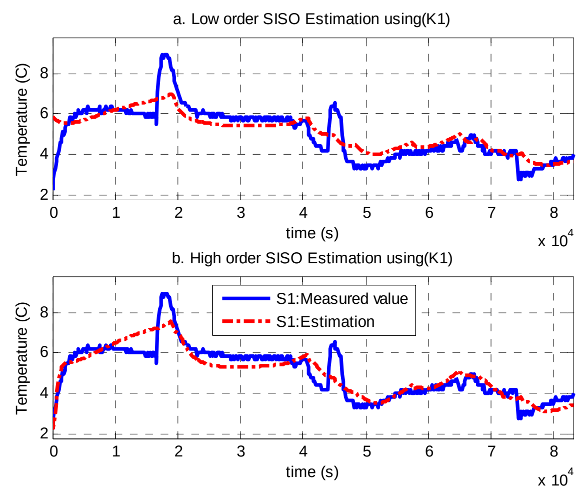

Fig. 14 Estimation using K1 (low and high order models) compare with actual measurements. (Sampling time: Ts= 150 s)

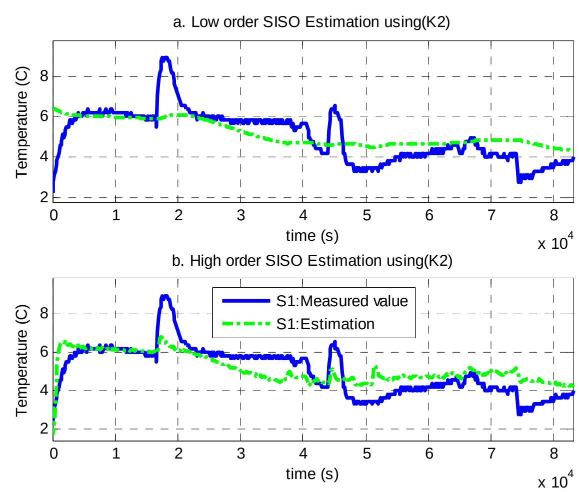

Fig. 15 Estimation using K2 (low and high order models) compare with actual measurements. (Sampling time: Ts= 150 s)

Fig. 14 and fig. 15 show that although K2_S1 has more covariance than K1_S1 in the estimation stage, as showed in fig. 13, better prediction is achieved by using K1 as predictor.

V. Estimation Procedure and Flowchart

Fig. 16 represents the flowchart of predictor, including direct relationship with the fault diagnosis and routing. To use either one or more KSNs provided that there are no additional conditions, one should follow these steps: (1) Large number of data of primary group of estimators (KSNs) and related DSN, enough to estimation is necessary (in our case 600 samples of K1, K2, and S1. (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.

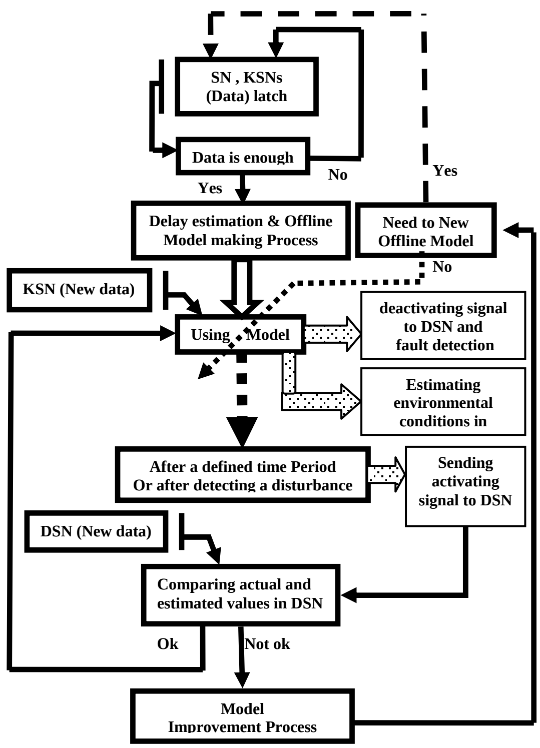

Fig. 16 Flowchart for proposed estimation technique

VI. Conclusion

This paper evaluated some important factors affected on near optimal modeling of the EPs in a constant volume closed space container. A simplified multivariable model using surrounding sensor nodes to estimate the EPs in some DSNs was introduced. Analysis of the proposed approach illustrated its high capability in diagnosis disturbances and reducing power consumption as a nature of the definition.

Developing additional approaches to choose the best KSNs, particularly, when there are some KSNs from different places which have nonlinear relation with the DSNs, could be a part of the future works. Other interesting task may be done to find the required minimum number of the KSNs to attain the best estimations. A comparison between the proposed method and the existing battery management techniques might be the other interesting activity.

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