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Wireless Monitoring and Predictive System for Thermocouples with Real Time Cold Junction Compensation and Wireless Sensor Networks

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ABSTRACT: In this paper, we would like to implement a system for the remote sensing of very high temperatures using thermocouples. Remote sensing of high temperatures has been a topic of interest for research and industry for a number of years. However, currently realized systems are not able to perform real-time cold junction temperature compensation in real time which can lead to errors in the calculated temperature data. Further, each thermocouple requires its own unique driver. The system we have proposed, is meant to be modular for use with any type and number of thermocouples. It is able to monitor the thermocouple output, as well as use predictive filtering to predict error free temperature values in real time. The cold junction temperature-voltage characteristic graphs of the various thermocouples have been plotted as well.

Keywords: Wireless sensor networks, thermocouples, cold junction compensation, wireless sensor networks, predictive filtering, Kalman filter.

I. INTRODUCTION

Remote sensing of ambient parameters is now possible using wireless sensor networks (WSN) [1, 24]. WSN offers several advantages over their wired counterparts as WSN can be easily reconfigured and offer flexibility which is not possible with wired systems [2].Thermocouples are special temperature sensors that use the Seebeck effect to measure temperature upto +1200 degrees Celsius while other temperature sensors such as LM 35,can only measure upto +150 degrees Celsius. Thermocouples often require peripheral hardware to interface with digital systems. However, these peripheral devices are often unable to perform cold junction temperature compensation and thus impacting the accuracy of the measurement of the thermocouple. A major problem with thermocouples is that each type of thermocouple requires its unique hardware driver which converts voltage into digital temperature. For a truly scalable system, it is imperative that this hardware dependence be removed.

In this paper, we would like to propose a system that can monitor as well predict the cold junction compensated temperature output of the thermocouple utilizing predictive filtering algorithms such as the extended Kalman Filter. Our proposed system does not require any peripheral hardware to let the thermocouple interface with the WSN. Unlike the peripheral hardware our system is hardware independent and able to interface with any type of thermocouple. This reduces the overall cost of deploying the system for large scale use. The body of the paper is as follows:

Historical background is provided in section II. The related work is discussed in section III. Section IV is about system layout. Section V, VI, VII provides a basic overview of predictive filtering, Kalman filters and K-type thermocouple compensation respectively. Desktop application and WSN Process flow is discussed in Section VIII. Results and Conclusions are discussed in Sections IX and X respectively. Section XI deals with the future scope of this system.

II. BACKGROUND

Thermocouples have been extensively used in manufacturing processes and power generation systems. They cover a niche which other temperature sensors cannot cover. Thermocouples are used in industrial ovens, in forges, in boilers, in pipelines to name a few areas of application [3,10, 13].

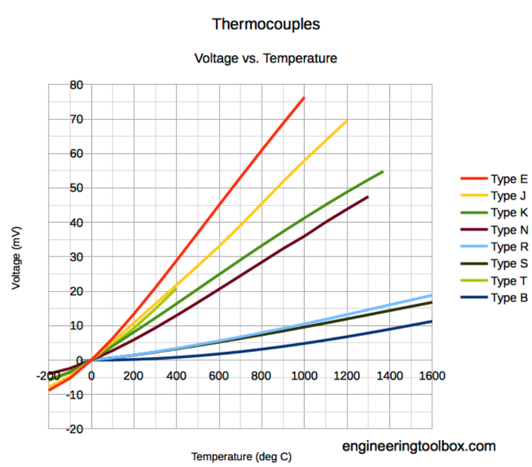
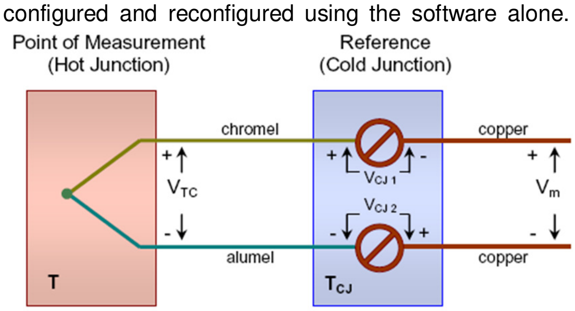


Fig. 1. Comparison of Voltage-temperature characteristics of various thermocouples. This image shows the various Voltage-Temperature graphs for the various types of Thermocouples, namely Type E, J, K, N, R, S, T & B. Depending on the area of application and proposed operation range, the thermocouple that is “best fit” may be chosen. (Source: https://www.engineeringtoolbox.com/docs/documents/496/thermocouples.png).

