

# Wireless Sensor Network for Temperature Estimations in an Asynchronous Machine Using a Kalman Filter

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**Abstract** – A 4<sup>th</sup>-order Kalman filter (KF) algorithm is implemented in a wireless sensor network (WSN) to estimate the temperatures of the stator windings, the rotor cage and the stator core of an asynchronous machine. The rotor speed, coolant air temperature, and the effective current and voltage are acquired by wireless transducer interface modules (WTIM) separately and are transmitted to a network capable application processor (NCAP) where the KF algorithm is implemented. The losses are calculated from the measurement and are processed together with the coolant air temperature by KF algorithm. As the resistance varies with the temperature, the rising resistance is compensated by the estimated stator windings temperature. Simulations and experiments were performed quite well on the test bench before the KF algorithm was implemented on a wireless sensor network. The real-time WSN temperature estimation system is independent from the control algorithm and can work under any load condition with very high accuracy.

**Keywords:** *Kalman filter; temperature estimation; asynchronous machine; thermal losses; wireless sensor network.*

## I. INTRODUCTION

With the development of the Internet of Things (IoT), WSNs have many applications such as the monitoring of the environment, the industry and the medical care. In this paper we focus on the monitoring algorithm implementation in a WSN. Due to the restrictions of the sensor nodes, such as low cost, low power, weak calculation power and small memory size, the algorithm should be simple and efficient. The temperature monitoring system of an asynchronous machine was examined for the implementation on a WSN.

Asynchronous machines are widely used in industrial and electrical vehicles. The thermal behavior of an asynchronous machine largely determines the maximum lifetime, the ability of over-load and the accuracy in high-performance controller [1]. The exceeding temperatures

in different regions may result in insulation deterioration as well as rotor faults [2]. So the temperature monitoring of the stator winding, the rotor cage and the stator core, can be used for thermal fault detection and predictive monitoring. It can protect the machine, extend the life span and contribute to the high performance of the machine [2].

## II. LITERATURE REVIEW ON TEMPERATURE ESTIMATION OF ASYNCHRONOUS MACHINES

The temperature can be measured directly by using mounted sensors. It is possible to fix a sensor on the surface of the stator core or inside the stator windings. The temperature of the rotor cage can be acquired using WSN, but the high cost and the instability of the measurement system make it unsuitable for industrial usage. As the resistances are the temperature dependent variables, temperatures of the stator windings and the rotor cage can be calculated by using the estimated resistances. A sensor less internal temperature monitoring method for an induction motor was introduced in [1]. J.K.AI-Tayie [5] proposed a method to estimate the rotor and stator temperatures using extended Kalman filter, when assuming that there is no rise in temperature of the coolant air temperature. The paper [3] presents an approach to estimate temperatures based on a thermal model. Thermal analysis based on lumped-parameter thermal network, finite-element analysis, and computational fluid dynamics were considered. The design of a state-of-the-art rotor temperature monitoring system for contact measurement was proposed in [4].

Building the thermal model of an electric machine is a complex multi-disciplinary problem, and it must also evaluate the main internal losses of the machine [6]. The most frequent estimation techniques rely on impedance calculation in steady state [7] [8]. The estimation of the stator resistance  $R_s$  and rotor resistance  $R_r$  was presented in [5] and [9], but none of them can estimate the resistances of stator and rotor simultaneously.

This paper describes the implementation of a temperature monitoring system in a WSN using a KF algorithm. The state-space of the system is presented in

section III. Section IV illustrates the KF algorithm and the tuning of the covariance matrix. In section V, the simulation of the KF is performed and the experiment results are described. Section VI discusses the implementation of the KF on WSN. Finally, the experiments on the test bench and conclusions are given.

