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Temperature Sensor Failure Detection and Diagnosis based on ARIMA Model

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Abstract

In industry, the use of temperature sensors is paramount, with real-time sensors being crucial for temperature fluctuations. However, such sensing systems may fail due to environmental or technical factors such as corrosion, sensor body fault, or wire fault in the assembly line. Therefore, a reliable sensor on that infrastructure is required to complete the process efficiently. In this context, this paper introduces Data Prediction and Early Detection of Errors in Temperature Sensors (DPEDETS), a method which helps the digital monitoring of sensor health conditions of a temperature system for stool monitoring DPEDETS. The methodology involves the autoregressive integrated moving average model (ARIMA) the mathematical concept test method to initiate a tentative assessment of sensory variation. Then, it detects and distinguishes confusion in the continuous transmission of sensory data, detecting premature sensory failure. The proposed DPEDETS method provides a reliable measurement of the time sensing data for the duration of sensing failure or temperature monitoring systems. The DPEDETS method has been tested on the temperature data collected from different types of temperature sensors. The results illustrate effectiveness of the DPEDETS process and sensory function of temperature monitoring on suites.

Keywords: sensor failure detection; ARIMA; prediction; time series modeling; forecasting;

1. Introduction

Temperature sensors find their use in almost every industry nowadays. Sensors are an integral part of various important economic-development monitoring systems and play as a momentous key role in maintaining the security and integrity of the system. Having said that in synchronic systems, sensors might sustain inaccurate data as a result of different dynamic features that include sensory exposure in the area of acute and neurological dysfunction. This inaccurate or false data from sensors can be temporary or everlasting. Temporary error data can occur negligently due to changes in sensory features and electrical equipment. That temporary data should not be caused by sensory failure. Instead, they need to be separated as unusual. However, regular false data is likely to indicate sensory failure and lead to a diminution in the performance of the plenary monitoring system. Hence, primordial detection of neurological breakdown is important to appropriate intervention strategy while scrutinization of the environmental conditions of critical infrastructural assets.

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We view temperature sensors as a boon, yes, it is but sometimes we have to look the other way as sensor failure can lead to fatal hazards, like a runaway inside chemical reaction plant cyclohexane/methylcyclohexane, N-brom+osusinimisobiotin and azobiotin (AZBN) formed due to excessive heat from the mixture. The accident was caused by a lack of both temperature control and alarm on the existing sensor. The starch dryer base is another that has caught fire. This accident may have been caused by an accidental accumulation of abnormally hot carbs. Due to the improper positioning of the temperature sensor, the automatic steam injection designed to prevent this type of event is not working properly and the vacuum distillation of the refinery is similar to a fire in the upper part of the furnace, this phenomenon is probably possible. Due to the freezing of many sensors, liquid hydrocarbons enter with a high flow rate. At that time we were unable to solve those problems but now we can definitely prevent such incidents with "DPEDET". What if sensor failure can be detected in advance? With this in mind, we have developed a system that assesses an error before it the Data Prediction and Early Detection of Errors in Temperature Sensors (DPEDETS) approach to detect the faulty temperature sensors. This work prompted the development of the DPEDETS approach, which has the following three features:

1. Forecasting: This refers to the method of predicting predetermination trends in statistics based on former statistical trends collated using the mathematical model. Predictive statistics will act as a visual sensor for comparison of the sensor data gathered from field systems for confounding and sensory failure. Further, in the case of fixed sensitivity, predictive data may be used to establish actual estimates [14].

2. Analyzing and detecting anomalies: Confusing patterns are unexpected results in data that are not as per normal behavioral trends. Sensory statistics that vacillate abruptly or infrequent events from the healthy ornamentation are marked as confusing. Therefore, it is important to find and classify anomalies.

3. Monitoring and compensating for sensor failures: The nerves often fail over time. Early detection of sensory failure will improve current temperature monitoring skills in order to effectively manage industrial temperature-based infrastructure. Also, it prevents erroneous data training predictive models. Once sensory failure is detected, erroneous sensor data points need to be included with the predictable data.

