Comparative study of the best estimators in a New Modeling Technique Using Wireless Sensor Networks

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Abstract: - This paper focuses on a comparative study of a new estimation method applied on a wireless sensor network, installed in a closed space container. We would like to pick out the best method among the existing identification methods such as ARX, ARMAX, OE, BJ and SS. we are looking for a way to reduce power consumption due to measuring and transmitting data in some desired sensor nodes (DSNs) and using the models to predict parameters in a fault diagnosis system. The DSNs are either turned to sleeping mode for reducing battery-consumption or may be inactive due to the energy depletion. We will do the estimation procedure with the least amount of computation and high accuracy to estimate temperature, relative humidity, and air flow as environmental parameters (EPs) instead of direct measurement.

Key-Words: - Prediction, estimation, model, temperature, relative humidity, air flow

1 Introduction

This paper investigates different alternatives from various identification methods to be applicable in an introduced Floating input approach (FIA) to estimate environmental parameters (EPs) containing temperature (*T*), relative humidity (*H*), and air flow (*F*) inside a closed space container as mentioned in [12]. FIA suggests a linear multi input-single output (MISO) dynamic model to be used between surrounding key sensor nodes (KSNs) and a desired sensor node (DSN).
We are looking for the best method to estimate the parameters of the proposed linear dynamic model between the KSNs and the DSNs to be utilized instead of a direct measurement of the EPs. Following [12] and [13], 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 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. 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 our case. 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. We include a brief introduction of a new grey-box hybrid model of the EPs between the reefer and a DSN. Then, we will use achieved linear multi input-single output (MISO) model to obtain some vital practical results.

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 reefer (inlet) and every sensor node.

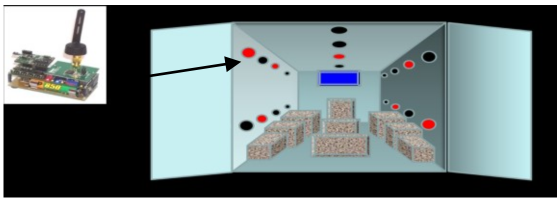

Fig.1. Container with wireless sensor network established.

Coupling among the EPs 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 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 the 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. The KSNs can be the system estimators, but we will select some of them as the estimator. 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 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 estimation of the EPs in a few DSNs and deactivate the DSNs when all conditions are normal and there are no big changes in the EPs. They 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. The DSNs can be considered in sleep mode or even failed. Several MIMO models will be established between the KSNs and a DSN (fig.3).

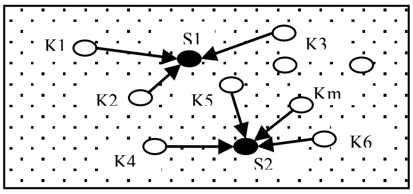

Fig.2. Proposed sensor network.

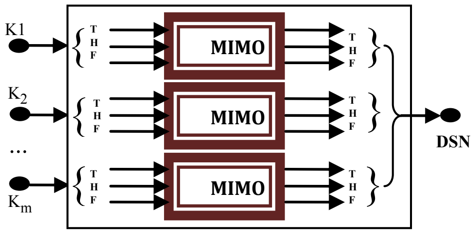

Fig.3. Block diagram of a MISO model of the EPs.

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, later simulations show that the accuracy will be increased with increasing the number of these estimators. 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. 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 on 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, could not help to increase the accuracy.

3 Problem Solution

In [13] we started with a hybrid model consisting of nonlinear interconnections to attain an estimation of the EPs in a desired place inside the container. 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. It is noted that, f and g are nonlinear interactions. N_T, N_H, and N_F are measurement Gaussian noise in the SNs. $G_{T,F}$ 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 of container as input and every SNs as output. Then, we introduced a new floating input approach (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 for determining these influences so that their parameters will be determined while operation. According with [12] to perform the nonlinear part we use some basic thermodynamic relations and we have:

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

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

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

$$\Delta H(t) = \left(2^{\frac{-[Z^{-1}(G_T * T_{in}) + N_T - Z^{-1}(M_T * T_0)]}{10.1}} - 1\right) * \\ Z^{-1}(M_H * H_0) + N_H(t) \quad (4)$$

