A NEW APPROACH FOR MODELING ENVIRONMENTAL CONDITIONS USING SENSOR NETWORKS

Mehrdad Babazadeh and Walter Lang

Institute for Microsensors, -actuators and -systems (IMSAS), University of Bremen, Otto-Hahn-Allee, Bremen, Germany

Keywords: Temperature, relative humidity, air flow, estimation, grey-box, model.

Abstract: An approach to estimate environmental conditions (ECs), temperature, relative humidity and air flow in a few desired sensor nodes in a wireless sensor network, slept for reducing battery-consumption or inactive due to either empty batteries or out-of-range is presented. A nonlinear, multivariable model containing the interconnections is extracted and using data of surrounding active sensor nodes is broken to the linear models. Unknown parameters of the model are verified by a multivariable identification method. The proposed approach is independent of the type of ventilation system. It can be used in different applications such as designing model base ECs controllers as well as an estimator in fault diagnosis methods.

1 INTRODUCTION

Identification, modeling and control of Temperature (*T*), relative Humidity (*H*) and air Flow (*F*) as the environmental conditions (ECs) in the air conditioned closed spaces have gained a lot of attractions during the last few years. Therefore, simple and precise mathematical models can play a key role in these areas. Improving such linear models or proposing new nonlinear models is very vital on this issue. As the first step, we try to achieve a simple mathematical model for the ECs using a wireless sensor network established inside the container loaded with freights. We utilize this model to introduce a new technique to estimate the EC in the place of some desired sensor nodes (DSNs). They may be either in sleep mode or out of service. As stated by the articles, there are three types of models: based on (Sohlberg, 2003), White-box models are made of theoretical considerations where the grey-box models are extracted from the first principles and parameters of the models are obtained by measurement and black-box models are identified only using measurement of the system input and output. The methods achieved to the white, grey and black-box models of *T* for air-handling units have been addressed in (Ghiaus, 2007) , (Shaikh, 2007), (Brecht, 2005), (Desta, 2004), (Frausto 2004). Some other works consider the effects of air flow pattern on the *T* in special cases (Moureh, 2004), (Rouaud,

2002) and (Smale, 2006) is a brief review of numerical models of airflow in refrigerated food applications. (Desta, 2004) outlines a method to achieve an accurate model of *T* in a closed space using both k-ε model and a data-base mechanistic (DBM) modeling technique. It doesn't consider the effect of the heat transfer from the neighboring zones.

All previous models are obtained between input (inlet) and a point of corresponding space. As attested by these methods, the ECs inside the container will change only due to variation in inlet. Some of the models obtained in the existing papers either linear or nonlinear don't consider all of important parameters of the ECs. Furthermore, particular conditions and the limit range of the parameter variations are necessary and despite the high precision, complexity makes them impractical in some applications.

If return to model making in the mentioned space, nonlinear multivariable nature and interconnections between the variables of the ECs in addition to the presence of the freight as an unpredictable, immeasurable disturbance, effects of dynamic of flow, surfaces and walls inside the container increase complexity of the model which we are looking for. Another important factor is disturbance which can be appeared in the different ways and may be cause a big estimation error: (i) Opening the door of the container; (ii) changing either direction or rate of the air flow by some obstacles; (iii) thermal or moisturize influences of

some freight. All attempts in the first step of the present research are towards introducing a grey-box nonlinear model between inlet and one DSN. We will use previous data of a deactivated sensor in addition to the present and previous data of some surrounding sensor nodes to estimate unknown parameters of the related simplified models. According to fig. 1 and also our main proposal in the energy management of the wireless sensor network, there will be a few special key sensor nodes (KSNs) those will send some specific information to main processor and or to the other sensor nodes. The KSNs should be in active mode during the normal operating mode. The KSNs have three major functions: (i) they measure environmental conditions alternatively; (ii) they evaluate measured values and do some estimation of the ECs in the DSNs and update previous models after measuring and receiving some new data; (iii) they will deactivate DSNs when the operational conditions are normal and there are no big changes in the ECs. Usually a while after loading the container, the ECs inside the container have less variations. This duration is the best time to utilize the method to take more DSNs to sleep mode and to estimate the ECS instead of the direct measurement. The KSNs can be located everywhere inside the container, even near the door or near to the inlet. If they are located in some key points, mismatch error due to no considering unpredictable phenomenon will be avoidable because depending on the floating input approach, uncertainties and disturbances are considered indirectly as the input change. It is also independent of the type of the ventilation system. Useful reference for sensor networks is (J. Elson, 2004).
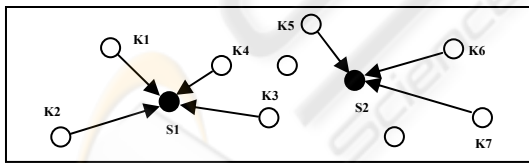

Figure 1: Proposed sensor network.

