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Microcontroller-Based Kalman Filter Measurement of Ambient Temperature

Mustafa ÇELİK [1,*], Tarık ERFİDAN [2]

[1] *Department of Electric Engineering, Kocaeli University, Kocaeli, Türkiye,* ***ORCID:*** *0000-0001-8397-4377*
[2] *Department of Electric Engineering, Kocaeli University, Kocaeli, Türkiye,* ***ORCID:*** *0000-0001-9635-5073*

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Abstract

Temperature measurement is critical in many aspects such as system safety, quality control, energy saving, and system performance. In industrial applications, temperature control is vital to prevent equipment from overheating and ensure worker safety. In energy management, energy savings are achieved by increasing the efficiency of heating, cooling, and air conditioning systems. Preventing overheating of electronic devices prolongs the performance and lifetime of these devices. In the health sector, temperature measurement is required for patient monitoring and correct operation of medical devices. In addition, in scientific research and the development of new technologies, temperature control is indispensable for the accuracy and reliability of experiments. In this context, temperature measurement is an essential component of maintaining operational excellence and safety standards in many industries.

In this study, ambient temperature measurement is performed with an STM32F407VG microcontroller using an LM35 temperature sensor. The response of the LM35 temperature sensor is noisy due to light, radiation, high-frequency signals, etc. The noise from the sensor measurements was minimized by a Kalman filter design. These noises can be reduced by software or hardware filters. Hardware filters increase the system cost. In this study, a Kalman filter, which is one of the software filters, was used. A comparison between the Kalman filter and the alpha-beta filter has shown that the Kalman filter is more reliable and faster for dynamic systems. Experimental results show that the filter works very well.

1. Introduction

Today, with the Internet of Things (IoT), the development of embedded systems has accelerated [1]. Temperature measurement is critical in many industrial, commercial, and home applications. Temperature sensors measure temperature and these are divided into two types: analog and digital sensors. Analog sensors produce an analog output voltage proportional to the temperature and an analog-to-digital converter (ADC) is required for this output voltage. Digital temperature sensors, on the other hand, measure temperature directly using a microcontroller without the need for an analog-digital converter. Temperature is a fundamental parameter in many chemical, biological, and physical processes. However, sensor data can often be affected by environmental noise and other factors [2, 3]. These noises can adversely affect the accuracy of temperature measurements. Inaccurate temperature measurement due to noise causes deviations from the actual temperature value and adversely affects the reliability and accuracy of the system. Noisy data can cause incorrect inputs to control systems. This leads to undesirable responses and unstable behavior in the system. As a result of continuous adjustments made by control systems, outputs can become oscillatory and unstable. Inaccurate temperature measurements can unnecessarily cause heating and cooling systems to operate, resulting in wasted energy and increased operating costs. In addition, the continuous operation of systems causes wear and tear on equipment, increasing maintenance costs. Inaccurate temperature measurements in critical systems can lead to system failures and potentially dangerous situations. For example, in industrial processes, overheating or cooling risks can occur. In health and safety applications, noisy data can cause dangerous situations. In this context, it is crucial to apply appropriate filtering techniques to improve the accuracy and reliability of data from temperature sensors. Kalman filter stands out as an effective method for correcting noisy data and improves the system's overall performance. A review of the literature

* Corresponding Author: mustafa.celik@kocaeli.edu.tr

reveals that expensive and specialized sensors are typically employed to attain high accuracy and resolution [4, 5]. In addition, these expensive sensors will produce output with special communication (serial communication), which will cause negativities such as the software becoming more complex and not being able to produce instantaneous responses due to its slow operation compared to the sensor used in this study [6, 7].

In this study, the data obtained from a low-cost LM35 temperature sensor is read by an STM32F407VG microcontroller. The Kalman and Alpha-Beta filters are applied to these data, and the performance differences, especially in sudden temperature changes, are investigated experimentally. While various filter approaches on IoT-based temperature measurement systems have been discussed in the literature [8], there is an absence of comprehensive optimization of the covariance matrices (Q and R) of the Kalman filter or a detailed comparison of Kalman and Alpha-Beta filters in these studies. In the present research, both filters are tested using the same microcontroller (STM32F407VG) and the same sensor (LM35), the responses of the filters to dynamic temperature fluctuations are analyzed experimentally and the suitability of the system for real-time applications with a sampling time of 1 second is emphasized.