### III. THE THERMAL MODEL OF THE ASYNCHRONOUS MACHINE

Heat transfer in the machine can be simplified as heat conduction in the solid parts and convection in the boundary layer of the flowing medium. However, radiation is not considered in this paper. The thermal network is analogous to an electrical network, as temperature to voltage, power to current, thermal resistance to electrical resistance and thermal capacitance to electrical capacitance. The heat sources of the machine are the losses of the power, which include the losses of stator winding, the rotor cage, the stator core, the rotor core, friction losses and stray load losses [11]. There is no core in the squirrel cage rotor, so the losses of the rotor core are zero. The friction losses and the stray load losses are dissipated to the environment. The other three losses generate the simplified thermal network of the machine in Fig. 1:

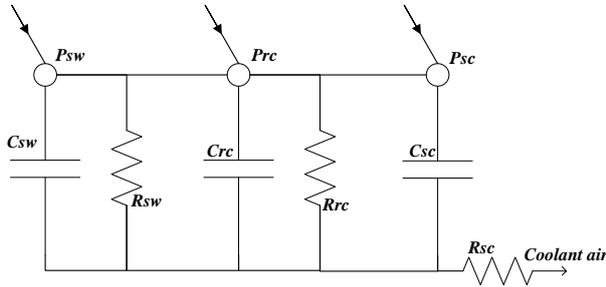


Fig. 1. Thermal network of the asynchronous machine

Based on the losses balance theory and the simplified thermal model in [10], the state-space can be defined as the following equations:

$$\frac{dT_{sw}}{dt} = \frac{-R_{sw}T_{sw}}{C_{sw}} + \frac{R_{sw}T_{sc}}{C_{sw}} + \frac{P_{sw}}{C_{sw}} \quad (1)$$

$$\frac{dT_{rc}}{dt} = \frac{-R_{rc}T_{rc}}{C_{rc}} + \frac{R_{rc}T_{sc}}{C_{rc}} + \frac{P_{rc}}{C_{rc}} \quad (2)$$

$$\begin{aligned} \frac{dT_{sc}}{dt} &= \frac{-R_{sw}T_{sw}}{C_{sc}} + \frac{R_{rc}T_{rc}}{C_{sc}} + \frac{R_{sc}T_c}{C_{sc}} \\ &+ \frac{(R_{sw}+R_{rc}+R_{sc})T_{sc}}{C_{sc}} + \frac{P_{sw}}{C_{sc}} \end{aligned} \quad (3)$$

where subscript *sw* indicates the stator winding, *rc* for the rotor cage, *sc* for the stator core and *c* for the

coolant air. Symbol *T* is the temperature above ambient, *R* is the thermal resistance, *C* is the thermal capacitance and *P* is the loss of the machine.

In the simplified thermal model,  $P_{sw}$ ,  $P_{rc}$  are ohmic losses, and  $P_{sc}$  is the frequency-dependent iron loss,  $R_s$ ,  $R_r$  are the DC resistances, in ohms, between any two line terminals,  $\omega_m$  is the mechanical speed of the rotor in *rad/s*,  $k_{iron}$  is the iron loss constant which is identified in [16]. The losses can be represented as:

$$P_{sw}(t) = I_{rms}^2 R_s(t) \quad (4)$$

$$P_{sc}(t) = k_{iron} \omega_m^2 \quad (5)$$

As the current of the rotor is not available to be measured or to be estimated using a simple method, the rotor cage losses can be calculated indirectly, which is defined by IEEE Power Engineering Society [12]:

$$P_{rc}(t) = (P_{in}(t) - P_{sw}(t) - P_{sc}(t))s(t) \quad (6)$$

$$P_{in}(t) = \sqrt{3}U_{rms}I_{rms} \cos \phi \quad (7)$$

$$s(t) = \frac{\omega_s - \omega_r(t)}{\omega_s} \quad (8)$$

where  $P_{in}$  is the input power of the machine,  $U_{rms}$  and  $I_{rms}$  are the root-mean-square values of voltage and current respectively.  $\omega_s$  is the synchronous speed,  $\omega_r$  is the rotor speed,  $s$  is the slip of the machine and  $\cos \phi$  is the power factor.