DPEDETS method uses the model named ARIMA i.e. the Autoregressive Integrated Moving Average model in this paper. A suggested temperature supervising system as an application background. The main grants to our suggested program are listed as follows:

1. Based on the model ARIMA that is used in predicting change in the behavior of temperature sensor that is used to create a framework for confusing discovery and sensation failure

2. Using the mathematical method, there is some confusion sensor data was obtained and segmented.

3. The sensory detection model was used by using the prediction method and error data was addressed using estimate values.

The remnant of this paper is arranged below. Section 2 gives a briefed introduction to review the work related to DPEDETS method. Section 3 describes proposed system of temperature sensor fault detection. Section 4 introduces the experimental set-up of DPEDETS model. Section 5 shows how well the suggested DPEDETS technique performs. Finally, Section VII concludes the paper.

2. Literature review

Identify failure of the sensor and inaccurate data accommodation (DPEDETS) a method to assist in the digital monitoring of health monitoring sensors. The DPEDETS approach adopts the seasonal auto-regressive integrated moving average model with a statistical speculation testing technique that enable tentative estimation of sensor variables. Then, after identifying the initial sensor failure, it finds and separates modifications in an ongoing stream of sensor statistics. In conclusion, the DPEDETS technique offers a trustworthy evaluation of sensor information in the case of sensor failure or throughout the wastewater monitoring system's scheduled maintenance window. The outcomes of the evaluation of the DPEDETS technique employing surface temperature data [1] demonstrated the effectiveness of the DPEDETS approach and its application to the surface temperature monitoring sensor suite. In modern society, sensors have become an important part of human life. Nerve safety and reliability have attracted the attention of various research institutes and researchers. Being among the essential components of the sensor, it ensures normal operation [2]. Recently, wireless sensor networks (WSNs) have become a crucial technology in various systems. Sensor nodes are prone to a variety of failures, such as hardware and software failures. If the quality of WSN service (QoS) is significantly reduced, the risk of errors increases. To achieve good QoS, it is necessary to develop an effective error detection method [3]. Requires automatic fault detection and sensory confirmation and severely affects control system performance. KPCA effectively captures the indirect relationship of dynamic processes involving key components of high-level functional areas through integration operators and indirect kernel functions [4]. Sensor nodes operate in insecure and unpredictable environments; sensors can fail and provide unexpected responses. Therefore, troubleshooting is a crucial component of wireless sensor networks. In this article, we have suggested a Support Vector Regression Defect Detection Algorithm that uses historical data to estimate the dimensions of sensor nodes. The reliability level of the sensor node is determined by the difference between its estimates and the actual measurements. In this article, we will also propose a problem-solving algorithm in line with the node credit level in conjunction with the genetic algorithm. Simulation results show that our suggested algorithm works well in terms of failure detection rate, failure recovery rate, and power consumption [5]. Gives a streamlined method for configuring sensors to detect sensor failure for a small number of sensors. To achieve maximal information redundancy, we outline sensor information redundancy and its measurement, as well as the performance evaluation standards currently in use for various setup options [6]. Integration system with intelligent fault detection and sensor isolation improves convenience and control reliability. As a result, without relying on extra gear, you can check if your sensors are working. This article examines insulation failure detection techniques using real-time hardware-based real-time sensors based on the standard IEEE 14 bus architecture. Results show that this approach is effective and suitable for flexible control in real-world settings [7]. Wireless sensor networks are becoming an integral part of computing and communication technologies. To monitor and identify occurrences that are time-sensitive and should be considered emergencies, many sensor nodes can be positioned in the desired region. Not every sensor node in the network will perform as expected every time, and some may fail for a variety of reasons. Error detection is considered an important factor in achieving quality of service and increased bandwidth and network lifespan [8].

Especially when it comes to the ARIMA model, TEP error diagnostics [9], consumer price index forecasting [10], wind farm reliability analysis [11], and Indian stock market prediction [12] are now in various fields. Improved so far ETC The existence of bugs/switch locations is not always visible so our algorithm must first detect their occurrence. Once we've done that, we need to adjust our viewing preferences accordingly. Mistakes destroy what we see and reduce its impact; Transition points (rapid changes in data properties) may require switching to a completely different sample schedule. Our solution is to use the Gaussian formalization approach, which allows for hypothetical sequential assumptions about the theoretical approach to problems of interest instability and decision-making [13].