The findings indicate that the Kalman filter demonstrates a substantially reduced mean squared error (MSE) value compared to the Alpha-Beta filter, thereby ensuring enhanced accuracy and stability in dynamic temperature fluctuations. Despite the Alpha-Beta filter boasting a simple and feasible structure, it falls short in achieving the superior noise reduction and fast response capability of the Kalman filter when confronted with sudden temperature changes. This finding demonstrates that with its optimized parameters, the Kalman filter can control sudden temperature changes with high accuracy and reliability, even in low-cost hardware. This superiority of the Kalman filter offers a significant advantage in meeting the accuracy and stability requirements for real-time applications. The study also analyses the critical effects of these parameters on the filter stability by testing different values of the Q (process noise) and R (measurement noise) matrices. This analysis provides a practical contribution by integrating the theoretical knowledge [9] about the Kalman filter in the literature into real applications. In contrast to the extant literature, which focuses on advanced methods such as the Unscented Kalman Filter (UKF) and sensor fusion [10], this research experimentally proves that the basic Kalman filter can provide high accuracy and reliability in low-cost systems. In this respect, the study provides an economical and effective solution for real-time embedded systems.

The findings of this study demonstrate that the outcomes achieved with the low-cost system and the Kalman filter, whose parameters have been optimised, are significantly superior to those reported in the existing literature [11-14].

In future research, the utilization of advanced Kalman filters (e.g. UKF, Extended Kalman Filter) and sensor fusion techniques are recommended for nonlinear systems and applications characterized by abrupt changes. Furthermore, the employment of adaptive parameter updates based on artificial intelligence and machine learning is proposed to improve filter performance. These advances will contribute to the provision of high-performance solutions with low-cost sensors in areas such as industrial automation and the Internet of Things (IoT). In this context, the present study makes an important contribution to both academic literature and practical applications.

2. System Developed

In this study, the ambient temperature was measured using the LM35 temperature sensor and STM32F407 microcontroller. Due to the noisy output of the LM35 temperature sensor, a Kalman filter was applied. With the applied Kalman filter, a more noise-free, linear graph was obtained. By changing the parameters of the Kalman filter, the responses of the Kalman filter to temperature changes are observed.

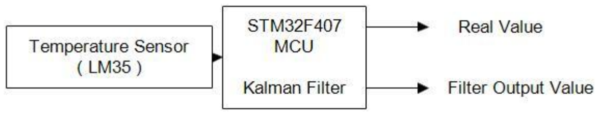

Figure 1. Realized system

2.1. LM35 Temperature Sensor

The LM35 is a widely used temperature sensor characterized by its accuracy and simplicity. The sensor provides an analog output directly proportional to temperature in degrees Celsius, with a conversion rate of 10 mV per degree Celsius [15]. This linear relationship allows for precise temperature readings, making it more accurate than thermistors and thermoelectric thermometers [16].

Figure 1 shows the system structure implemented in this study. The actual temperature value is compared with the Kalman-filtered temperature value.

The LM35 sensor has been integrated into different systems for temperature monitoring and control. For example, it is used in IoT applications for patient monitoring [17], remote temperature monitoring systems [18], and smart home security access systems. The sensor's ability to sense a wide temperature range from -55°C to 150°C makes it versatile for different environments and applications. The

LM35 sensor is also used in research involving the monitoring of thermal conditions in various environments. It has been used in monitoring thermal conditions in distributed energy resources networks [19], in greenhouse prototypes for plant growth, and in designing systems that monitor thermal conditions. The reliability and applicability of the sensor make it a favored choice in these studies.

Overall, the accuracy, simplicity, and wide temperature range of the LM35 temperature sensor make it a valuable component in various fields such as health, agriculture, and environmental monitoring. Here, precise temperature measurements are vital for effective operations and control. Figure 2 shows the LM35 internal block diagram.