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

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

(T_0, H_0) are initial conditions of the EPs between inlet and the SNs, respectively. $G_{T,F}$ 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. 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). Assuming excited KSNs as inputs, the input in defined MISO system will change and output nodes (DSNs) will be influenced of such new inputs. 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:

$$\begin{pmatrix} T_{DSN} \\ H_{DSN} \end{pmatrix} = \begin{pmatrix} M(G_{Ti} * U_{Ti}) & 0 \\ 0 & P(G_{Hi} * U_{Hi}) \end{pmatrix} \tag{7}$$

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

4 Estimation alternatives

Several tests were 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. According with fig.4, we chose two KSNs and a DSN. Inlet (Reefer) provides *F*, *T*, and *H* inside the container and there are a few obstacles against the natural path of the air flow 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 will have different EPs as well as delays in K1, K2, and S1. We are looking for the prediction of the EPs in S1. As the first step in the 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 that 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 we will have the new predictions in the DSNs.

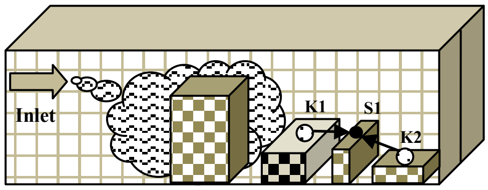

Fig.4. A container with inlet, KSNs (K1, K2), and one DSN (S1).

According with [10], using model identification methods 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:

$$y(t) = \frac{B(q)}{F(q)} * u(t - nk) + \frac{C(q)}{D(q)} * e(t) \tag{8}$$

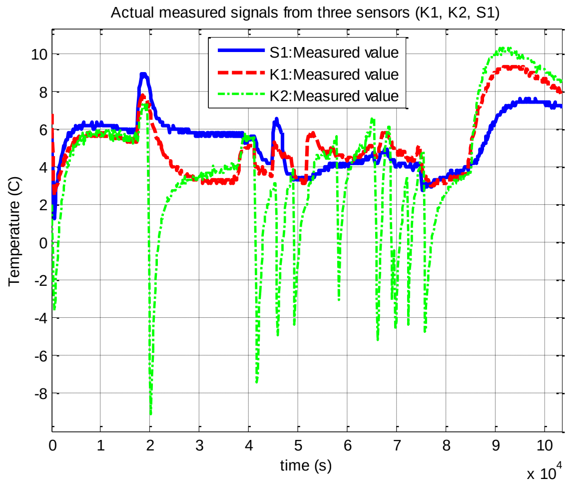

Fig.5. Actual *T* inside the container in three points (Ts= 150 s).

The quality of estimation depends on several parameters: 1. Applying different estimation methods such as ARX, ARMAX, OE, BJ and SS to see the corresponding differences. 2. Difference of accuracy of the estimation using different number of data samples in learning stage. 3. Investigation of different fit-indexes to find the best estimators. 4. Observing the influence of the number of KSNs and model order on the estimators. 5. Difference between online and offline estimation methods. As said before, models of T, H, and F can be independent if we use proper KSNs as estimators. Fig.5 shows the measurement results in three SNs. 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 permanent turning off, opening the door and unloading the freight.

4.1 Comparisons different estimation 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 two separate experiments. Whereas order one can't cause a good performance, a third order linear model is chosen and its parameters is obtained via different methods.

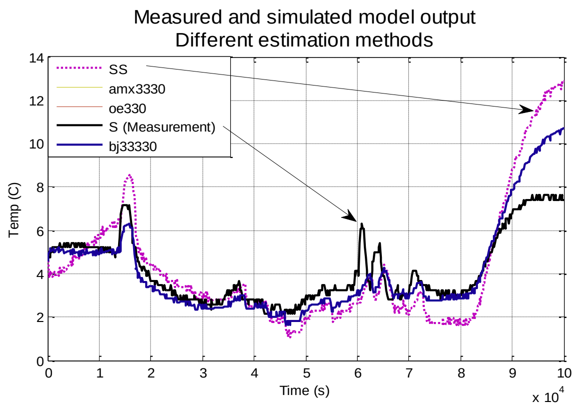

Fig.6. Prediction using different estimation methods.