3. Proposed System

The three processes that make up the proposed DPEDETS system are input data, ARIMA, and fault kinds. Input Data: To do the process on something or to apply ARIMA first we require some data or readings. In our case we have taken two data i) healthy data and ii) faulty data. For that purpose, we have used 4 different temperature sensors, Thermocouple sensor (K type), RTD PT100 (resistance temperature detector-platinum), Thermistor, LM35 (limiting magnitude). We have used different modules for hardware setup like MAX31865 module for RTD PT100 sensor, MAX6675 module for Thermocouple Sensor. Data Streamer in Microsoft Excel was there which was the main platform for us, using which we had recorded temperature readings.

ARIMA: ARIMA, an abbreviation for an ‘Auto-Regressive Integrated Moving Average’, is a prediction algorithm based on the assumption that the knowledge of past values in a timeline can be used alone to predict future values. We have considered four sub-parts ARIMA model i.e., Autocorrelation, Difference, Prediction, Comparison. Autocorrelation is helpful to find out the data is stationary or not. If data is not stationary then we will make the difference of healthy data and shifted healthy data (shifted by one step), if data is already stationary then skip the difference part. The next step is a prediction of future trends using stationary data. We have predicted the upcoming data and compared it with original data and then we found the drift of actual data from that predicted one.

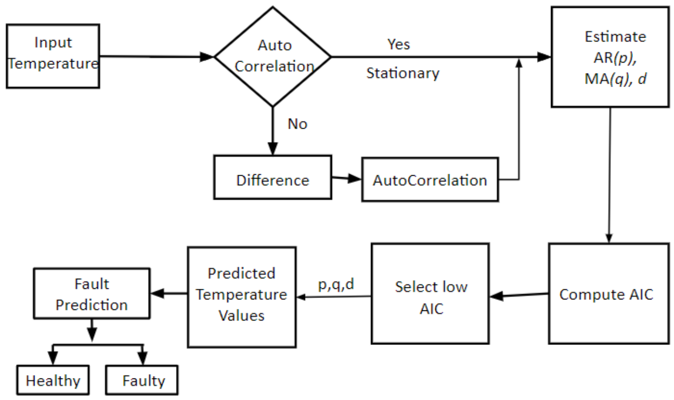

Fig. 1 Block representation of the suggested DPEDETS system

In ARIMA, there are two autonomous models: AR and MA. Here, AR denotes the order p autoregressive process, which can be written as AR (p). The evolving variable is regressed using the AR(p) inside the time series in comparison to its previous values [1].

$$AR(p)t = c+\phi\_1 x\_(t-1)+\phi\_2 x\_(t-2)+\cdots+\phi px\_(t-p)+\varepsilon\_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

The genuine value of AR(p)t at time period t is AR(p)t , φ1, φ2, . . . , φp a limited number of weight parameters for the AR(p), where c is a constant and p is the model's order and the preceding standard deviations are x_(t-1),x_(t-2),..,x_(t-p). The identical distribution of εt is, εt~ IN(μ, σ2), where μ is mean which is equal to 0 and σ2 is a constant variance. The moving average process of order q, which is represented by the mathematical equation (2) and may be abbreviated as MA, is a component of the ARIMA model (q). The MA(q) model's historical mistakes are employed as explanatory variables.

$$MA(q)_{-l} = c + \varepsilon_t + \theta_L \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta q \varepsilon_{t-q} \ldots\ldots\ldots\ldots (2)$$

The MA(q) model's actual value at time t is MA(q)t, where q is the model's order and 1, 2,..., q are its collection of weight parameters that is finite. c is a constant. In line with AR(p), it is assumed that MA(qt)'s is a white noise process with uniformly distributed random variables that have a zero mean and constant variance. The model named, ARIMA combines the AR(p) and MA (q). The mathematical definition of the model in (3) can be written as ARMA (p, q).

$$AR(p)_t + MA(q)_t = 0 + \phi_1 x_{t-1} + \phi_2 x_{t-2} + \cdots + \phi_p x_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t \ldots\ldots\ldots\ldots (3)$$

Consequently, $AR(p)_t + MA(q)_t$ is the prognosticator of the *ARMA(p, q)*, which incorporates the baseline values of AR(p) and the historical delusions of *MA (q)*. You may write the $AR(p)_t + MA(q)_t$ equation as x. In *ARMA(p, q)*, the order values of the p and q in the *AR(p)* and *MA(q)* models are not more than 2 [14]. As a result of simplification, (3) becomes (4). For the sake of clarity, the constant term c is ignored [12] in which the autoregressive p term and the moving average term q are represented by the order of the models, and the order of the models p and q is altered to (5).