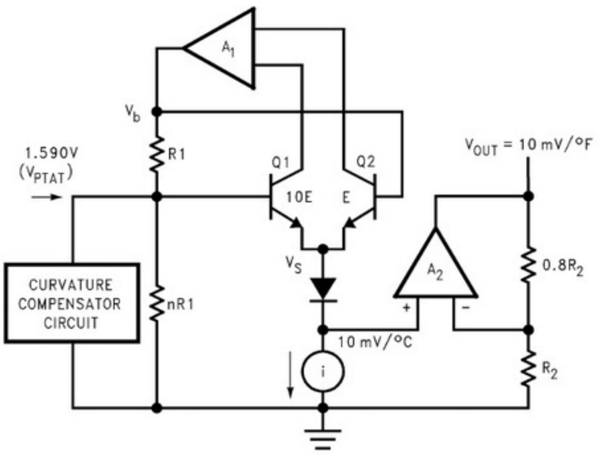

Figure 2. LM35 internal block diagram

2.2. STM32 Microcontroller

STM32 microcontrollers manufactured by STMicroelectronics offer a powerful and flexible development platform that addresses a wide range of applications. These microcontrollers are powered by ARM Cortex-M cores and are available in a variety of memory sizes, peripherals, and connection options. STM32 series are widely used in many different fields such as industrial control systems, smart home devices, medical devices, and automotive applications.

STM32 microcontrollers have different core variants from ARM Cortex-M0 to Cortex-M7. These cores offer high performance, low power consumption, and a wide feature set. STM32 comes with a wide range of various peripherals. These include standard connection protocols such as ADC, DAC, USART, SPI, I2C, and USB. These peripherals allow microcontrollers to fulfill different application requirements. There are many different development programs for STM32. These include integrated development environments such as STM32CubeIDE, STM32CubeMX, Keil µVision, IAR Embedded Workbench, and open-source tools such as GNU Tools for ARM Embedded Processors (GCC). Each of them has different features and tools to facilitate the development process. In this study, a processor with 168 MHz speed and 1 MB RAM was used.

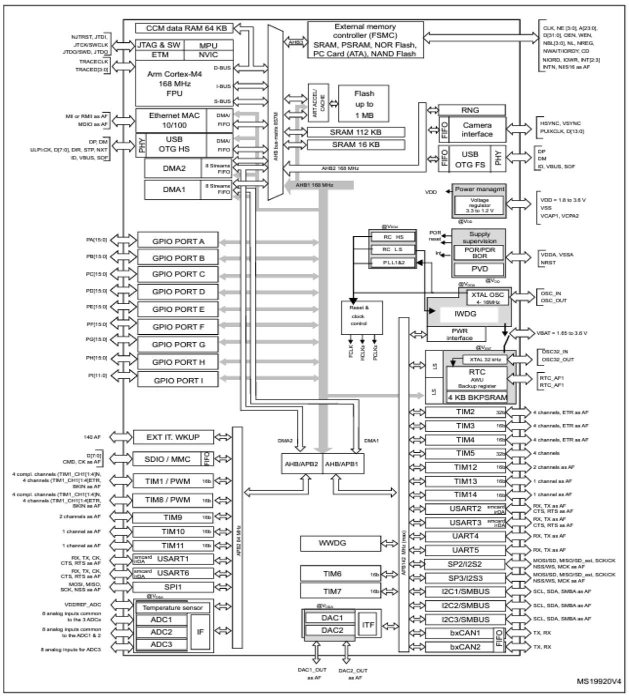

Figure 3. STM32F407VG Block diagram

Figure 3 shows the block diagram of the STM32F407VG microcontroller, which provides an understanding of its peripherals.

2.3. Kalman Filter

The Kalman filter is an algorithm that updates the state of a system with noisy output by estimation and measurement in the process. The Kalman filter, first discovered by Rudolf E. Kálmán, allows the output to be formed in a more linear formation by making accurate estimations in cases where the system is noisy and uncertain. The Kalman filter consists of two stages: prediction and update [20].

The prediction phase is the phase in which the future state of the system is predicted according to its general state and dynamic model.

The measurement phase is the phase where the final state is updated by using the measured values and the predicted values when new measurements are taken. Kalman filter is used in vehicle tracking systems to track the position and speed of vehicles, in autonomous driving systems [21] to understand the current state of the vehicle by processing the vehicle's environmental conditions and sensor data, and in navigation systems [22] to predict the speed and trajectory of aircraft and spacecraft, in robotics [23] for position and motion control in mobile robots and drone technology, in finance for market predictions and risk management. In health, it monitors and analyzes biomedical signals such as heart rate and blood pressure.

In some applications and complex situations, variants of the Kalman filter have been developed to obtain more precise solutions. For example, the Unscented Kalman Filter (UKF) handles nonlinear systems using a deterministic sampling approach to more accurately capture the mean and covariance of state variables compared to the Extended Kalman Filter (EKF) [24].