The temperatures of the stator winding and rotor cage increase largely, which leads to a 40% rise of the reference resistances. The temperature dependent characteristic of the resistance is used to compensate the ignored increasing resistance.  $R_s$  is replaced by the following equation:

$$R_s(t) = R_{sRef}(t)(1 + \alpha_s T_{sw}(t)) \quad (9)$$

where  $R_{sRef}$  is the stator winding resistance in the reference temperature.  $\alpha_s$  is the temperature coefficient of the stator winding (copper).

The state-space equations of the system can be acquired by calculating the losses  $P_{sw}$ ,  $P_{rc}$  and  $P_{sc}$  which are defined in equations (4)-(6), and importing them into equations (1)-(3). By summarizing the previous equations, the system can be rewritten as a 4<sup>th</sup>-order linear time-continuous system in the state-space model form:

$$\mathbf{x}'(t) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t) \quad (10)$$

$$\mathbf{z}(t) = \mathbf{C}\mathbf{x}(t) + \mathbf{D}\mathbf{u}(t) \quad (11)$$

where:

$$\mathbf{x} = [T_{sw}, T_{rc}, T_{sc}, T_c]^T \quad (12)$$

$$\mathbf{z} = T_c \quad (13)$$

$$\mathbf{u} = [P_{sw}, P_{rc}, P_{sc}, 0]^T \quad (14)$$

$$\mathbf{A} = \begin{bmatrix} \frac{-R_{sw}}{C_{sw}} & 0 & \frac{R_{sw}}{C_{sw}} & 0 \\ 0 & \frac{-R_{rc}}{C_{rc}} & \frac{R_{rc}}{C_{rc}} & 0 \\ \frac{R_{sw}}{C_{sw}} & \frac{R_{rc}}{C_{rc}} & \frac{-(R_{sw}+R_{rc}+R_{sc})}{C_{sc}} & \frac{R_{sc}}{C_{sc}} \\ 0 & 0 & 0 & 0 \end{bmatrix} \quad (15)$$

$$\mathbf{B} = \begin{bmatrix} \frac{1}{C_{sw}} & 0 & 0 & 0 \\ 0 & \frac{1}{C_{rc}} & 0 & 0 \\ 0 & 0 & \frac{1}{C_{sc}} & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \quad (16)$$

$$\mathbf{C} = [0, 0, 0, 1] \quad \mathbf{D} = 0 \quad (17)$$

In the state equations,  $\mathbf{x}(t)$  is the state vector,  $\mathbf{u}(t)$  is the control vector.  $\mathbf{A}$  and  $\mathbf{B}$  are constant matrixes which are the system transition matrix and the input matrix respectively. In the measurement equation,  $\mathbf{C}$  is the output matrix, which is a row vector in this system.  $\mathbf{D}$  is the feedthrough matrix which is zero here.  $T_c'$  is considered to be zero due to the temperature slowly varies with time.

#### IV. KALMAN FILTER ALGORITHM

Kalman filter is a set of mathematical equations that provides efficient computational (recursive) means to estimate the state of a process in a way that minimizes the mean of the squared error [3]. It is assumed that the process noise  $\omega_k$  and the measurement noise  $v_k$  are random white Gaussian noise with zero mean. Their variance can be described by covariance matrix  $\mathbf{Q}$  and  $\mathbf{R}$  respectively.

##### A. The Prediction Stage of the Kalman Filter

The KF estimates a process by using a feedback control: the filter estimates the process state at some time and then obtains feedback in the form of (noisy) measurements [3]. As such, the equations of KF can be divided into two groups: prediction equations and correction equations.