$$x_t = c + \varepsilon + \sum_{n=1}^{p} \quad \phi_n x_{t-n} + \sum_{m=1}^{q} \quad \theta_m \varepsilon_t - m$$

……………. (4)

$$x_t - \sum_{n=1}^{p} \phi_n x_{t-n} = \varepsilon_t + \sum_{m=1}^{q} \theta_m \varepsilon_{t-m}$$

……….. (5)

In time-series statistics, the backshift operator B influences a value in the series to get its previous value [1]. In equation (6), it is formally defined as the relevant epoch's backward observation by the time series.

$$B^k x_t = x_{t-k} \text{……….. (6)}$$

The model ARMA(p, q) is typically modified by (6). The ARMA model equation (p, q) in (5) may be written as in using the lag operator (7) [9].

$$\left(1 - \sum_{\Pi=1}^{p} \phi_n B^n\right) x_1 = \left(1 + \sum_{m=1}^{q} \theta_m B^m\right) \varepsilon_t \;\; \dots\dots\dots \quad (7)$$

Only stationary time series statistics are appropriate for the *ARMA (p,q)* model. However, the sensor statistics that the system is generating exhibits non-stationary behaviour. Let’s see that with the help of the graphs of autocorrelation of non-stationary behaviour of our four temperature sensors. In the below figure graphs of autocorrelation of non-stationary behaviour of four temperature sensors are plotted. According to these graphs data which we have gathered from sensors show trend as it is increasing data.

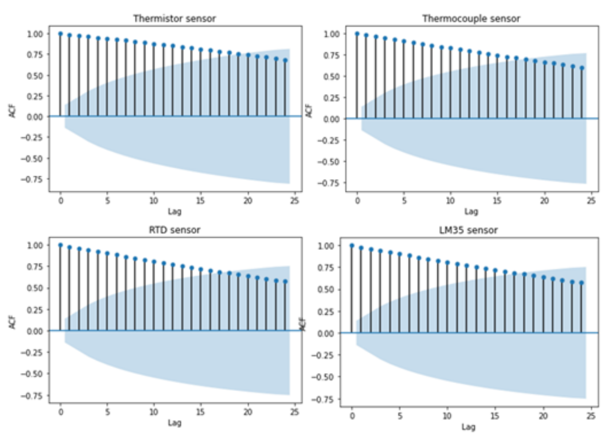

Fig 2 Autocorrelation responses before stationary data

But to apply our ARIMA model, we need stationary data only so first we need to make it stationary and for this we have a method known as Difference. Below graph shows the difference in the data values which we obtained by shifting the values by one. Now it has become stationary.

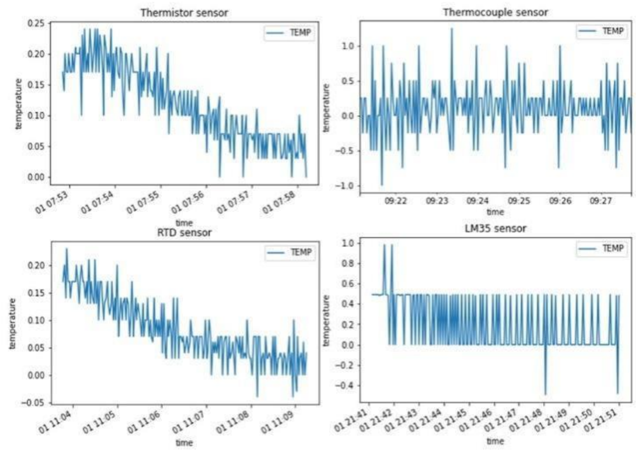

Fig. 3 Different (shifting by 1)

We again check the autocorrelation of these graphs to see whether we are getting correct stationary or not. Below graphs shows the autocorrelation after applying the method of differencing and it is observed that graph is now symmetric along the both axes. Now we are ready to apply ARIMA model on our data.