As a result, the Kalman filter and its variables are very important in state estimation, data fusion, and control applications in various fields. Researchers are continuously improving these filtering techniques to overcome specific challenges and increase their robustness and accuracy in managing complex systems with uncertainties.

The Kalman filter consists of two stages: prediction and update.

Prediction phase;

$$\hat{x}_k = A\hat{x}_{k-1} + Bu_k \tag{1}$$

$\hat{x}_k$: Estimated state vector at time k
A: State transition matrix
$\hat{x}_{k-1}$: Updated state vector at time k-1
B: Control matrix
u_k : Control input at time k

$$P_k = A\,P_{k-1}A^T + Q \tag{2}$$

P_k : Estimated error covariance matrix at time k
P_{k-1} : Updated error covariance matrix at time k-1
Q : Noise covariance matrix

The prediction stage of the Kalman filter estimates the future state and error covariance of the system based on the current state and system dynamics. State estimation is the process of predicting the future state using the current state of the system and control inputs. Covariance estimation calculates the uncertainty of the estimated state. These steps estimate the future state and uncertainty based on the dynamic model of the system and process noise.

Update phase;

Kalman gain is calculated by the formula given in the equation.

$$K_k = P_k^{-1}\,H_k^T\;(H_k\,P_k^{-1}\,H_k^T\; + R_k) \tag{3}$$

K_k : Kalman gain
P_k^{-1} : Unupdated error covariance matrix
H_k : Measurement Matrix
R_k : Covariance matrix of measurement noise

The state update is done with equation 4.

$$\hat{x}_k = \hat{x}_k{}^{-1} + K_k(z_k - \;H_k\,\hat{x}_k{}^{-1}) \tag{4}$$

$\hat{x}_k{}^{-1}$: Previous estimation
z_k : Measurement vector
$\hat{x}_k$: Current estimation

Updating the error covariance matrix (P_k) ;

$$P_k = (I - K_kH_k)P_k{}^{-1} \tag{5}$$

$P_k{}^{-1}$: Prior error covariance matrix
I : Unit matrix
P_k : Updated error covariance matrix

These equations summarize the basic steps and calculations in the measurement update phase of the Kalman filter.

2.4. Alpha-Beta Filter

The alpha-beta filter represents a relatively simple yet highly effective filtering method comprising estimation and correction stages. It is particularly well-suited to monitoring dynamic systems, including applications such as sensor data with noisy outputs, speed and position estimation of moving objects, radar, and tracking systems.

The filter operates in two distinct phases: prediction and update.

Position update ;

$$x_{t+1} = x_t + \;\alpha * (z - x_t) \tag{6}$$

Velocity update ;

$$v_{t+1} = v_t + \;\beta * \frac{(z-x_t)}{\Delta t} \tag{7}$$

x_t : predicted position
v_t : predicted velocity
z : measured position
Δt : time interval
α : The position gain (values between 0 and 1)
β : The velocity gain (values between 0 and 1)

The alpha-beta filter represents an effective solution for the basic monitoring and prediction of future events. However, for more complex or variable systems, the use of more advanced algorithms, such as the Kalman filter, may be preferable.

3. Result and Discussion

In this study, ambient temperature measurements were performed using the LM35 temperature sensor, and these measurements were read with the STM32 microcontroller. A Kalman filter is applied to reduce the noise in the measurements and to obtain more accurate results. The study aims to improve the accuracy of temperature measurements and demonstrate the Kalman filter's effectiveness.

Figure 4 shows the connection diagram of the LM35 and STM32F407. The analog output of the LM35 temperature sensor is connected to the analog PA0 input of the microcontroller.

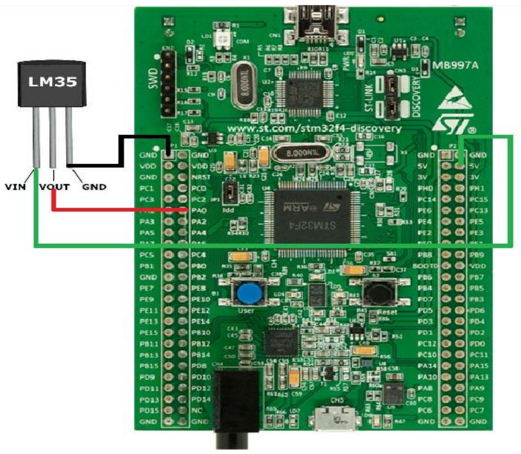

Figure 4. Connection diagram

A voltage is calculated according to the measured output value of the analog-to-digital converter (ADC) defined on the PA0 pin of the microcontroller. The calculated voltage value is substituted in equation 7 and the voltage-temperature conversion is performed and the temperature value is determined.