Due to the critical nature of these systems, it is imperative that the data measured by the thermocouples be correct. The slightest inaccuracies can lead to critical failures and system shutdowns. An emergency shutdown can be very expensive to the organization depending on the size and nature of the industry [6, 14]. The result can be catastrophic and may even lead of great material losses as well as loss of human life. Thermocouples are analog sensors which produce their own output voltage. This voltage needs to be converted to a digital value before it can be used by modern day digital control systems. Most thermocouples are provided with interfacing hardware to connect them to these digital systems. Structurally, the thermocouple maybe divided into 2 parts – the hot junction and the cold junction. The 'hot junction' is the end of the thermocouple that is in contact with the environment or entity whose temperature is to be measured, whereas the cold junction is the end where the wires for sensing the analog output are connected. The temperature to voltage equation of a thermocouple requires the temperature of both of these junctions to accurately compute the thermocouple temperature. The cold junction temperature can only be detected by external sensors. Systems often have inherent errors in them. These inherent system errors are classified as random errors and cannot be detected or rectified using standard methods of error detection and prediction. For this reason, special predictive filters are used to detect the errors in monitoring systems and predict the true value.

To make a "Plug and Play" system, it is necessary that we remove any hardware dependencies in our system. Modern day control systems are required to be scalable, flexible and modular. Removing hardware dependencies makes it cheaper to deploy the system and removes the need to keep spares. The system may be directly configured and reconfigured using the software alone.



$$V_m = V_{TC} - (V_{CJ\,1} + V_{CJ\,2}) = V_{TC} - V_{CJ}$$

Fig. 2. Structural diagram of a thermocouple showing the hot and cold junctions of the thermocouple. T is the hot junction temperature, T_{CJ} is the cold junction temperature. In the equation V_M is the measured voltage, V_{TC} is the thermocouple voltage, V_{CJ1}, V_{CJ2} are the cold junction voltages and V_M is the total measured voltage.

Sections V and VI explains how predictive filtering is done to find the error free output for the system, and which predictive filter is used for the process. Section VII explains how the system is able to carry out cold junction temperature compensation in real-time to get the correct reading from the system.

III. RELATED WORK

In the paper titled "A Wireless Portable High Temperature Data Monitor for Tunnel Ovens", Ricardo Mayo Bayon *et al,* [16] have discussed a wireless sensor network built specially for monitoring high temperatures inside tunnel ovens. Their proposed design consists of "eBiscuits" that are able to measure temperature data from various locations inside the oven. Also in the paper titled, "High Temperature Wireless Sensor Network Monitoring System for Coalmine Fire", by Margaret Richardson Ansah *et al* [15], they have discussed a wireless sensor network consisting of the JN5139 microcontroller and the MAX 31855 (IC to convert K-type thermocouple temperature to digital output) and a K-type thermocouple. The problems associated with using IC solutions for data conversions have been discussed in section VII.

IV. SYSTEM LAYOUT, SCHEMATIC & CONFIGURATION

The process of generating wireless sensor networks is completed in two steps, a hardware part and a software part. In the first part, the nodes of the wireless sensor network communicate with each other wirelessly, to establish a wireless sensor network. This communication allows the nodes known as routers to send sensor information back to the controller node.

The controller node is connected to the PC via a SPI port on the Xbee USB explorer. The second part of the wireless sensor network is realized through the use of the Java software application. The Java software application makes use of the Xbee Java API. The Xbee Java API is a set of tools and methods which allow a Java desktop application to interface with all the nodes on a Xbee wireless sensor network.

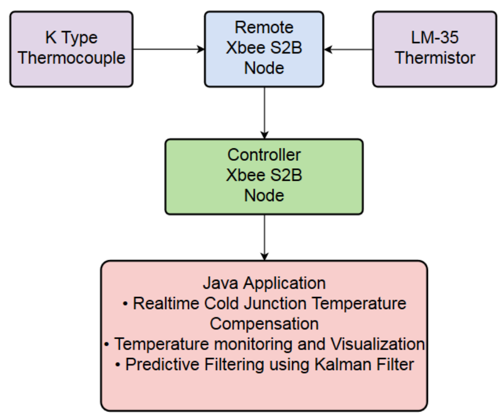


Fig. 3. Flowchart explaining the structure of the proposed "Wireless Monitoring and Predictive System for Thermocouples with Real Time Cold Junction Compensation and Wireless Sensor Networks" (Flowchart created using:https://online.visual-paradigm.com/diagrams.jsp#diagram:proj=0&type=Flowchart)

The desktop application is able to collect the sensor data from any node on the wireless sensor network, as well as reconfigure them. The data from the thermocouple attached to the wireless nodes is read in real-time. The desktop application is able to perform predictive filtering on the data. The desktop application can also visualize the data and store it on disk for further analysis.