The equations of prediction stage shown in (18) and (19) are responsible for projecting forward (in time) the current state and error covariance estimates to obtain a priori estimates for the next time step. Equation (18) is used for updating the state vector from previous sampling time  $k-1$  to current time  $k$ . The equation (19) is state of updating error covariance matrix.

$$\hat{\mathbf{x}}_k^- = \mathbf{A}_d \hat{\mathbf{x}}_{k-1}^- + \mathbf{B}_d \mathbf{u}_{k-1} \quad (18)$$

$$\hat{\mathbf{P}}_k^- = \mathbf{A}_d \mathbf{P}_{k-1} \mathbf{A}_d^T + \mathbf{Q} \quad (19)$$

The model (10) (11) is a time-continuous system, which is discretized by Euler's approximation, so that the sampled data can be used in the KF algorithm. The time-discrete model is defined as equation (20)

$$\mathbf{x}(k) = \mathbf{A}_d \mathbf{x}(k-1) + \mathbf{B}_d \mathbf{u}(k-1) \quad (20)$$

where  $\mathbf{A}_d = \mathbf{E} + \tau \mathbf{A}$  and  $\mathbf{B}_d = \tau \mathbf{B}$ ,  $\mathbf{E}$  are  $4 \times 4$  unit matrixes,  $\mathbf{C}_d$  is equal to  $\mathbf{C}$ ,  $\tau$  is the sampling time.

$$\mathbf{A}_d = \begin{bmatrix} 1 - \frac{R_{sw}\tau}{C_{sw}} & 0 & \frac{R_{sw}\tau}{C_{sw}} & 0 \\ 0 & 1 - \frac{R_{rc}\tau}{C_{rc}} & \frac{R_{rc}\tau}{C_{rc}} & 0 \\ \frac{R_{sw}\tau}{C_{sw}} & \frac{R_{rc}\tau}{C_{rc}} & 1 - \frac{(R_{sw}+R_{rc}+R_{sc})\tau}{C_{sc}} & \frac{R_{sc}\tau}{C_{sc}} \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (21)$$

$$\mathbf{B}_d = \begin{bmatrix} \frac{\tau}{C_{sw}} & 0 & 0 & 0 \\ 0 & \frac{\tau}{C_{rc}} & 0 & 0 \\ 0 & 0 & \frac{\tau}{C_{sc}} & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \quad (22)$$

##### B. The Correction stage of KF

The equations of the correction stage are responsible for the feedback-i.e. for incorporating a new measurement into a priori estimation to obtain an improved a posteriori estimation [3]:

$$\mathbf{K}_k = \mathbf{P}_k^- \mathbf{H}_k^T (\mathbf{H}_k \mathbf{P}_k^- \mathbf{H}_k^T + \mathbf{R})^{-1} \quad (23)$$

$$\hat{\mathbf{x}}_k = \hat{\mathbf{x}}_k^- + \mathbf{K}_k (\mathbf{z}_k - \mathbf{H}_k \hat{\mathbf{x}}_k^-) \quad (24)$$

$$\mathbf{P}_k = (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k) \mathbf{P}_k^- \quad (25)$$

where  $\mathbf{K}_k$  is Kalman gain and the measurement matrix  $\mathbf{H}_k$  is a row vector  $[0, 0, 0, 1]$ .

#### V. SIMULATION AND TEST

The asynchronous machine model, connected with the simplified thermal model in Dymola is compiled as a *DymolaBlock* in SIMULINK. The *DymolaBlock* and the KF algorithm block are simulated in Simulink.

##### A. The Combined Simulation Models

The combined physical model consists of two parts. One is the squirrel cage asynchronous machine with losses, and the other is the simplified thermal model. The electronic and magnetic behaviors as well as six parts losses of the machine can be simulated with the asynchronous machine model which is explained in [11] [13] [14]. The simplified thermal model which can estimate the temperatures is described in [10].