$$adc_{voltage} = (adc_{value} * 3000)/4095 \tag{6}$$

$$adc_{temperature} = (adc_{voltage})/10 \tag{7}$$

Since the ambient temperature is not a parameter that changes very fast, the temperature value read every 1 second (Timer2) was filtered by processing with a Kalman filter. In STM32, temperature data is converted to digital data using ADC (Analog Digital Converter). ADC results are read when the ADC interrupt is completed. By applying the Kalman filter to the measured data, the noise in the measurements was reduced and more accurate temperature values were obtained.

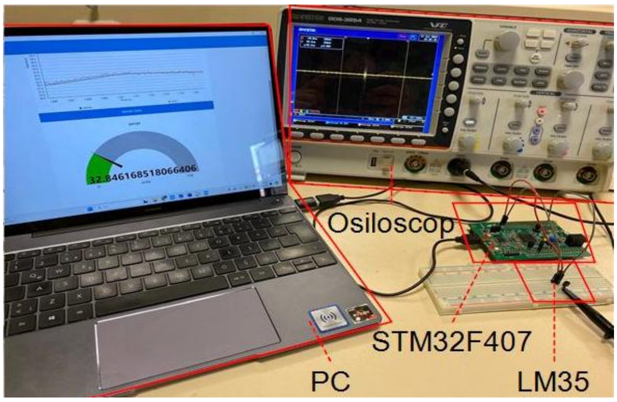

Figure 5. Experimental study

Figure 5 shows the experimental study. STM32F407 microcontroller-based temperature measurement with LM35 is observed in the STM32CubeMonitor program. When the temperature is 32.8 °C, the analog output voltage of the LM35 temperature sensor is expected to be 328 mV according to equation 6.

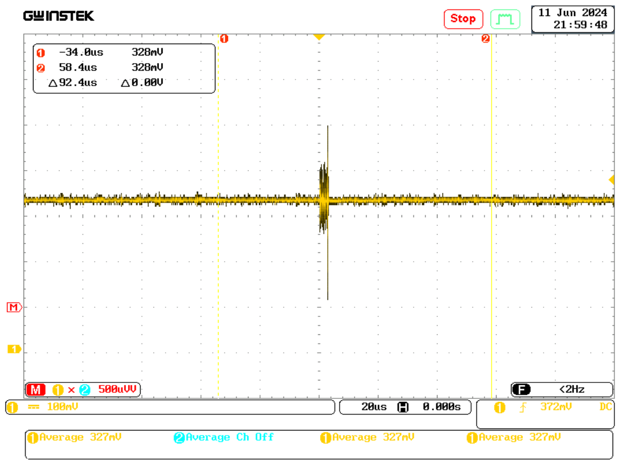

Figure 6. Analog output voltage

The oscilloscope image in Figure 6 shows that the output voltage is 328 mV.

Figure 7 shows the flow diagram of the system. After defining the required variables, a 1 s triggered ADC interrupt was initiated. When the interrupt occurs, the actual temperature and the temperature values calculated by the Kalman filter are sent to the PC.

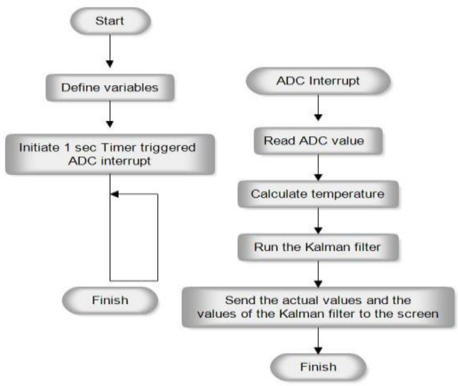

Figure 7. Flow diagram

The Kalman filter updates the system state using current measurement data and previous predictions. In the prediction step, the state transition matrix A and the process noise covariance matrix Q are used to predict the next state and error covariance. In the measurement step, using the measurement matrix H and the measurement noise covariance matrix R, the innovation covariance is calculated by comparing the predicted state and measurement data. After the innovation covariance S and the Kalman gain K are calculated, the state vector and the error covariance matrix are updated by multiplying the Kalman gain by the innovation covariance. This process provides a more accurate estimation by reducing measurement noise. These steps are repeated for each temperature measurement and the Kalman filter is applied to the temperature value obtained from the LM35 sensor.