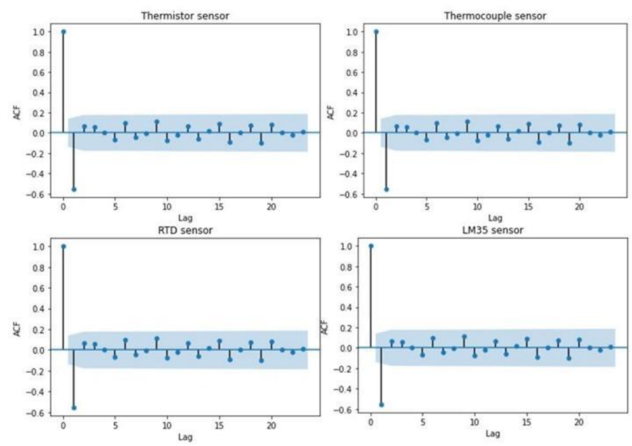

Fig. 4 Autocorrelation responses after stationary data

To deal with the dynamic character of system temperature statistics, the model ARIMA has been recommended regarding the application described so far, in this paper for forecasting system temperature readings. By using this model, homogeneous non-stationary behaviour by predicting the right gap worth of the procedure for constant ARMA (p, q). The difference can be expressed mathematically as (8), where (1 - b) d = d. The mathematical formula for the generalised ARIMA model is (9) and is abbreviated as ARIMA (p, d, q).
$x_t = \Delta^d x_t$….(8)

$$\left(1+\sum_{n=1}^{p}\phi_n B^n\right)\Delta^d x_t = \left(1+\sum_{m=1}^{q}\theta m B^m\right)\varepsilon_t \text{……… (9)}$$

where the three numbers p, d, and q represent the locations of the moving average, integrated, and autoregressive components, respectively, of the ARIMA (p, d, q) model. The degree of difference is controlled by the integer d.

3.1 Selection of parameters in ARIMA model

The Hindman and Khandaker algorithms are used to automatically calculate the p, d, q, p, d, and q order parameters for the ARIMA (p, d, q) (p, d, q) SP model [15-16]. The Shin (KPSS) test, a unit root test, is used to determine the differential term d and d. The procedure chooses the values for p, q, p, and q by subtracting the same information standard (AIC) stated in [15] if the values of the D and D differentiating parameters are known (11). *AIC = -2 log (l) + 2 (p + q + p + q +* K_n*)* (11) where L is the maximum potential for the reference model *ARIMA (p, d, q) (P, D, Q)*$_{sp}$, intersected Data *(Δ) d (ΔSp)*. Number of estimated parameters for calculating phase forward predictions set to $^{D}S_{T}$ and K_n

3.2 Prediction of intervals

The upper and lower boundaries of a prediction interval, which depicts where the observable variable will fall in the future with a particular level of probability, are estimated using historical observations as a starting point. Taking into consideration that g 0 s standard deviation for the Gaussian distribution σg, and then the probability distribution follows *(St+f |St, St−1, St−2,.. .)* of a imminent observable value *xt+f* of the method will be normal with mean *xˆ(f)* and standard distribution is given in (12) [14].

$$\sigma(f) = \left(1 + \sum_{j=1}^{f-1} \psi_j^2\right)^{\frac{1}{2}} \sigma g \qquad \dots\dots\dots \quad (10)$$

The variate *[〖[x〗 _(t+f)- x_(t(f))]/[σ(f)]]* will have a typical distribution inside the unit. As a result, given xt+f, xf /2(f) will offer the prediction interval's boundaries with probability (1). /2 is the deviation of the unit normal distribution that has been surpassed by a factor of /2. The ARIMA (p, d, q)(P, D, Q)xp model's prediction interval may be calculated mathematically using [13–14].

$$x_{t+f}(\pm) = x_t(f) \pm \frac{\mu_\lambda}{2\left(1 + \sum_{j=1}^{f-1} \psi j^2\right)^{\frac{1}{2}} \sigma g} \quad \dots\dots\dots\dots\dots (11)$$

Where, the ordinary normal distribution's percentiles are represented by /2. /2 Equals 95% in this study article. The predicted value x t+f from the ARIMA (p, d, q)(P, D, Q)xp model will fall between the upper and lower bounds of the interval x t+f (+) and (), i.e. Probability{*x_(t+f) (-)<x_(t+f) (+)}*. Fig. 5 below shows the graph between our actual data and the data that we have predicted for our four sensors Thermistor, Thermocouple, RTD and LM 35 respectively.