V. PREDICTIVE FILTERING

Predictive filters are tools that are used to carry out state prediction and parameter estimation. They make use of the Bayesian rule of conditional probability to predict the behavior of a system having some inherent error [17]. They belong to a group of estimation techniques. They combine the uncertain prediction from the system's dynamics and error in observation [18]. There are a number of predictive filters, such as the Kalman Filter, the extended Kalman Filter, the particle Filter, and the unscented Kalman Filter.

Mathematical models are often used to describe physical systems and real objects. The state vector of a model is a set of parameters used to describe real world objects [19]. The indirect measurements which are used to measure the parameters of a system are known as observations. The observations might not always be accurate.

The predictive filters are used to estimate and predict the optimal state of a system. They use models to change the values of the parameters and uncertainties. They then combine the estimates and the measured values to calculate the optimal state.

The Kalman Filter is the simplest predictive filter. It represents the errors as Gaussian random variables, in the form of a mean and covariance matrix. It models the linear dynamics and observations. It should be noted that the Kalman Filter can only be used for linear systems. For non-linear systems, extended and scented Kalman filters need to be used.

VI. KALMAN FILTER

Kalman filters are a special class of predictive filters, which are often referred to as estimators. Kalman filter is known as an optimal estimator. An estimator is an algorithm that can predict or estimate the correct value of the output, input or any other parameter of a system based on observations which are known to have a certain degree of error associated with them.

The Kalman filter is a recursive filter. It is able to 'filter' noise from the observed data to estimate the correct state of the system's parameters based on past observations [20]. It should be noted that the Kalman filter is a linear estimator and can be used to filter 'Gaussian' or linear noise – i.e. noise that is defined throughout the range of the system's parameters.

The Kalman filters have been used in the navigation systems and gyroscopes of space satellites and ballistic missiles, in RADARs for target tracking, for pose (position and orientation) measurement in SLAM, and other modes of localization mapping used in robots [21].

The advantages of using Kalman filters include widespread use which make it easy to apply, it is easy to understand and deploy as per the user's requirements and the fact that it is able to perform real time estimation of the system's parameters. Kalman filters can be applied to discrete dynamic systems which contain some inherent noise / error components. We require information about the state of the system. This information allows us to predict the future and the past outputs of the systems, without the error components. To better understand how predictive filtering works, the predictive filtering algorithm is briefly explained as follows:

State equation:

$x\ (k+1) = F\ (k).x(k) + G(k).u(k) + v\ (k)$

$where\ k = 0,1,2\ \ldots.$

where x (k) is the state vector, u (k) is the known input vector, v(k) is (unknown) zero mean white *process* error components with covariance

$E\left[v(k).v(k)'\right] = Q(k)$

Measurement Equation:

$z(k) = F(k).x(k) + w(k)\ \ where\ k = 0,1,2$

w(k) is unknown error components

$E\left[w(k)w(k)'\right] = R(k)$

Kalman Filter Equations are given as follows

$Initialization: \hat{x}_m(0) = x_0, P_m(0) = P_0$

$Step\ 1(S1): Prior\ update\ /\ Prediction\ step$

$\hat{x}_p(k) = A(k-1)\hat{x}_m(k-1) + u(k-1)$

$P_p(k) = A(k-1)P_m(k-1)A^T(k-1) + Q(k-1)$

$Step\ 2(S2): A\ posteriori\ update$

$/\ Measurement\ update\ step$

$Results\ from\ above, re-introducing\ time\ index\ k$:

$P_m(k) = ({P_p}^{-1}(k) + H^T(k)R^{-1}(k)H(k))^{-1}$

$\hat{x}_m(k) = \hat{x}_p(k) + P_m(k)H^T(k)R^{-1}(k)(\bar{z}(k) - H(k)\hat{x}_p(k))$

(https://www.ethz.ch/content/dam/ethz/special-interest/mavt/dynamic-systems-n-control/idsc-dam/Lectures/Recursive-Estimation/Lecture%20Notes/lecture07.pdf)

For non-linear estimations, the extended Kalman filter and the unscented Kalman filters may be used.

VII. THERMOCOUPLE COMPENSATION

Thermocouples are special temperature measuring devices which can measure temperatures up to +1200 degrees Celsius. This makes them different from other temperature sensors such as thermistors and RTDs which cannot measure beyond +120 degrees Celsius.

The thermocouple requires two inputs to measure temperature instead of one, which is the case for a majority of temperature sensors. The two inputs for the thermocouple are: the voltage (usually in milli-volts) at the hot junction (which is contact with the surface whose temperature is to be measured) and the temperature at the cold junction [9, 23].

Most integrated circuit solutions which offer a means to convert the micro-voltage measured at the hot junction of the thermocouple into a digital value, do not have any means for measuring and / or calibrating the cold junction temperature. This leads to incorrect measurement of the cold junction temperature, as well as incorrect measurement of the temperature.