Table 1. Kalman filter case parameters.

	R	Q
Case 1	0,1	0,0001
Case 2	0,01	0,0001
Case 3	0,1	0,001
Case 4	0,1	0,01

The Kalman filter's process noise covariance matrix Q and measurement error covariance matrix R are changed according to Table 1 and the Kalman filter's responses to temperature changes are observed in the following cases.

As can be seen in Figure 8, the raw data from the LM35 temperature sensor contains significant noise. After the Kalman filter was applied, the fluctuations and noise in the measurements were reduced and more consistent and accurate temperature values were obtained.

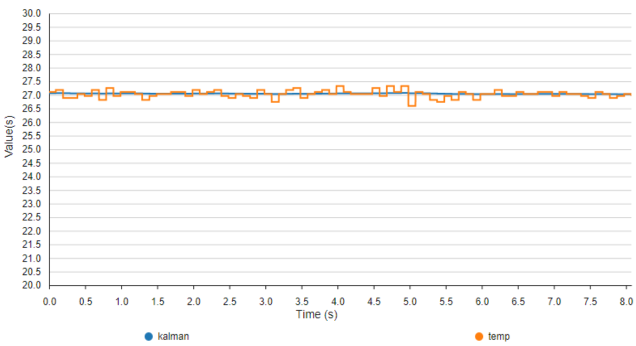

Figure 8. LM35 temperature value with Kalman filter applied

When the raw data and the Kalman-filtered data are compared, it is observed that the data obtained with the Kalman filter is closer to the actual temperature value.

The error rate is approximately 5 percent before the Kalman filter is applied, while it decreases to 1 percent after the filter is applied. This method can be used especially in applications where precise temperature measurements are required.

To understand the effectiveness of the Kalman filter, the sensor is exposed to an external heat source. In Case 1, the measurement error covariance matrix is set to R = 0.1 and the process noise covariance matrix is set to Q = 0.0001.

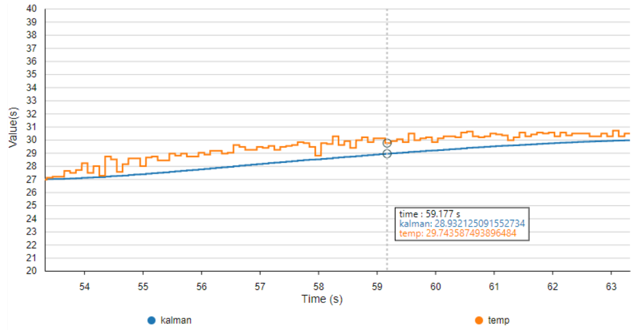

Figure 9. LM35 temperature increase graph

Figure 9 shows the output graph of the temperature sensor with the Kalman filter applied with the parameters in case 1. The response of the Kalman filter is observed by increasing the sensor temperature. It is seen that the output graph of the Kalman filter is more noise-free and the error rate is less when the sensor temperature increases noisily. Due to the delay in response time to sudden temperature changes, the response of the Kalman filter is observed by changing the parameters of the measurement error covariance matrix R and the process noise covariance matrix Q of the Kalman filter. The measurement error covariance matrix R defines the magnitude of the noise in the measurement data. The smaller the R matrix, the faster the Kalman filter measurements are updated. The response time of the filter to temperature changes decreases. The process error covariance matrix Q represents the uncertainties and noise in the system model. As the Q matrix becomes larger, the Kalman filter makes more frequent measurements and the response time of the filter decreases.

In Case 2, the measurement error covariance matrix is reduced by making R = 0.01 and the response of the Kalman filter is observed in Figure 10. It is seen that the filter responds faster to the temperature increase compared to the previous design.