2 PROBLEM FORMULATION

Fig. 2 shows a general scheme of the system, inside the container between the inlet and a spatial position. It is a complicate, time and place dependent, multi-variable system. It consists of three inputs, three outputs, disturbance and noise. Due to the coupling in the ECs, doing independent experiments in the actual container is difficult. It completely depends

on the initial conditions so that a change in the T or relative humidity of the inlet may change both T and H in all positions of the space. Variation in the rate of input air flow changes the measurement results and disturbance may change all the results so that based on the existing conditions, measured values might be different even in the same place.
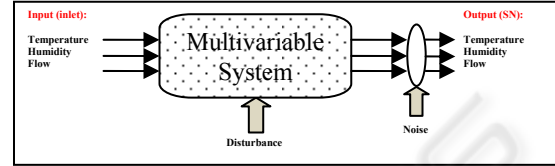

Figure 2: Schematic of Container as a MIMO model.

Floating input approach identifies multivariable models between the KSNs and the DSNs, not between the inlet and a DSN. Every non modeled disturbances which excite some KSNs, is modeled as an implicit input change, not a pure disturbance. Now, the new input nodes (KSNs) in the defined multi-input and single-output (MISO) system change output nodes (DSNs). Fig. 3 shows K1, K2, K3 and K4 as the KSNs and S1 as the DSN.
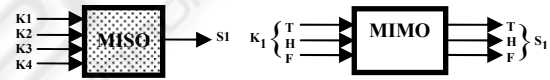

Figure 3: Models between the KSNs and a DSN.

The first step for modeling is using linear transfer function matrix. Without considering noise we have:

$$\begin{pmatrix} T_{SN} \\ H_{SN} \\ F_{SN} \end{pmatrix} = \begin{pmatrix} G_T & -G_{HT} & 0 \\ -G_{TH} & G_H & 0 \\ 0 & 0 & G_F \end{pmatrix} * \begin{pmatrix} T_{in} \\ H_{in} \\ F_{in} \end{pmatrix} \quad (1)$$

(T_{SN}, H_{SN} and F_{SN}) and (T_{in}, H_{in} and F_{in}) are respectively measured value of (T, H and F) in SN and inlet. Whereas T and H have opposite effects on each other, we assign negative sign for the interconnection. It is assumed that F has no direct effect on the steady state values of T and H, but it influences on the speed of their variations. However, the effect of F are included in all G_T, G_H, G_{HT} and G_{TH} (which are transfer functions between different parameters of the ECs) with some exponential functions that we will mention later. To investigate validity of the model we employ a reverse lemma and some assumptions in different border conditions.

Assumption 1, steady state values of T and H:

$$T_{in} = T_{max} \quad , \quad H_{in} = H_{min} = 0 \tag{2}$$

$$T_{Oss} = \lim_{t \to \infty} Z^{-1}(G_T * T_{max}) \tag{3}$$

$$H_{Oss} = -\lim_{t \to \infty} Z^{-1}(G_{TH} * T_{max}) \tag{4}$$

$$\text{Must: } T_{Oss} \leq T_{max} \quad , \quad H_{Oss} \geq 0 \xrightarrow{\text{Then}} \tag{5}$$

$$0 \leq |G_H|, |G_{TH}| \leq 1, |T_{max}| \geq 0 \to H_{oss} \leq 0 \tag{6}$$

It can't be correct because, negative H can't be occurred. We consider some permissible margins so that T and H locate in the mentioned margin:

$$\text{Assumption 2: } T_{in} = T_{max}, H_{in} = H_{min} \neq 0 \tag{7}$$

$$0 \leq Z^{-1}(G_H * H_{min} - G_{TH} * T_{max}) \\ \leq H_{Omax} \tag{8}$$

$$Z^{-1}\frac{G_H * H_{min} - H_{Omax}}{G_{TH}} \leq T_{max} \leq Z^{-1}\frac{G_H * H_{min}}{G_{TH}} \tag{9}$$