We have incorporated a LM-35 thermistor to measure the cold junction temperature of the thermocouple in real time. This lets us calibrate and measure the cold junction temperature, as it changes over the operation of the system. This leads to more accurate measurements when compared to off-the-shelf IC solutions which are used to convert thermocouple voltages. For measuring the cold junction temperature V_{cj} from the voltage, we use the following formula [22]:

$$v_{cj} = v_0 + \frac{(T_{CJ} - T_0)(p_1 + (T_{CJ} - T_0)\left(p_2 + (T_{CJ} - T_0)\left(p_3 + p_4(T_{CJ} - T_0)\right)\right))}{1 + (T_{CJ} - T_0)(q_1 + q_2(T_{CJ} - T_0))}$$

Rational polynomial calibration equation for converting type K thermocouple cold junction temperature to thermocouple voltage where T_{CJ} is the cold junction temperature, V_{CJ} is the computed cold junction voltage, and the T_0, V_0, p_i and q_i are coefficients.

The American NIST institute has released a list of coefficients in the above equation for the various thermocouples to perform cold junction compensation.

Table 1: Table of coefficients to calculate the cold junction compensated voltage. All temperatures are in degrees. The data was taken from the National Institute of Standards and Technology (NIST) (website: http://srdata.nist.gov/its90/main/).

Attribute	Type-B	Type-E	Type-J	Type-K
T_{min}	0	-20	-20	-20
T_{max}	70	70	70	70
T0	42.0	2.5000000 E+01	2.5000000 E+01	2.5000000 E+01
V0	3.3933898 E-04	1.4950582 E+00	1.2773432 E+00	1.0003453 E+00
P1	2.1196684 E-04	6.0958443 E-02	5.1744084 E-02	4.0514854 E-02
P2	3.3801250 E-06	- 2.735789 E-04	- 5.413863 E-05	- 3.8789638 E-05
P3	- 1.479329 E-07	- 1.913016 E-05	- 2.289579 E-06	- 2.8608478 E-06
P4	- 3.357144 E-09	- 1.394880 E-08	- 7.794713 E-10	- 9.5367041 E-10
Q1	- 1.092040 E-02	- 5.238278 E-03	- 1.517334 E-03	- 1.3948675 E-03
Q2	- 4.978292 E-04	- 3.097018 E-04	- 4.231451 E-05	- 6.7976627 E-05
Attribute	Type-N	Type-R	Type-S	Type-T
T_{min}	-20	-20	-20	-20
T_{max}	70	70	70	70
T0	7.0000000 E+00	2.5000000 E+01	2.5000000 E+01	2.5000000 E+01
V0	1.8210024 E-01	1.4067016 E-01	1.4269163 E-01	9.9198279 E-01
P1	2.6228256 E-02	5.9330356 E-03	5.9829057 E-03	4.0716564 E-02
P2	- 1.54839E-04	2.7736904 E-05	4.5292259 E-06	7.1170297 E-04
P3	2.1366031 E-06	- 1.081964 E-06	- 1.338028 E-06	6.8782631 E-07
P4	9.2047105 E-10	- 2.309834 E-09	- 2.374257 E-09	4.3295061 E-11
Q1	- 6.407032 E-03	2.6146871 E-03	- 1.065044 E-03	1.6458102 E-02
Q2	8.2161781 E-05	- 1.862147 E-04	- 2.204242 E-04	0.0000000 E+00

VIII. DESKTOP APPLICATION ANDWIRELESS SENSOR NETWORK (WSN) PROCESSFLOW

The wireless sensor networks generated through Xbee radio modules have a lot of flexibility in terms of deployment. [4, 7] They can be used to generate auto-discovering, self-healing networks. They are able to auto-discover remote Xbee modules [8]. They can auto configure and connect to these modules, without requiring any input from the user [5]. In case of an Xbee module malfunctioning, the network is able to function without it. Networks with diverse Xbee radio modules can also be synthesized, and they possess the ability to transmit and receive data from any Xbee radio module connected to the network [11].

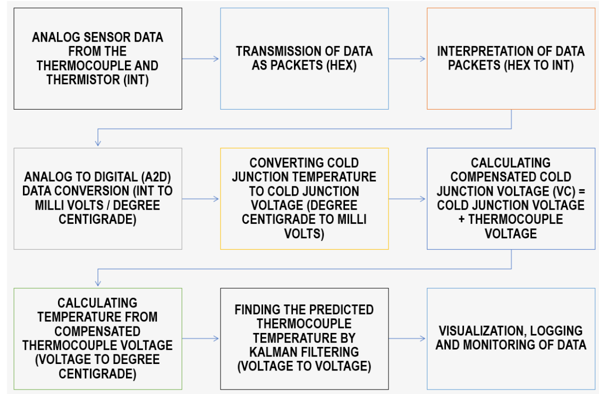


Fig. 4. Flowchart explaining the algorithm for the Wireless Monitoring and Predictive System for Thermocouples with Real Time Cold Junction Compensation and Wireless Sensor Networks.

