Empirical Issues of a new Environmental Parameters Modeling Technique Using Wireless Sensor Networks

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Abstract: - With the aim of energy management in a wireless sensor network established in a closed space container, this paper introduces a way to decrease the total power consumption due to measuring and transmitting data in a few desired sensor nodes (DSNs). The DSNs either will be turned to sleeping mode for reducing battery-consumption or even they may be inactive due to the energy depletion. We estimate temperature, relative humidity, and air flow as environmental parameters (EPs) instead of the direct measurement. A new technique of the model making and then assessment the validity of the proposed model using some experiments will be investigated. Introduced estimators use linear models between surrounding key sensor nodes (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.

Key-Words: - Temperature, relative humidity, air flow, estimation, grey-box, model

1 Introduction

One part of attractive applications of sensor networks in field of control systems is identification, modeling and control of temperature (T), relative humidity (H), and air flow (F) as the environmental parameters (EPs) in the air conditioned closed space containers. According with the present proposal, to achieve a model based energy management in a wireless sensor network; a simple and applicable model plays an indispensable role. We are looking for a way to estimate the EPs in some desired sensor nodes (DSNs) instead of the direct measurement. There are some white, grey, and black-box models of T for air-handling units have been addressed in [1], [2], [4], [5], [6]. The effect of air flow pattern on T is given by [7], [8]. 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, [5] outlines a methodology to achieve an accurate model of T in a closed space. 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.

2 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 arises difficulties of doing independent experiments and the measurement results completely depend on the initial conditions.

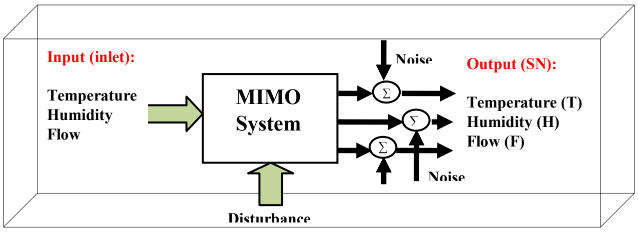

Fig. 1. Container as an input-output model.

Any change in T or 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. 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: (i) they measure EPs in a defined period; (ii) 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); (iii) they deactivate the DSNs when all conditions are normal and there are no big changes in the EPs. The DSNs can be considered in sleep 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).

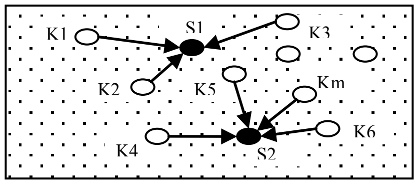

Fig. 2. Proposed sensor network.

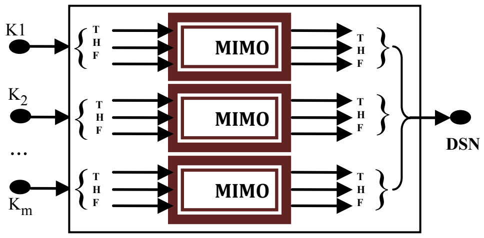

Fig. 3. Block diagram of a MISO model of the EPs.

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? 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.

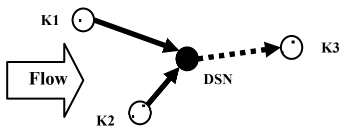

Fig. 4. Impression of the KSNs on a DSN.

Because of chaotic nature of the F direction 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.