The combined model in Dymola is compiled as a *DymolaBlock* in Simulink. The configuration and implementation of the Dymola model in Simulink is described in detail by Fish [17]. The KF algorithm is implemented as an S-Function, and is connected with the *DymolaBlock* in Simulink. In the complete simulation model, three-phase stator currents are the measurements. Three-phase voltages and the coolant air temperature are the control vectors. All of them can be exported from the *DymolaBlock* as input for the KF. The estimated temperatures from the KF can be compared with the temperatures calculated by the simplified thermal model. The whole simulation model in Simulink is shown in Fig. 2 below:

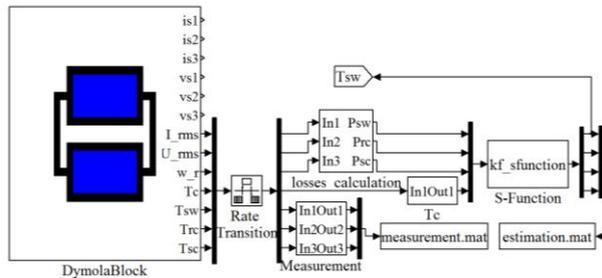


Fig. 2. Modeling and simulation in Simulink

### B. The Experiment in Simulation

The parameters of the asynchronous machine and the thermal model are identified in [15] [16]. For all the experiments, the fixed simulation step is set to 0.1 ms. Sampling time set by the *Rate Transition* block is 1 s. The process noise covariance matrix and measurement covariance matrix are obtained by the trial-and-error method to get best-fit results between filter stability and convergence time:

$$Q = \text{diag}[0.001 \quad 0.001 \quad 0.001 \quad 0.1] \quad R = 0.1$$

From the state-space equations (1) - (3), losses of the thermal model largely determine the accuracy of the estimated temperatures. In order to prove the assumption, three different methods for getting losses were proposed when the system is running.

The first method is to export losses directly from the *DymolaBlock* to the KF. The second is to calculate the losses based on the equations (4) - (8), where  $R_s$  is taken as a constant. The third method is to calculate the losses the same way as in the second method, but for every simulation step, the estimated temperature of  $T_{sw}$  is sent back to the *losses calculation* block to compensate the ignored stator winding resistance rise defined in equation (9). For every method, two experiments are performed. One is the continuous full-load S1, which means that the machine runs at the rated condition until the temperatures of three-parts reach a stable state. The other experiment is

called S6, which is an intermittent load with six minutes no-load followed by four minutes full-load.

The estimation results from the third method are as following: maximal deviation of the stator winding is 0.2 K, of the rotor cage 0.35 K and of the stator core is 0.18 K. Under an intermittent load S6, the maximal error of the stator winding, the rotor cage and the stator core are 0.55 K, 0.7 K and 0.3 K.

### C. The Experiment Results based on the Test Bench

Experiments on the test bench were performed based on the parameters which are identified in the theses [15] [16]. The temperatures of the stator winding, the stator core and the coolant air are measured by data acquisition card NI PCI-6023E. The temperature of the rotor cage is measured by the wireless sensor network.

All the signals are processed by the KF algorithm off-line. The comparisons between the measured and estimated temperatures are shown in Fig. 3 and Fig. 4. All the temperatures can be estimated accurately under S1 with the maximum error of 1.5 K, and under S6 with the maximum error of 4.5 K from the rotor cage.