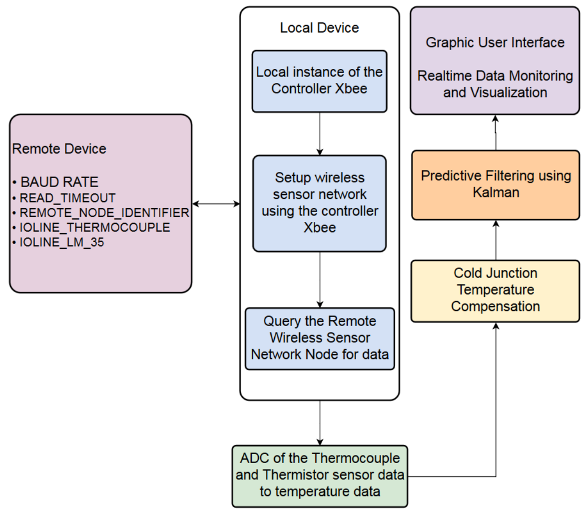


Fig. 5. Flowchart explaining the structure of the Java software for the wireless monitoring and Predictive System for Thermocouples with Real Time Cold Junction Compensation and Wireless Sensor Networks (Flowchart created using :https://online.visual-paradigm.com/diagrams.jsp#diagram:proj=0&type=Flowchart)

The software starts by creating a local instance of the controller Bee by specifying the COM port and BAUD rate. The remote device / router Xbee is instantiated and then the controller Xbee searches for the remote Xbee using its unique name. The remote device is configured using the software. The BAUD rate, the read time out and the digital general purpose input-output (DGIO) pin configuration is completed. The remote node then starts transmitting data to the controller. The data is then transmitted to the software application. Consequently, the software carries out analog to digital conversion of the data to get the hot junction thermocouple voltage and cold junction temperature. The cold junction temperature is converted to the cold junction voltage. It is then added to the thermocouple voltage to get the cold junction compensation voltage. Then the cold junction compensated voltage is converted into the temperature.

The Kalman filter is then applied on the temperature to get the predicted temperature. The data is then displayed on the graphic user interface for monitoring, visualization and logging of the data.

IX. RESULT

a.) Generation of the wireless sensor networks (WSN)
The wireless sensor network was successfully established using the desktop application and data transmission established. This is also evident from the status LEDs on the wireless sensor network.

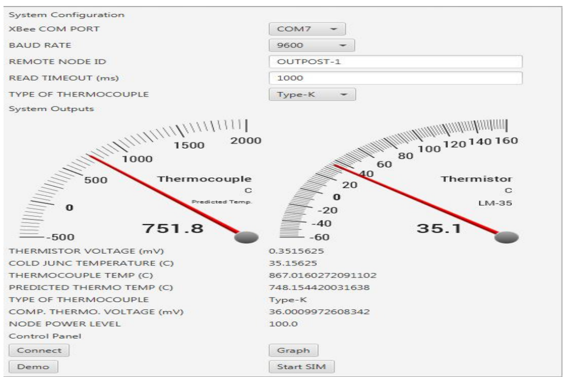


Fig. 6. Screenshot from the desktop software while the system is operational, transmitting, processing and visualizing data in real time.

b.) Capturing and processing of real-time data from the WSN
The desktop application is able to capture the thermocouple voltage and cold junction temperature. It then performs analog to digital conversion (ADC) to convert the step input into the required units.

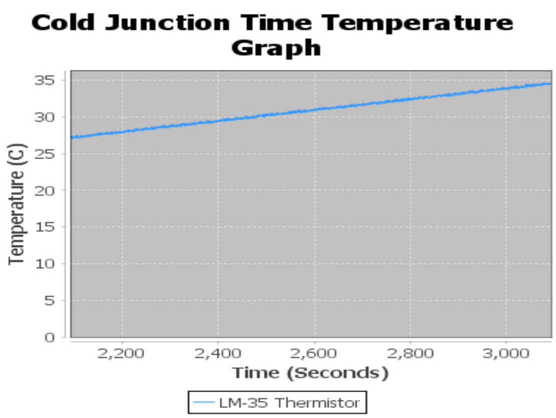


Fig. 7. Time-temperature graph showing the thermistor temperature measured from a remote node over time.

c.) Real-time Cold-Junction Compensation
The system is able to perform real-time cold junction compensation. It converts the cold junction temperature into the corresponding voltage. This voltage is then added to the thermocouple voltage to get the cold junction compensated voltage.

d.) Temperature voltage characteristics of all types of thermocouples
Based on the data from the National Institute of Standards and Technology (NIST), we are able to plot the cold junction temperature to voltage characteristic curves of the E, J, K, N, R, S, T and B type of thermocouples. In our research, we were unable to find these characteristic graphs cited in any other technical documentation or literature.