3 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.

$$\begin{pmatrix} T_{SN_i} \\ H_{SN_i} \\ F_{SN_i} \end{pmatrix} = \begin{pmatrix} G_{T_i} & -G_{HT_i} & 0 \\ -G_{TH_i} & G_{H_i} & 0 \\ 0 & 0 & G_{F_i} \end{pmatrix} * \begin{pmatrix} T_{inlet} \\ H_{inlet} \\ F_{inlet} \end{pmatrix} \quad (1)$$

For the sake of simplicity we omitted the operator Z in the above 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 [11], 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.

$$\begin{pmatrix} T_{SN_i}(t) \\ H_{SN_i}(t) \\ F_{SN_i}(t) \end{pmatrix} = \begin{pmatrix} Z^{-1}(G_{T,F} * T_{inlet}) + g_{(H_{inlet},F_{inlet})} + N_T \\ f_{(T_{inlet},F_{inlet})} + Z^{-1}(G_{H,F} * H_{inlet}) + N_H \\ Z^{-1}(G_F * F_{inlet}) + N_F \end{pmatrix} \quad (2)$$

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 use a general form in the below for the linear part of the hybrid model:

$$G_{T,F} = K_T \frac{\prod_{i=1}^{mT}(Z - Z_i)}{\prod_{j=1}^{nT}(Z - P_j)}, \quad G_{H,F} = K_H \frac{\prod_{i=1}^{mH}(Z - Z_i)}{\prod_{j=1}^{nH}(Z - P_j)} \quad (3)$$

The poles and zeros (P_j and Z_i) are functions of *F* so that higher *F* causes faster response of *TH*. According with [11] 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:

$$H = H_0 * 2^{\frac{-(T-T_0)}{10.1}}, \quad T = T_0 - \frac{10.1}{\ln 2} * \ln\frac{H}{H_0} \quad (4)$$

Interconnections can be obtained in the following:

$$\Delta T(t) = T_0 - \frac{10.1}{\ln 2} * \ln\frac{Z^{-1}(G_H * H_{in}) + N_H(t)}{Z^{-1}(M_H * H_0)} \quad (5)$$

$$\Delta H(t) = \left(2^{\frac{-[Z^{-1}(G_T * T_{in}) + N_T - Z^{-1}(M_T * T_0)]}{10.1}} - 1\right) * Z^{-1}(M_H * H_0) + N_H(t) \quad (6)$$

We can write above relations in the other forms:

$$T_{SN}(t) = Z^{-1}(G_{T,F} * T_{inlet}) + \Delta T(t) \quad (7)$$

$$H_{SN}(t) = Z^{-1}(G_{H,F} * H_{inlet}) + \Delta H(t) \quad (8)$$

$$\Delta T(t) = g(.) + N_T \quad , \quad \Delta H(t) = f(.) + N_H \quad (9)$$

$$T_{SN}(t) = T_{linear\ (from\ T_{inlet})} + T_{nonlinear\ (from\ H_{inlet})} \quad (10)$$

$$H_{SN}(t) = H_{linear\ (from\ H_{inlet})} + H_{nonlinear\ (from\ T_{inlet})} \quad (11)$$

$G_{T,F}$ 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 (4) when obtaining nonlinear parts of (10) and (11). 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. In the domain Z we will have:

$$T_{DSN} = G_T * T_{KSN} \quad , \quad H_{DSN} = G_H * H_{KSN} \tag{12}$$

$$\begin{pmatrix} T_{DSN} \\ H_{DSN} \end{pmatrix} = \begin{pmatrix} M(G_{Ti} * U_{Ti}) & 0 \\ 0 & P(G_{Hi} * U_{Hi}) \end{pmatrix} \tag{13}$$

(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.

4 Simulation

As an example showed in fig. 5, we assume 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 1 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 and 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 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.

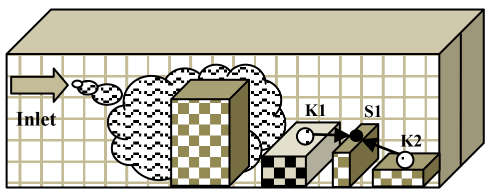

Fig. 5. A container with inlet, KSNs (K1, K2), and one DSN (S1).