According with fig.6, we used 500 samples out of 691 to make a model and then used the remained samples to validate the model. It represents that the methods BJ, ARMAX and OE provide a better fit 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 methods such as Box-Jenkins in addition to achieving to the same quality of estimation leads us to choose this method among the other methods.

4.2 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 from 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 shows 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 for estimating and then investigated validity of models when complete range of measured-data applied. Obviously, when the number of data is too many reduced, some methods can't be converged and the performance level fells down.

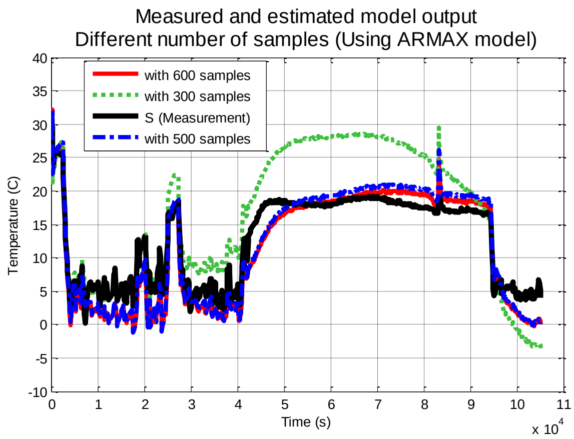

Fig.7. Comparison of different data number used for model making

Achieved model can be used for predicting the EPs in the new situations provided that it already consists of relatively similar variations in the estimation section.

Having ARMAX method, fig.7 shows increasing the data number from 200 to 500 out of 691 provides better prediction 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 in quality of estimation.

4.3 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:

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

$$\mathrm{AIC} = \log(\mathrm{V}) + 2\frac{d}{N}, \mathrm{V} = \det\left[\frac{1}{\mathrm{N}} * \sum_{1}^{\mathrm{N}} \varepsilon\,(\varepsilon)^{\mathrm{T}}\right] \tag{10}$$

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

$$\mathrm{Covariance(K1, S1)} = \begin{bmatrix} \mathrm{Cii} & \mathrm{Cij} \\ \mathrm{Cji} & \mathrm{Cjj} \end{bmatrix} \tag{12}$$

$$\mathrm{NC} = \mathrm{Normalized\ Cov.\,(K1, S1)} = \frac{\mathrm{C_{ij}}}{\sqrt{\mathrm{C_{ii}} * \mathrm{C_{jj}}}} \tag{13}$$

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, the more (NC and FIT %) and less SSE, cause more careful estimation. The bold numbers in the rows show the best estimators. In case using enough number of data MISO high order models cause the best estimations. Then we suggest the MISO models and some sensor nodes which have the most NC with data of output. Those KSNs have more correlation with the DSN.

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

Actual K1	Actual K2	Ave. (K1 , K2)	Low order K1	High order K1	Low order K2	High order K2	Low order Multi	High order Multi	Index	Results:	Used Nr. of Samples	Total Samples
0,975	0,939	**0,979**	0,720	0,918	0,807	0,920	0,824	0,951	**NC**	0,979	**400**	**702**
			18,5	38,0	28,5	40,8	29,5	**62,1**	**Fit (%)**	62,1		
		72,3	141,6	107,7	124,3	102,9	122,5	**65,8**	**SSE**	65,8		
0,975	0,939	**0,979**	0,684	0,955	0,805	0,964	0,826	0,979	**NC**	0,979	**600**	**702**
			19,7	59,9	32,8	71,2	33,2	**79,4**	**Fit (%)**	79,4		
		72,3	139,5	69,7	116,7	50,0	116,0	**35,7**	**SSE**	35,7		
0,975	0,939	**0,979**	0,681	0,951	0,881	0,962	0,852	0,979	**NC**	0,979	**702**	**702**
			19,9	61,4	41,1	70,3	35,3	**79,6**	**Fit (%)**	79,6		
		72,3	139,2	67,1	102,3	51,6	112,4	**35,5**	**SSE**	35,5		

4.4 Model order and number of KSNs

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, using of both K1 and K2 has more covariance than using only one of them, because a MISO model can consider the effect of environment around of a DSN.