$$T_{Omin} \leq Z^{-1}(G_T * T_{max} - G_{HT} * H_{min}) \\ \leq T_{Omax} \tag{10}$$

$$Z^{-1}\frac{G_T * T_{max} - T_{Omax}}{G_{HT}} \leq H_{min} \leq \\ Z^{-1}\frac{G_T * T_{max} - T_{Omin}}{G_{HT}} \tag{11}$$

$$\text{Assumption 3: } Z^{-1}\frac{G_H * H_{max} - H_{Omax}}{G_{TH}} \leq \\ T_{min} \leq Z^{-1}\frac{G_H * H_{max}}{G_{TH}} \tag{12}$$

$$T_{Omin} \leq Z^{-1}(G_T * T_{min} - G_{HT} * H_{max}) \\ \leq T_{Omax} \tag{13}$$

$$Z^{-1}\frac{G_T * T_{min} - T_{Omax}}{G_{HT}} \leq H_{max} \\ \leq Z^{-1}\frac{G_T * T_{min} - T_{Omin}}{G_{HT}} \tag{14}$$

$$\text{We should have: } T_{max} = Z^{-1}\frac{G_H * H_{min}}{G_{TH}} \tag{15}$$

$$H_{min} = Z^{-1}\frac{G_T * T_{max} - T_{Omax}}{G_{HT}} \tag{16}$$

$$T_{min} = Z^{-1}\frac{G_H * H_{max} - H_{Omax}}{G_{TH}} \tag{17}$$

$$H_{max} = Z^{-1}\frac{G_T * T_{min} - T_{Omin}}{G_{HT}} \tag{18}$$

Having H_{min} and H_{max}, other input limitations will be verified. Then there are the specific bands for inputs so that outputs of linear model will be located in the admissible areas. Accordant with the lemma, linear model (1) can't be a proper model. The nonlinear model will be made based on the basic knowledge of the nonlinear nature of the interconnections. Considering some linear transfer functions for direct effects and obtained nonlinear functions for the interactions, we have:

$$\begin{pmatrix} T_{SN} \\ H_{SN} \\ F_{SN} \end{pmatrix} = \begin{pmatrix} G_{T,F} * T_{inlet} + g_{(H,F_{inlet})} + N_T \\ f_{(T,F_{inlet})} + G_{H,F} * H_{inlet} + N_H \\ G_F * F_{inlet} + N_F \end{pmatrix} \tag{19}$$

$g(.)$ and $f(.)$ are nonlinear interconnections between T and H which are influenced by F. As stated by (Ghiaus, 2007) and (Zerihun Desta, 2004), model of T can be a first-order transfer function. We also use the effect of the parameters with the same dimensions in the following:

$$G_T = \frac{M_T}{(\alpha_T * S + 1)} \quad , \qquad G_H = \frac{M_H}{(\alpha_H * S + 1)} \tag{20}$$

$$\alpha_T = f(Flow) \ , \ \alpha_H = g(Flow) \tag{21}$$

α_T and α_H illustrate speed of the responses and M_T and M_H steady state values of T and H. They 74have reverse relation with F. Then, the further flow rate, the less α_T and α_H. The SNs can detecte variations in the ECs showed by ΔT, ΔH and ΔF.

If the position of the SNs is close, we can assume that all models in mentioned MISO system, showed in fig. 3 are independent. It can be considered as several single-input and single-output (SISO) systems. Now, they should be combined using a multivariable identification method. Accordant with the thermodynamic relations, with 10.1 ºC increasing T, H will be reduced to the half and we have:

$$H = H_0 * 2^{\frac{-(T - T_0)}{10.1}} \ , \ T = T_0 - \frac{10.1}{\ln 2} * \ln\frac{H}{H_0} \tag{22}$$

$$T_{SN}(t) = Z^{-1}(G_T * T_{in}) + \Delta T(t) \tag{23}$$

$$\Delta T = g(.) + N_T \ , \qquad \Delta H = f(.) + N_H \tag{24}$$

$$\Delta T = \frac{-10.1}{\ln 2} * \ln \frac{Z^{-1}(G_H * H_{in}) + N_H(t)}{Z^{-1}(M_H * H_0)} \qquad (25)$$

$$H_{SN}(t) = Z^{-1}(G_H * H_{in}) + \Delta H(t) \qquad (26)$$

$$\Delta H = \left[\left[2^{\frac{-[Z^{-1}(G_T * T_{in}) + N_T - M_T * T_0]}{10.1}} - 1 \right] \\ * M_H * H_0 \right] + N_H(t) \qquad (27)$$