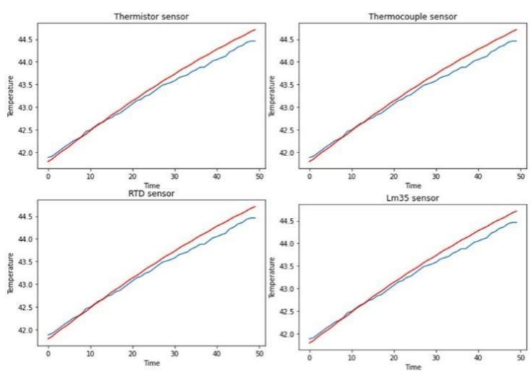

Fig. 5 Prediction Plots

The DPEDETS method, which is the one suggested in this work, combines assessment analysis and diagnostic techniques to offer an advanced data analysis solution. The ARIMA model ARIMA (p, d, q) Sp (P, D, Q) is used as part of the DPEDETS method's estimated data component to estimate temperature fluctuation. The following Algorithm 1 shows the optimal solution to obtain the ARIMA model:

Algorithm 1

1. procedure FINDOPTIMALARIMA

2. aic ← in f
3. for p ← 0 to 3 do
4. for d ← 0 to 2 do
5. for q ← 0 to 3 do
6. model ← fit (arima(p,d,q_drift)) ←True
7. allow mean ←True(x)
8. aic_curr ← compute_AIC(model)
9. if aic_curr<aic then
10. model_opt← model
11. aic ←aic_curr
12. return model_opt

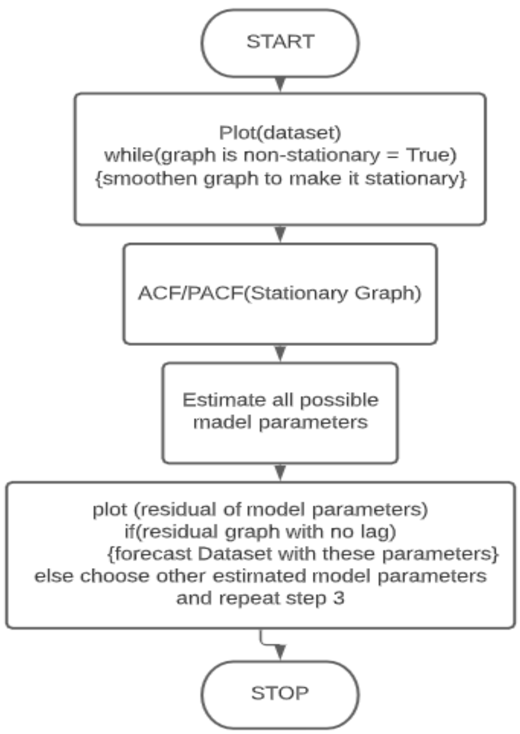

Fig. 6 Flow Chart

Types of Faults: What we have done so far is to find fault, but we need to find out what went wrong. Any type of error that has a specific threshold, i.e. a certain range of drift from the actual data, we can classify the error types using random categories. Here, we have created three different types of defects in insulation, wire loose, and wire removal and all these types of defects have their own range of variations. Therefore, by using the differences we calculated with programming and daily healthy and erroneous data, we showed the wrong type. This section goes into great depth about how the temperature information from the system was utilised to make the forecast in this study. The Sensor Suite provides temperature statistics. A time series st with data values equal to the interval time may be used to visualize the temperature statistics coming from the sensor array t, t - 1, t - 2, St, St − 1, St − 2, by. ,. Twenty minutes pass between each of the two sensor readings. [9]

4. Experimental set-up

There are some common components used in all the systems namely: Arduino Uno, Relay, 100 Watt Lamp, Thermocouple, Thermister, RTD, etc.