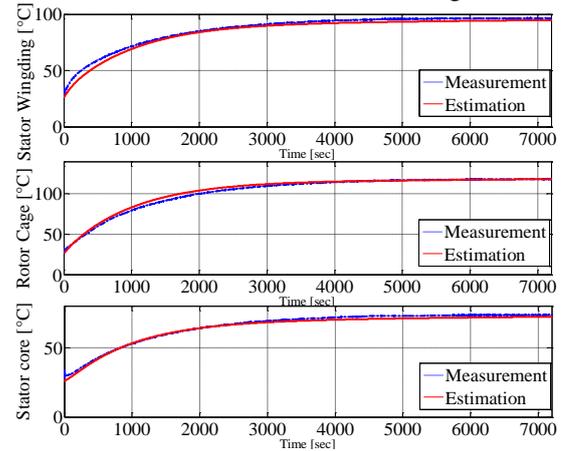


Fig. 3. Comparison of simulated and estimated temperatures under S1

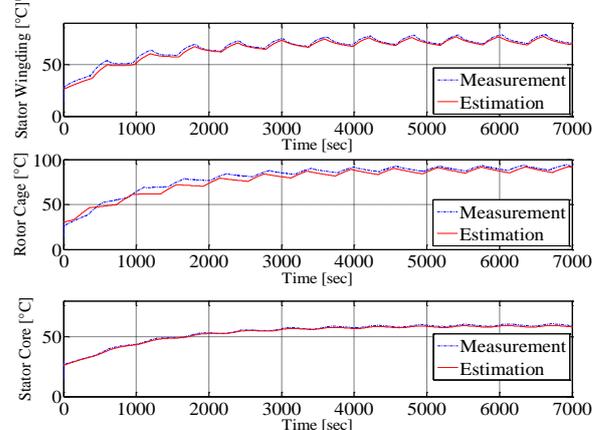


Fig. 4. Comparison of simulated and estimated temperatures under S6

## VI. THE IMPLEMENTATION OF THE TEMPERATURE ESTIMATION SYSTEM ON THE WIRELESS SENSOR NETWORK

### A. Overview of the System

The wireless sensor network was implemented based on IEEE1451.0 and IEEE1451.5 standard by using Contiki OS. The communication between NCAP and WTIM is through 6LoWPAN. The wireless sensor node is a *Preon32* module from Virtenio GmbH. It contains 32-bit ARM microcontroller with 64 KB SRAM, 2.4 GHz wireless transceiver which is compliant to IEEE 802.15.4 standard. Two 12-bit analog-to-digital converters (ADC) with a maximum sampling rate of 1 M samples/s are provided [18].

Root-Mean-Square of current and voltage, rotor speed and coolant air temperature from three other WTIMs are transmitted to NCAP, where the Kalman filter is implemented using fixed point. Fig. 5 shows the structure of the temperature estimation system on WSN.

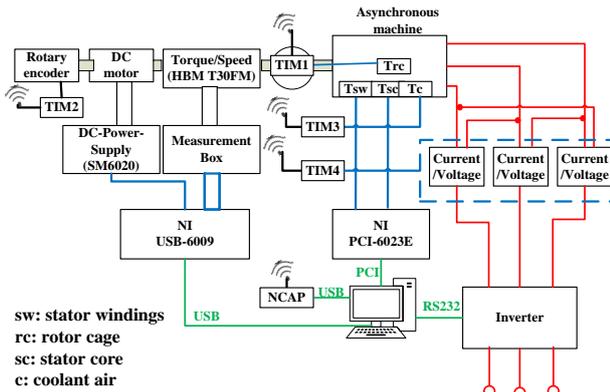


Fig. 5. Structure of the temperature estimation system

### B. Implementation of Data Acquisition System in WTIMs

Hall sensors were mounted on the conditioning board with low pass filter to process analog three-phase currents and voltages. FIR filter was implemented in a 32-bit ARM microcontroller for the digital filtering using Contiki OS. The sampling rate is 2000 Hz. However, by using *etimer*, the effective value could be calculated every 1 second with a block size of 40 samples/block. A Rotary encoder, mounted to the end of the machine shaft, was connected to a conditioning board with another WTIM. The numbers of the pulse are counted and transferred into the real rotor speed in *rad/s*. The coolant air temperature was measured by PT1000 and transformed to the physical unit in K.

When the WTIMs are powered on, the processes are started automatically. Data are acquired by WTIMs and transmitted to NCAP every 1 second when WTIMs receive the *StartTrigger* command.