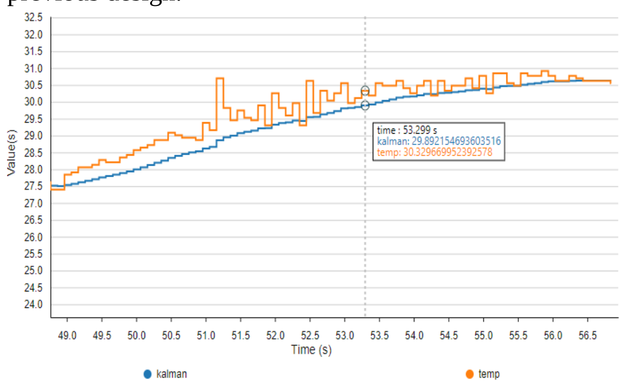

Figure 10. Kalman filter graph with reduced R matrix

In Figure 11, the response of the Kalman filter to the temperature change is analyzed when the process noise covariance matrix Q is set to a value larger than the value in case 1. It is seen that the response time to temperature increase accelerates.

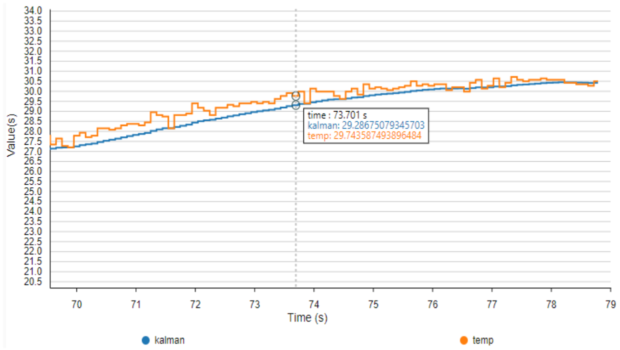

Figure 11. Kalman filter graph with Q=0.001

Figure 12 shows the response of the Kalman filter to temperature change when the process noise covariance matrix Q is set to a value larger than the value in case 3.

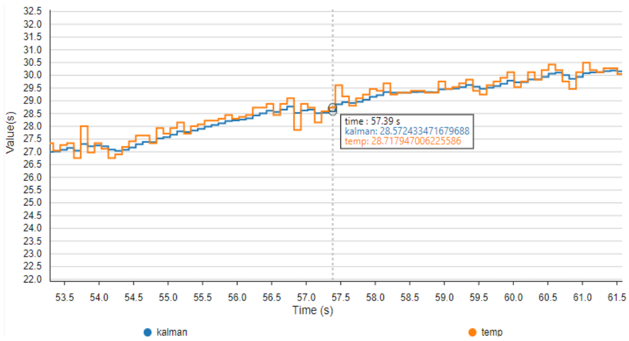

Figure 12. Kalman filter graph with Q=0.01

It is seen that the response time to temperature increase is faster than in case 3.

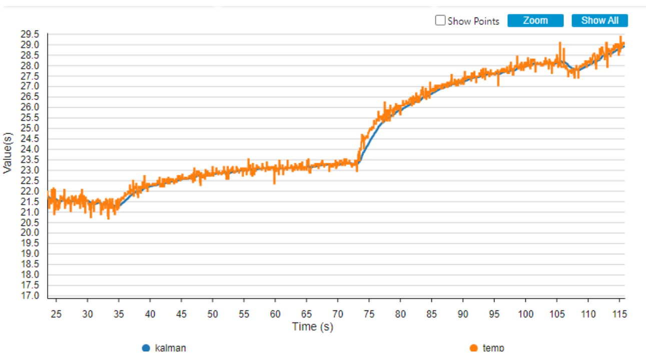

Figure 13. Kalman filter graph designed with the parameters in Case 1

In Figure 13, it is seen that the Kalman filter designed with the first determined parameters in the system reacts more slowly to sudden temperature changes, but gives a noiseless output compared to the other cases.

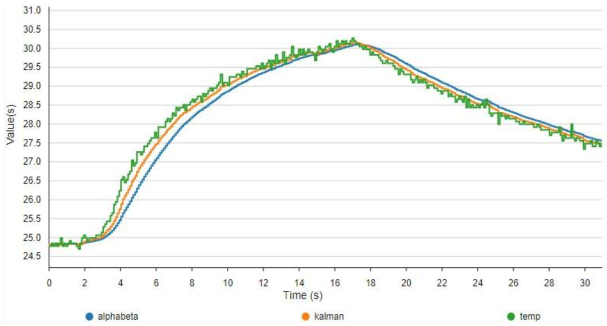

Figure 14. Comparison of temperature measurement data using Kalman and Alpha-Beta filters

To evaluate the superiority of the Kalman filter in comparison to the Alpha-Beta filter, the sensor temperature was increased and decreased. The results obtained from this experiment are presented in Figure 14. The overall squared error for both filters is shown in Table 2.