1. Arduino Uno: A microcontroller board called the Arduino Uno R3 is based on the ATmega328P. It comes with everything you need to start using a tiny controller, including a USB cord to connect to your computer and an AC-DC converter or battery to power it. The third and most current improvement to the Arduino Uno is called the R3. The Arduino board and IDE software are currently fresh releases and are updated versions of the Arduino reference. A series of USB-Arduino boards and a standard model called Uno-board were created for the Arduino platform.2. Relay: Control DC or AC signal and can handle 220V AC load Open and open the normally closed contact normally. We use relays to change the temperature by delaying the lights on or off.
3. Lamp: We used 100-watt lamps for temperature variation and breadboard and jumper wires for connections.
4. Thermocouple sensor: Thermocouple and MAX6675 are utilised in this configuration as components. The Type-K thermocouple's signal is digitally processed by MAX6675, which also handles cold-junction correction. Data is produced in a read-only, 12-bit resolution format that is SPITM compliant. This converter shows a thermocouple accuracy of 8 LSB for temperatures between 0 C and +700 C, resolves temperatures up to 0.25 C, and permits readings up to +1024 C. The 8-pin SO packaging for the MAX6675 is compact.

Fig. 7 Thermocouple setup

RTD PT100: The parts used in this configuration are MAX31865 and RTD PT100 (3 wires). The most typical RTDs used in industrial applications are those made of platinum. Because platinum can survive a broad range of temperatures and has great long-term stability and corrosion resistance. Range of measurement: -50 C to +450 C. The resistance-to-digital converter MAX31865 is simple to use and designed for platinum resistance temperature detectors (RTDs).

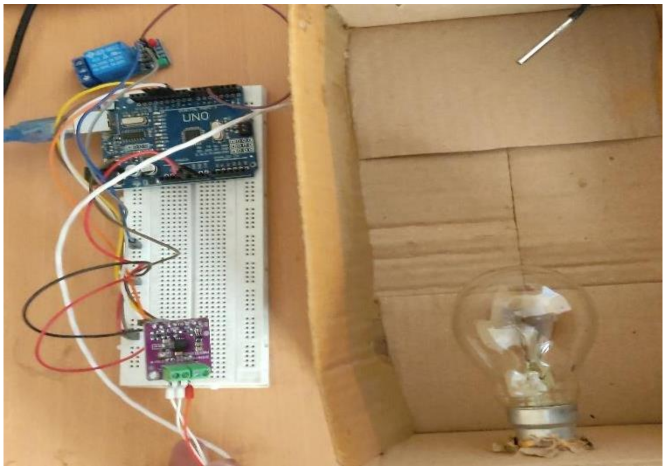
Fig. 8 RTD setup

Thermistor: The thermistor is a solid temperature sensor that works as a bit of electrical protection but is sensitive to heat. Thermistors can be used to produce an outgoing electric analog with a variable temperature range and thus can be called a transducer.

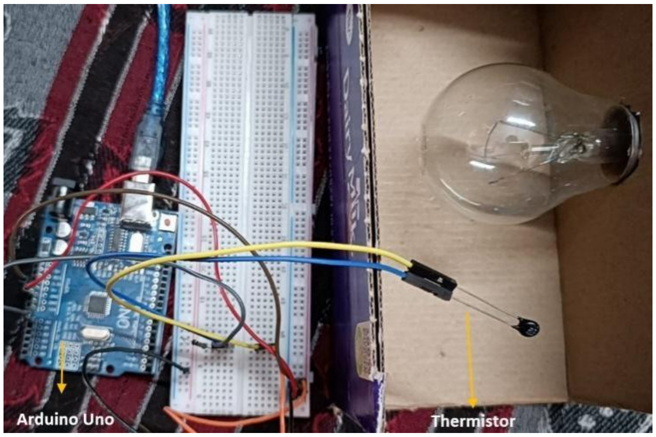

Fig .9 Thermistor setup

LM35: The component utilised the LM35 temperature sensor in this configuration. The immediate temperature is represented by the analogue signal that the LM35 heat sensor generates. It is simple to modify the output voltage to give a temperature measurement in Celsius. The lm35 has the benefit of not requiring external measurement over the thermistor. Additionally, the covering prevents overheating. Direct Celsius (centigrade), linear + 10-mV/°C scale feature, 0.5 °C precision (25 °C), fully-rated -55 °C to 150 °C broad, appropriate for distant applications, and operating from -4 to 30 V As long as the channel current is less than 60-A, the air is stable, the temperature is less than 0.08 C, the output is modest, and there is only a 1-mA load, nothing is unstable. 1 0.1. The LM35 has a temperature range of 55 to 150 degrees centigrade. The accuracy level is very high when operating at optimal temperature and humidity levels. Converting the output voltage to centigrade is also easy. It consumes about 60 microamperes of current.