Z^{-1} is unit delay in field of Z transform. It is probable that the amounts of T_{oss} and H_{oss} are changed because of the variation in air flow pattern. However, we consider it on the transfer functions G_T and G_H when running the on-line estimation. From previous results, we will derive a time dependent, nonlinear, multivariable matrix equation and a function of the several KSNs. Uk is a function to obtain the effects of the KSNs on a DSN.

$$\begin{pmatrix} T_{DSN} \\ H_{DSN} \end{pmatrix} = \bigcup_k \begin{pmatrix} T_{KSN\,(i)} \\ H_{KSN\,(i)} \end{pmatrix} \qquad (28)$$

3 SIMULATIONS

Results of the SISO system with initial conditions in the table 1 has been shown in fig.4. It is noted that a part of the parameters such as time constant of *T* in simulations have been inspired of actual behavior of a real experiment and the rest are based on primary assumptions of the authors.

Table 1: Initial conditions for inlet and S1.

	T_0	H_0	F_0
inlet	10	30	15
DSN(S1)	9	28.5	13.5

According to fig. 4 Set points of *T* at 2000, *H* at (12000 and 35000) and F at (4000 and 7000) seconds change. An obstacle as a disturbance changes the rate of the air flow and influences on the speed of the responses. However, it will not change the steady state value of the ECs. The initial conditions of *T* and *H* in output are different with those in input (inlet) and after changing *T* in input, output changes slowly to a new equilibrium point because the amount of flow is low in the beginning. At 4000 and 7000 seconds air flow increases respectively to $F_{max}/2$ and F_{max} and immediately the

responses of *T* and *H* become faster. When *H* in inlet does not change, *H* in output changes only due to changing T in output. There is a similar story for T in output independent of T in input which varies with the variation of H in output. Dashed curves show the ECs in a desired place inside the container.
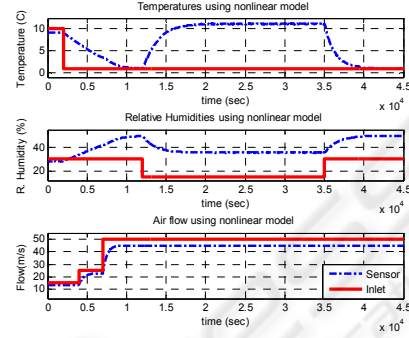

Figure 4: ECs in SN when the ECs in input change.

4 AN INDIRECT SOLUTION

We employ the advantages of the sensor network and introduce floating input approach. We assum that m numbers of the KSNs are measuring the conditions when input is inlet and we have:

$$T_{out} = G_T * T_{in} + \Delta T, H_{out} \\ = G_H * H_{in} + \Delta H \qquad (29)$$

$$\Delta T = g(.) * G_{dyn\,(H-T)} + N_T \qquad (30)$$

$$\Delta H = f(.) * G_{dyn\,(T-H)} + N_H \xrightarrow{\text{yields}} \qquad (31)$$

$$T_{SN} = T_{linear\,(from\ T)} + T_{non-lin.(from\ H)} \qquad (32)$$

$$H_{SN} = H_{linear\,(from\ H)} + H_{non-lin.(from\ T)} \qquad (33)$$

We can suppose that the nonlinear interconnections from the inlet are both in the KSNs and the DSNs. Then, we can remove these parts when we consider the KSNs as the input:

$$T_{DSN} = G'_T * T_{KSN} \ , \ H_{DSN} = G'_H * H_{KSN} \qquad (34)$$

G'_T, G'_H are the linear transfer functions between a KSN and a DSN and its unknown parameters should be verified using a system

identification technique. Now, we will have some SISO matrix equations which should to be solved. M and P are functions for combining linear effects. We use them in the identification method, indirectly. U_{Ti} and U_{Hi} are new inputs, in the m numbers of the KSNs. G'_{Ti} and G'_{Hi} are linear transfer functions of T and H, written between the KSNs and the DSN.