### C. Implementation of the KF Algorithm in NCAP

Normally NCAP is implemented for data acquisition from different WTIMs wirelessly. However, in this application, the preprocessed data from different WTIMs are acquired and processed as the inputs of KF algorithm. The operation of NCAP can be summarized as follows: as soon as NCAP is powered on, the main process starts automatically. The *TIMDiscovery* command is called in a condition loop to discover the specified WTIM until all three WTIMs are found. After discovering the WTIMs, *StartTrigger* command is broadcasted to trigger all the WTIMs for periodic data acquisition and transmission. Then NCAP waits for the data from different WTIMs. The received messages will be stored in the buffers which are identified by the ID of the WTIM. For every step, data from three WTIMs will be passed to the KF algorithm and be processed. Temperatures are estimated on-line with the fixed-point arithmetic, which can largely improve the calculation speed of the algorithm.

## VII. THE EXPERIMENTS

Two experiments were performed on the test bench using the WSN temperature estimation system. The structure of the whole system is shown in Fig.5. TIM4 is used to acquire the instantaneous three-phase currents and voltages with the sampling rate of 2000 Hz. The average effective value of the current and voltage are calculated in TIM4 every one second. TIM3 is for coolant air temperature and TIM2 is for the rotor speed. The KF algorithm which is implemented in NCAP will estimate the temperatures when receiving the input data from the WTIMs.

The comparisons of the estimated and measured temperatures are shown in Fig.6 and Fig.7. One is continuous full-load test S1 and the other is intermittent-load S6. Under S1 condition, the maximum deviation is 2.3 K from rotor cage, and S6 with maximal error 3.5 K from rotor cage.

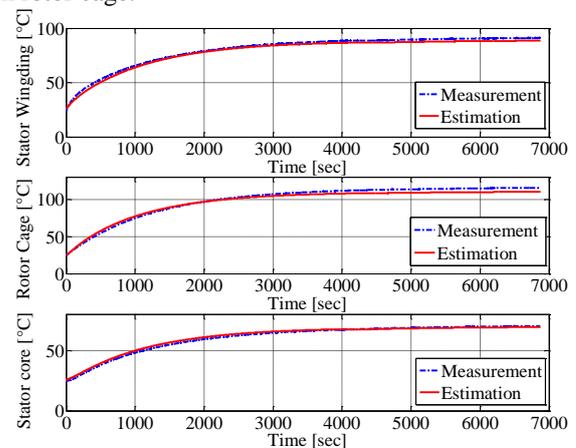


Fig.6. Comparison of the estimated and measured temperatures under S1

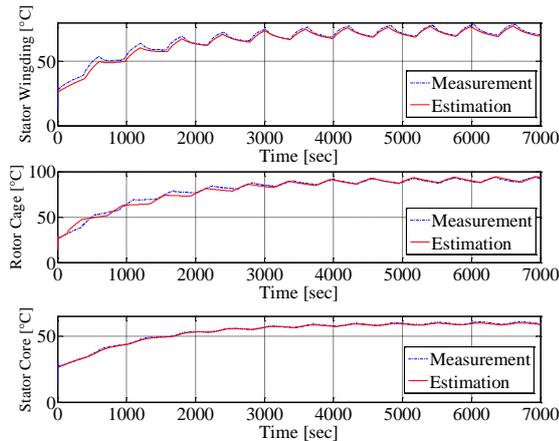


Fig.7. Comparison of the estimated and measured temperatures under S6

### VIII. CONCLUSIONS

This paper proposes a method to estimate the temperatures of the stator winding, the rotor cage and the stator core of an asynchronous machine using the KF on a WSN. The 4<sup>th</sup>-order KF was first implemented in Matlab and then in NCAP. Three distributed WTIMs served as data acquisition systems. The fixed-point arithmetic provides a high accuracy to estimate the temperature. The experiments prove that the implementation is suitable for real-time temperature monitoring on a resource limited wireless sensor node.

The implemented KF algorithm is independent from the control strategy and the running conditions of the machine. That means no matter what the rotor speed is, and what the mechanical load is, as long as there are currents through the stator winding, the temperature can be estimated correctly.

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