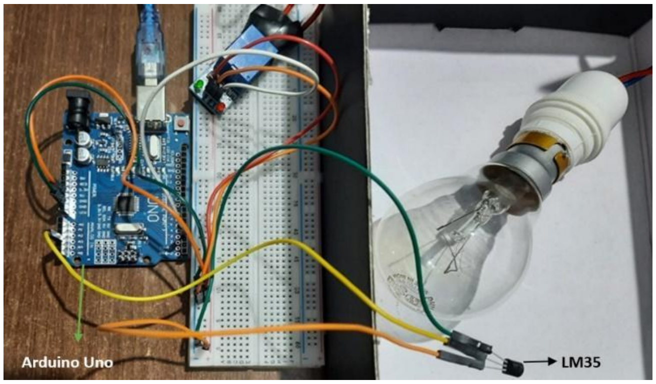

Fig. 10 LM35 setup

The suggested DPEDETS technique is examined in this section utilizing system-provided temperature sensor data. While monitoring the campaign period, the high-temperature sensor showed strong behavior and did not produce erroneous data for a long time. However, the sensor generated some erroneous data during the laboratory test. Therefore, as we explore the DPEDETS approach, the inclusion of confusing data based on laboratory data in a timeline series found during a field test. We now consider a detailed experimental analysis for four temperature systems.

5. Experimental result analysis

A predictive data frame that has been created can be transformed into a CSV file. With the aid of projected figures, we can determine what kind of inaccuracy took place. The red line in the following picture represents expected data, whereas the blue line represents sensory data. In Fig. 6.1 the first graph is a thermistor sensor data graph. We compare two data sets; suddenly there is a big difference between the two readings, which is why we conclude that there is a sensory error.

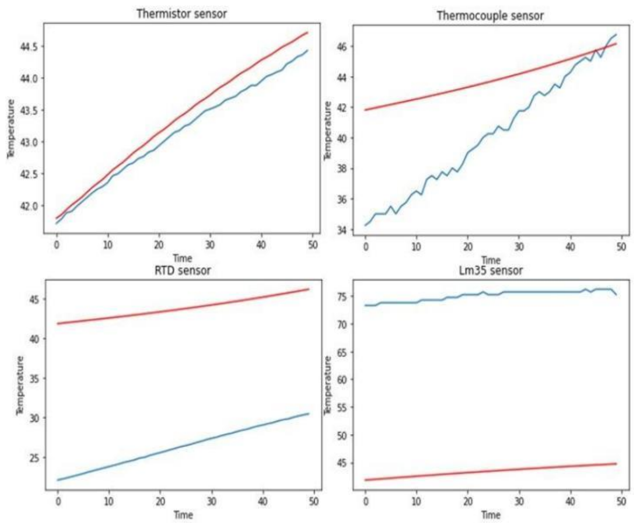

Fig. 11 Faulty sensor responses

We compared two sets of data, there was a lot of difference between the two readings and the difference was even bigger, so we concluded that there was a sensor error. The third graph shown is the graphical database of the RTD PT100 sensor. We compared two data sets, and there is a lot of variation between the two curves, and the difference is also huge, which is why we conclude that there is a sensory error. The fourth graph is the graphical data graph of the LM35 shown. We compared two data sets, and there is a lot of variation between the two curves, and the difference is also huge, which is why we conclude that there is a sensory error.

6. Conclusion

This paper introduces a method called DPEDETS, which detects premature neurological failure based on real-time exposure. Data were taken from industrial temperature sensors. The DPEDETS method uses the ARIMA model to evaluate sensory data to understand temporal adaptive capabilities. This assessment method is employed as a framework to offer an additional indicator of body sensitivity. Used as a reference to the DPEDETS method for misinterpreting expected data from the ARIMA model, early detection of sensory failure, and data retention. The DPEDETS method involves both predictive and diagnostic methods. In case of confusion, the algorithm separates the false data and finds the data number and related estimates. In addition, in the case of persistent error data, detection can be a very quick sensory failure and requested data retention process to provide predictable measures. Experimental tests indicate that the DPEDETS method can be used in industrial temperature monitoring systems with high accuracy and efficiency.

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