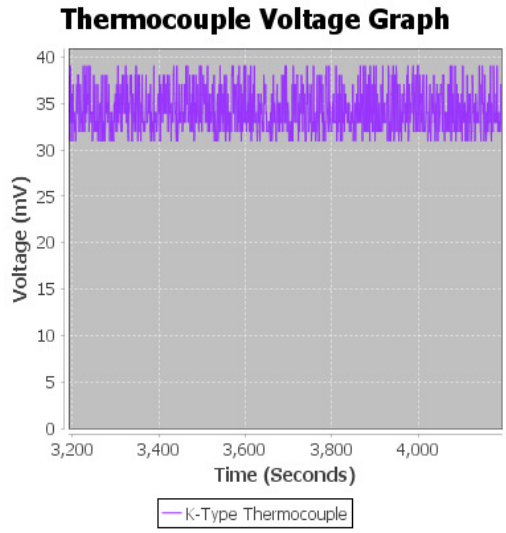


Fig. 8. This time-voltage graph shows the thermocouple voltage measured from the same remote node over time.

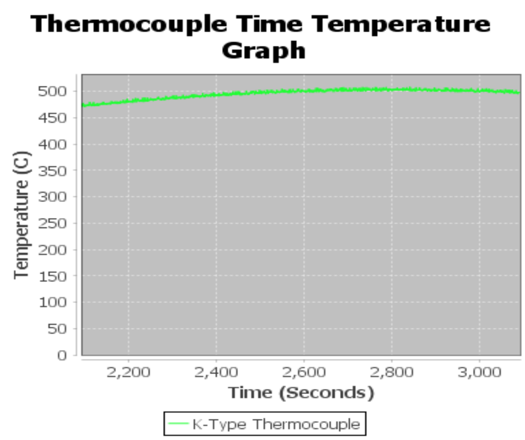


Fig. 9. This time-temperature graph shows the variation of temperature of the thermocouple, calculated from the cold junction compensated thermocouple voltage, over time.

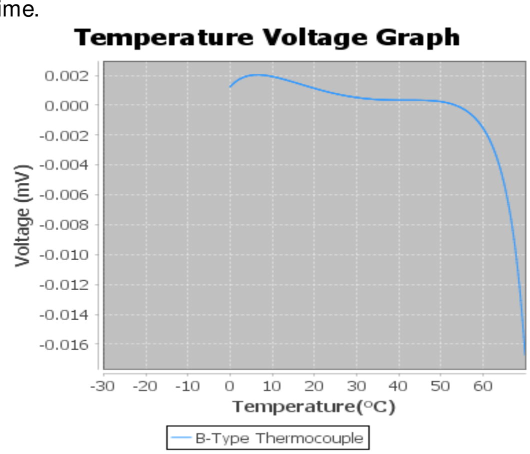


Fig. 10. Temperature-voltage graph of B-type thermocouple (plotted using our desktop application).

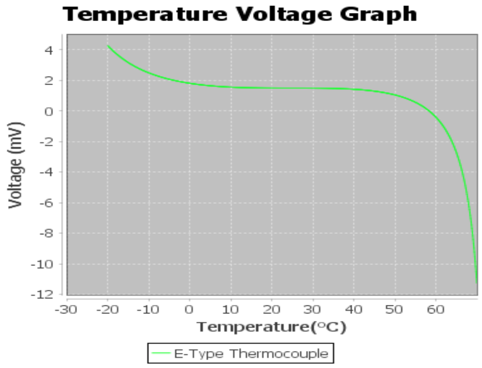


Fig. 11. Temperature-voltage graph of E-type thermocouple (plotted using our desktop application).

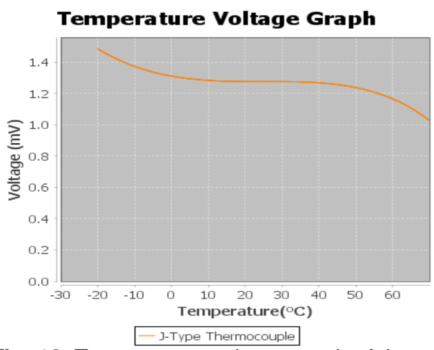


Fig. 12. Temperature-voltage graph of J-type thermocouple (plotted using our desktop application).