$$\begin{pmatrix} T_{DSN} \\ H_{DSN} \end{pmatrix} = \begin{pmatrix} M(G'_{Ti} * U_{Ti}) & 0 \\ 0 & P(G'_{Hi} * U_{Hi}) \end{pmatrix} \quad (35)$$

5 RESULTS

As an example, showed in fig. 5, there are two KSNs and one DSN attached to the walls, there are some obstacles so that the change-rate of the ECs near to the SNs is different with those in inlet. There are also different amounts of initial conditions for different SNs because of their positions or corresponding measurement errors (table 2). The simulation results has been shown in fig. 6.
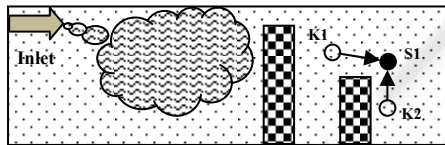

Figure 5: A container with inlet, KSNs and DSN.

Table 2: Initial conditions.

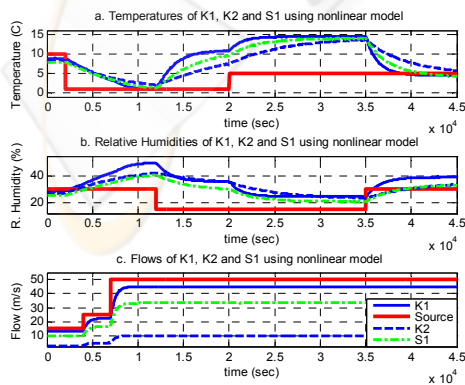|	T_0	H_0	F_0
inlet	10	30	15
K1	9	28.5	13.5
K2	8.5	27	3
S1	8	25.5	10

Figure 6: Outputs when T, H and F in input change.

As shown in fig. 6, curves of K1, K2 and S1 are according with the data extracted from models introduced in equations (23) and (26) and curves related to the inlet are the set points. The relations of T, H and interconnections are updated based on the amount of F at the related instant of the simulation.

6 OFF-LINE IDENTIFICATION

Refer to equation (35), there are separate MISO systems for T as well as H. All unknown parameters should be determined using an off-line identification technique. Then, we assume that KSNs are active and there is a failure on the DSN or it is in sleep mode and having new inputs we will have the new estimations of the ECs in the DSNs using existing transfer functions. The temperature estimation results have been shown in fig. 7 and fig. 8 with the SISO and MISO models, respectively. To show capability of the method, the results have been plotted together with the previous results of the EC in S1 from introduced nonlinear model. the measured T of K1 in the vicinity of S1, without any variation in T of inlet and K2. We obtain its effects on S1 when estimated by K1 and K2 compare with a regular estimation method using model obtained from inlet-DSN. The Solid wide curves illustrates nonlinear model output and dashed curves represent obtained results separately using linear models and then with MISO estimation using output error (OE) method in system identification toolbox of Matlab:

$$\frac{B_i(Z)}{F_i(Z)} = \frac{(b_0 + b_1 * Z^{-1} ... + b_m * Z^{-m})}{(1 + a_1 * Z^{-1} ... + a_n * Z^{-n})} \quad (36)$$

$$y(t) = \sum_{i=1}^{nu} \frac{B_i(Z)}{F_i(Z)} u_i(t - nk_i) + e(t) \quad (37)$$
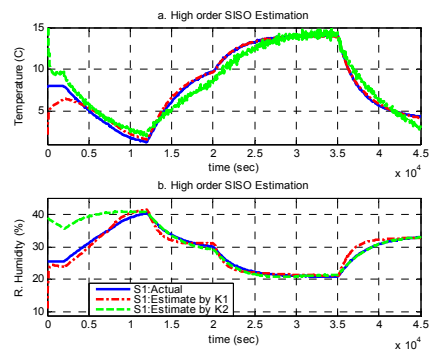

Figure 7: Actual and estimated T and H, model with the order three using K1 and K2, separately.