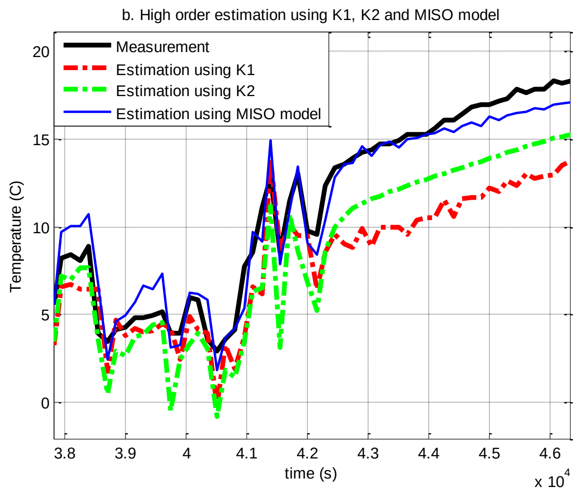

Fig.8. Estimation using K1 (FIT%= 40.78).

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. (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 when we use both one and two KSNs as estimator. We chose infrequent cases, so the prediction in normal operation mode will have good accuracy. According with this comparative study MISO model causes better fit than SISO. Despite the MISO is more robust than SISO, sometime SISO is better. With proper KSN, SISO needs less calculation and gives reasonable prediction.

4.5 On-line or Off-line and average method

When 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 good choice. In this case off-line estimation which uses all previous data of system is better. However, it is proper to use in short horizon predictions. Then, it is applicable in fault diagnosis. The simplest way to estimate the EPs in a sensor node is finding the average of the EPs from the KSNs. WE showed in [13] that some time 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.

4.6 Prediction improvement

In the actual case, there will be several stages of learning and predicting. In the first learning stage we make a model and in the first predicting stage we use the model to predict output having the inputs. Although we would like to have a continuous curve consists of learning and prediction stage, always value of prediction will be different. We don't want it differ from the first data of the next measurement stage. Using the existing model obtained from the previous learning stage to find the EPs while absence of output data, the last point of prediction should coincide the next first measured data. Fig.9 shows both learning and Prediction stages. To move the curve to blue curve we use (14). Blue solid curve shows the capability of this method. It is noted that t0 and t1 are the starting time of first and second measurements, respectively. $\hat{y}_{\text{last}}$ is the last point of prediction and y_{first} is the first point of second measurement and $\hat{y}_{\text{new}}(t)$ shows the new improved prediction.

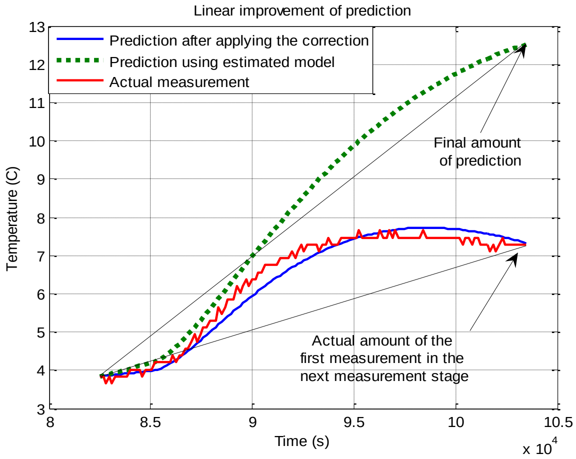

Fig.9. Comparing the result of primary prediction and its improvement.

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

7 Conclusion

This supplementary paper evaluated different identification methods to achieve the optimum method of implementing a new method of estimation of environmental parameters inside a closed space container. We used system identification toolbox of Matlab in addition to several program to simulate different conditions. This work used actual results of measurements to evaluate the best estimators, which was adaptable with the Floating Input Approach (FIA). The effects of different numbers of data samples in addition to different numbers of inputs on the accuracy of estimations were investigated. Implementing such approaches could be a part of the future works. Other interesting task may be calculating the amount of energy saving when applying FIA. A comparison between the proposed method and the existing battery management techniques might be of interest.

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