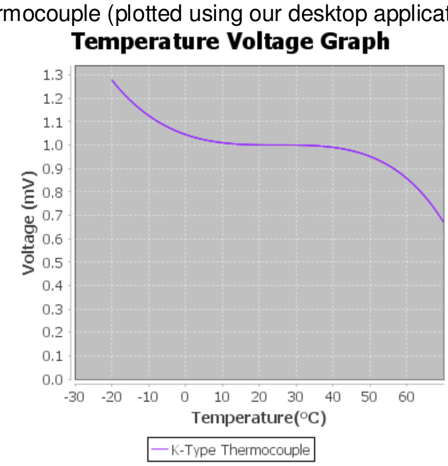


Fig. 13. Temperature-voltage graph of K-type thermocouple (plotted using our desktop application).

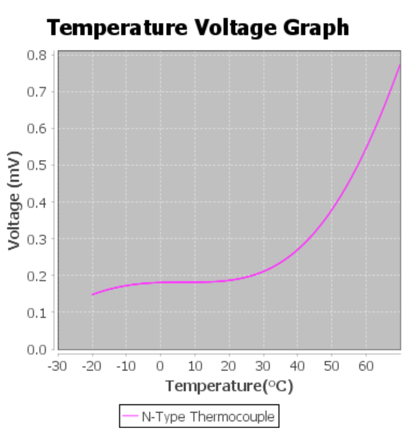


Fig. 14. Temperature-voltage graph of N-type thermocouple (plotted using our desktop application).

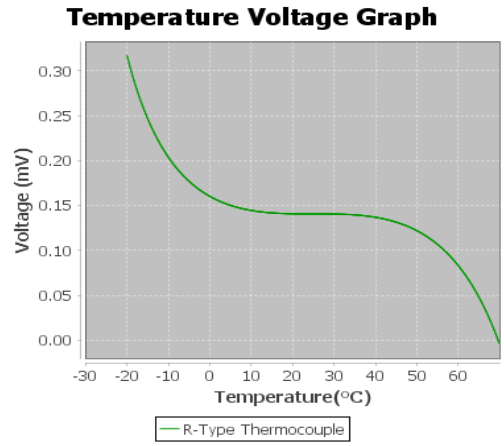


Fig. 15. Temperature-voltage graph of R-type thermocouple (plotted using our desktop application).

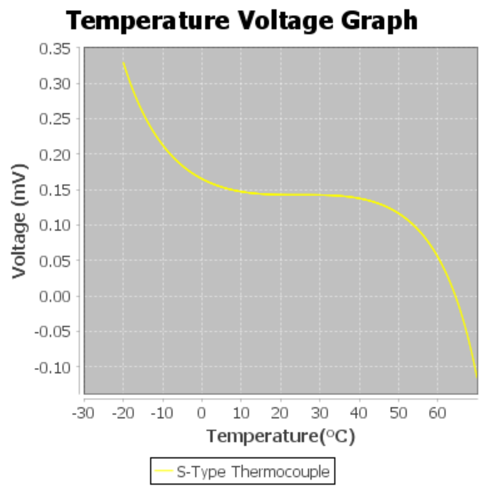


Fig. 16. Temperature-voltage graph of S-type thermocouple (plotted using our desktop application).

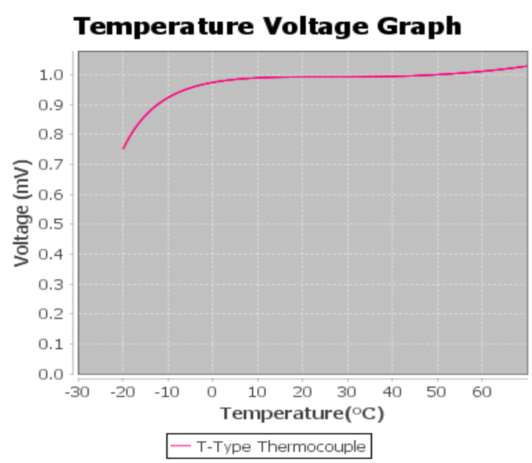


Fig. 17. Temperature-voltage graph of T-type thermocouple (plotted using our desktop application).

e.) Real-time predictive filtering using Kalman Filters
The cold junction compensated voltage was converted into the thermocouple temperature. The thermocouple temperature was then filtered to get the predicted temperature.