Table 1. 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

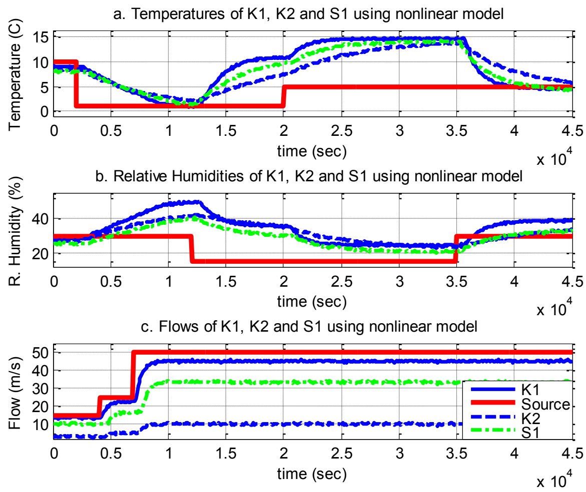

Fig. 6. Outputs when T,H and F in inlet change in different times with sample time: Ts= 90 s.

$(T_0, H_0$, 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. According with [10], using ARMAX model identification method and input-output data; we will identify two sets of linear transfer functions of *T* and *H* both for K1_S1 and K2_S1:

$$A(Z) * y(t) = B(Z) * u(t - nk) + C(Z) * e(t) \tag{14}$$

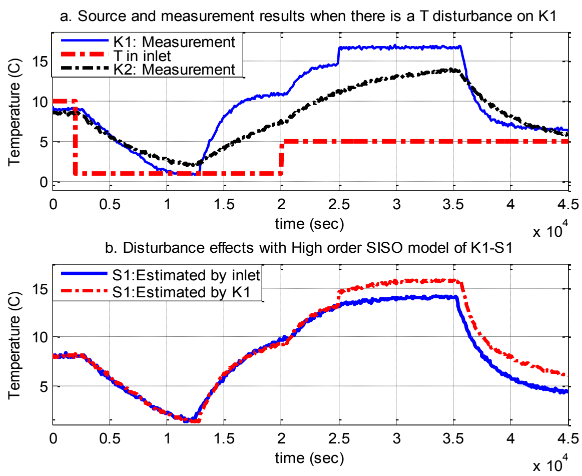

Fig. 7. (a) *T*, measured in inlet, K1 and K2; (b) estimation using inlet and K1with a disturbance at 25000 s with sample time:Ts= 150 s.

Fig. 7 shows capability of the proffered method 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.

5 Estimation Based on Measurements

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.

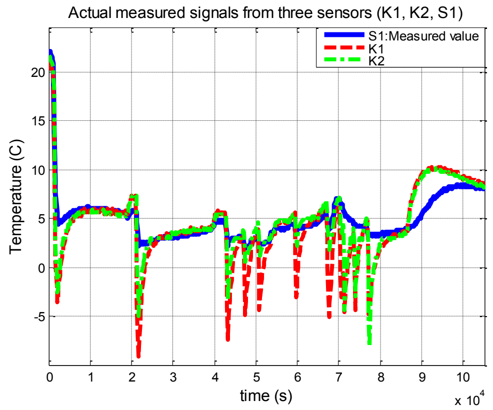

Fig. 8. Actual *T* inside the container in three points (Ts= 150 s).

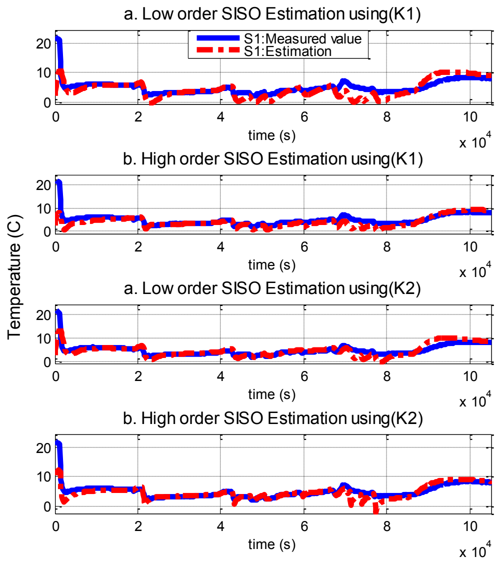

Fig. 9. Estimation using K1 and K2 (separately) compare with actual measurements with sampling time: Ts= 150 s.