To achieve a desired speed and regard to the nonlinear nature of the responses that we have still in the SNs, we utilize a linear transfer function with the order more than two. Whereas the higher order models will cause some difficulties in the application, we don't use the order more than three. Separate estimations using SISO models have less accuracy than those using MISO models.
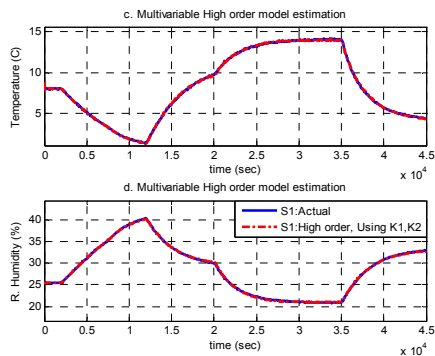

Figure 8: *T* and *H*, actual, estimation using high order multivariable model from K1, K2.

More important results are obtained when there is a disturbance in vicinity of the SNs influences some of the KSNs. fig. 9 shows the variation of *T* at 25000 seconds which affects both K1 and S1. Model obtained from inlet-S1 can't show this influence on S1 because there are no influences on the inlet. However, floating input method can estimate it because at least one KSN senses it.
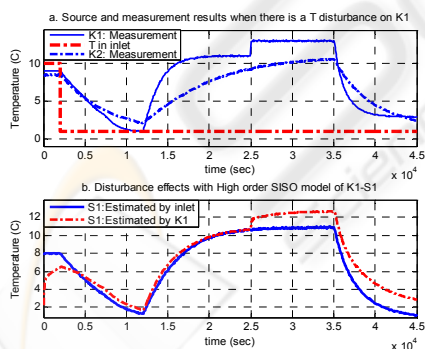

Figure 9: a. measured *T* in inlet, K1 and K2 and b. estimation using inlet and K1with existing a disturbanc.

7 CONCLUDING REMARKS

This paper propuses a new hybrid model for environmental conditions inside a container and shows that it has much more accuracy for wide range of parameter variations compared to other conventional linear models between inlet and a desired place. The new technique provides a simplified multivariable model based on the surrounding sensor nodes used for estimating the ECs in the desired nodes. The simulation results and mathematical proofs for different situations endorse the capability of the proposed technique. At the end, it should be noted that the comparison among different multivariable estimation methods and their implementations as well as finding the minimum number and the best place of the KSNs are real challenges main concerns on this issue.

REFERENCES

Ghiaus, C., Chicinas, A. and Inard, C., April 2007, "Grey-box identification of air-handling unit elements, *Control Engineering Practice*", Vol.15, Issue 4, pp. 421-433.

Shaikh, N. I and Prabhu, V., May 2007,"Mathematical modeling and simulation of cryogenic tunnel freezers", *Journal of Food Engineering*, Vol. 80, Issue 2, pp 701-710.

Smale, N.J., Moureh, J. and Cortella, G., Sep. 2006, "A review of numerical models of airflow in refrigerated food applications", *International Journal of Refrigeration*, Vol. 29, Issue 6, pp. 911-930.

Van Brecht, A., Quanten, S., Zerihundesta, T., Van Buggenhout, S. and Berckmans, D., 20 Jan. 2005, "Control of the 3-D spatio-temporal distribution of air temperature", *International Journal of Control*, 78:2, pp. 88- 99.

Zerihun Desta, T., Van Brecht, A., Meyers, J., Baelmans, M. and Berckmans, D., June 2004, "Combining CFD and data-based mechanistic (DBM) modeling approaches, Energy and Buildings", Vol. 36, Issue 6, pp 535-542.

Frausto, H. U. and Jan G. Pieters, Jan.2004, "Modeling greenhouse temperature using system identification by means of neural networks", *Neurocomputing*, Vol. 56, pp.423-428.

J. Moureh and Flick, D., Aug. 2004; "Airflow pattern and temperature distribution in a typical refrigerated truck configuration loaded with pallets", *International Journal of Refrigeration*, V. 27, Issue 5, pp. 464-474.

Rouaud, O. and Havet, M., May 2002, "Computation of the airflow in a pilot scale clean room using K-ε turbulence models", *International Journal of Refrigeration*, Vol. 25, Issue 3, pp. 351-361.

Sohlberg B., May 2002, Apr. 2003, "Grey box modeling for model predictive control of a heating process", *Journal of Process Control*, Vol. 13, Issue 3, pp. 225-238.

J. Elson and D. Estrin. Sensor Networks: A Bridge to the Physical World, chapter 1. Wireless Sensor Networks. Kluwer Academic Publishers, 2004.