Table 2. Mean squared error analysis of Kalman and Alpha-Beta filters on temperature data

Time (s)	Alpha Beta	Kalman	Temp	Alpha Beta MSE	Kalman MSE
0	24.7984	24.7898	24.762	0.13%	0.08%
3	24.9561	25.0128	25.128	2.96%	1.33%
7	27.647	27.9891	28.278	39.8%	8.36%
10	28.8388	29.027	29.085	6.02%	0.33%
14	29.7209	29.812	29.963	5.88%	2.29%
18	30.0352	29.9952	29.816	4.77%	3.18%
22	29.0897	28.942	28.791	8.91%	2.27%
25	28.4963	28.3792	28.278	4.75%	1.02%
30	27.8192	27.7205	27.619	4.01%	1.03%

The Kalman filter yielded more precise results with a lower mean squared error (MSE) compared to the Alpha-Beta filter in both the 0–3 s and 3–30 s time intervals. In the 0–3 s interval, where the temperature remained constant, the Alpha-Beta filter exhibited an MSE of 1.87%, while the Kalman filter demonstrated an MSE of 1.17%. However, in the 3–30 s interval, where the temperature increased, the error rate of the Alpha-Beta filter increased significantly, reaching 13.88%. In contrast, the Kalman filter exhibited a considerably lower MSE of 3.15%. This suggests that the Kalman filter provides more stable and reliable results, particularly in situations characterised by significant temperature fluctuations. In this context, the Kalman filter is a more robust filtering method that should be preferred in noisy and dynamic systems.

4. Conclusions

In this study, using the STM32F407VG microcontroller, temperature data from the LM35 temperature sensor were read in the CubeMonitor program and the Kalman filter was applied to the noisy output. The experimental results show that by using the Kalman filter, the noise in the measured temperature data is reduced and more accurate temperature data are obtained. The parameters of the Kalman filter (A, B, C, Q, R, P and K) were configured correctly and the filtering process was performed successfully. It was observed that the temperature values obtained with the Kalman filter were more stable and reliable than the raw data. ADC conversions and Kalman filter calculations were performed in real time with the microcontroller.

By changing the parameters of the measurement error covariance matrix R and process noise covariance matrix Q of the Kalman filter, the responses of the filter to sudden temperature increases were observed. It is seen that the Kalman filter, which has a more noise-free output, reacts more slowly to the temperature change than the designs with smaller R and larger Q matrices. Analysis of the outputs from designs that increase the response time of the Kalman filter indicates that the resulting graphs display considerable noise. Determining the optimal state is achieved by correctly setting the Q and R matrices, choosing the initial covariance correctly, the accuracy of the system and measurement models, and using the appropriate time step. The parameters of the Kalman filter must be carefully tuned according to the requirements and specific conditions of the application. A balanced selection of these parameters ensures a fast and accurate response of the filter.

In a comparative analysis of the Kalman filter and the alpha-beta filter, the Kalman filter demonstrated a mean squared error (MSE) of 1.17% under constant temperature conditions and 3.15% when temperatures were increasing and decreasing. In contrast, the alpha-beta filter exhibited an MSE of 1.87% when the temperature was held constant and 13.88% under conditions of increasing and decreasing temperatures.

This study aims to achieve highly accurate and reliable measurement results by processing the noisy outputs of the low-cost LM35 temperature sensor using a microcontroller-based Kalman filter algorithm. This approach makes a meaningful contribution to the cost-performance balance through the software-based optimization of low-cost sensors. The superior accuracy and stability displayed by the Kalman filter in comparison to the Alpha-Beta filter provide a unique assessment of the applicability of filtering methods in dynamic systems within the existing literature. Further research could concentrate on comparative studies of Extended and Unscented Kalman filter approaches, as well as more sophisticated techniques such as multi-sensor fusion and AI-supported adaptive parameter optimization. By enhancing energy efficiency through integrated hardware-software solutions, these methods may gain broader applications in IoT, embedded systems, and mobile technologies, thus deepening both theoretical and practical contributions in academic and industrial contexts.

Declaration of Ethical Standards

The author(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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