ARMAX method was chosen after studying different methods and some practical points were obtained to pick the best estimators out. 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 for K1 and S1 as an example:

$$\text{Covarianc}\,(\text{K1},\text{S1}) = \text{C} = \begin{bmatrix} 8.4600 & 4.6996 \\ 4.6996 & 6.5285 \end{bmatrix} \tag{15}$$

$$\text{NC}(\text{K1},\text{S1}) = \frac{\text{C}_{\text{ij}}}{\sqrt{\text{C}_{\text{ii}} * \text{C}_{\text{jj}}}} = \begin{bmatrix} 1 & 0.6324 \\ 0.6324 & 1 \end{bmatrix} \tag{16}$$

Table 2. Normalized Covariance in Different Situation

models	NC compare with S1	
	Order (1)	Order (3)
Estimation using K1	0.5005	0.6324
Estimation using K2	0.5189	0.7638
K1	0.7707	
Average of K1 and K2	0.8086	
K2	0.8324	
MISO Estimation using K1, K2	0.5714	0.8387

Table 2 shows that different estimations in S1 using different KSNs have different correlations with the actual measurements. Figure 9 and table 2 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.

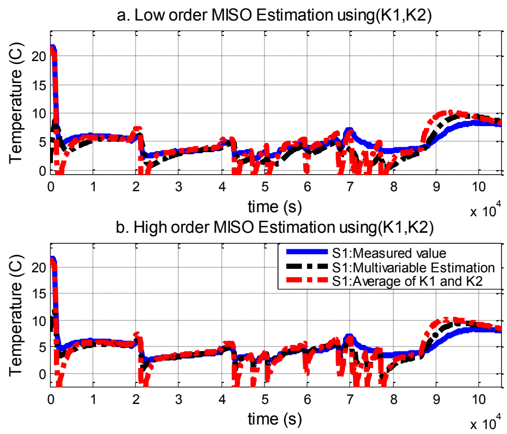

Fig. 11. MISO Estimation using K1 and K2 and average of them

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.

6 Estimation Procedure and Flowchart

Fig. 12 represents the flowchart of estimating 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 following 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.

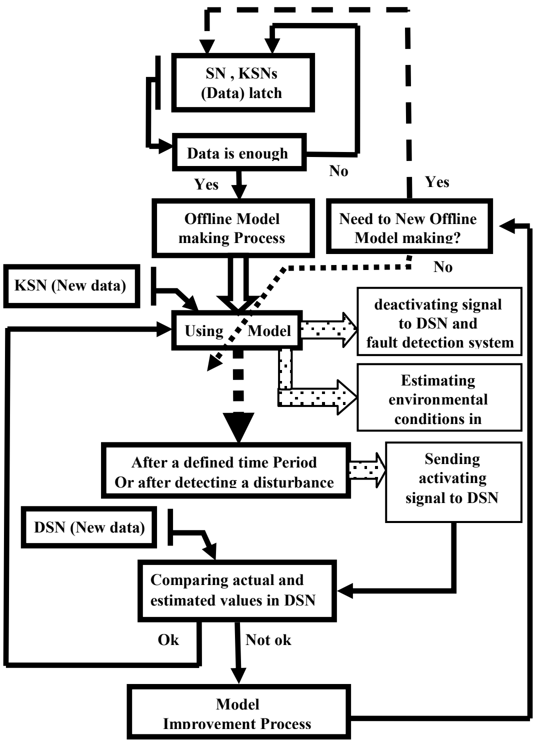

Fig. 12. Flowchart for proposed estimation technique.

7 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 and comparing of the experiments and simulations illustrated high capability of the recommended techniques. Developing additional approaches to choose the best KSNs to reduce mismatch error and implementing such approaches 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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