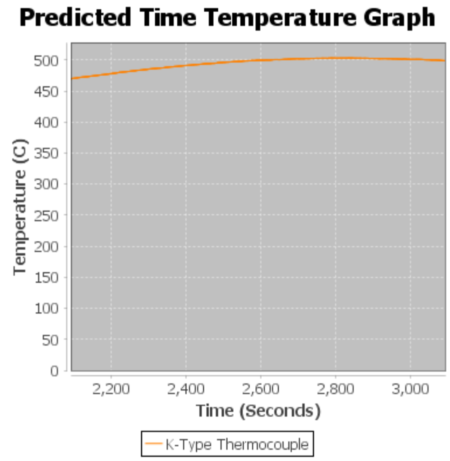


Fig. 18. This graph shows the predicted cold junction compensated temperature of the K-type thermocouple. All of these graphs have been generated in real time in the desktop application.

f.) Comparison of the predicted and observed data

It can be seen that in the following graph that the predicted thermocouple voltage-temperature graph is a lot smoother than the former. It has a lot less noise, thus demonstrating the need for predictive filtering.

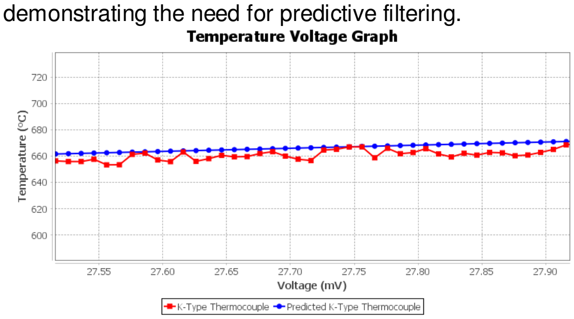
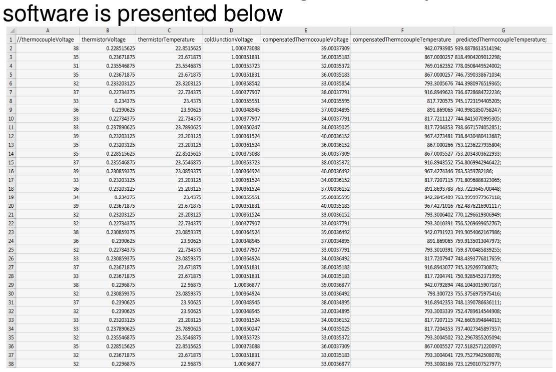


Fig. 19. Voltage-temperature graphs for unfiltered/unpredicted and predicted K-type thermocouple.

g.) Logging of the data in a comma separated value (CSV) file.

The data from the wireless sensor network was automatically logged to a CSV file for further analysis. A screenshot of the CSV file generated by the desktop software is presented below



	A	B	C	D	E	F	G
1	//thermocoupleVoltage	thermistorVoltage	thermistorTemperature	coldJunctionVoltage	compensatedThermocoupleVoltage	compensatedThermocoupleTemperature	predictedThermocoupleTemperature;
2	38	0.228515625	22.8515625	1.000373088	39.00037309	942.0793985	939.6878613514194;
3	35	0.23671875	23.671875	1.000351831	36.00035183	867.0000257	818.4904209012298;
4	31	0.235546875	23.5546875	1.000353723	32.00035372	769.0162352	778.0508449524002;
5	35	0.23671875	23.671875	1.000351831	36.00035183	867.0000257	746.7390338671034;
6	32	0.233203125	23.3203125	1.000358542	33.00035854	793.3005676	744.3980976519365;
7	37	0.22734375	22.734375	1.000377907	38.00037791	916.8949623	736.6728684722236;
8	33	0.234375	23.4375	1.000355951	34.00035595	817.720575	745.1723194405205;
9	36	0.2390625	23.90625	1.000348945	37.00034895	891.869065	740.9981850758247;
10	33	0.22734375	22.734375	1.000377907	34.00037791	817.7211127	744.8415070995305;
11	33	0.237890625	23.7890625	1.000350247	34.00035025	817.7204353	738.6671574052851;
12	39	0.23203125	23.203125	1.000361524	40.00036152	967.4273481	738.6430480413687;
13	35	0.23203125	23.203125	1.000361524	36.00036152	867.000266	753.1236227935804;
14	35	0.228515625	22.8515625	1.000373088	36.00037309	867.0005527	753.2034303622933;
15	37	0.235546875	23.5546875	1.000353723	38.00035372	916.8943552	754.8069942946422;
16	39	0.230859375	23.0859375	1.000364924	40.00036492	967.4274346	763.5359782186;
17	33	0.23203125	23.203125	1.000361524	34.00036152	817.7207115	771.8096888323065;
18	36	0.23203125	23.203125	1.000361524	37.00036152	891.8693788	763.7223645700448;
19	34	0.234375	23.4375	1.000355951	35.00035595	842.2845409	763.9999977967118;
20	39	0.23671875	23.671875	1.000351831	40.00035183	967.4271016	762.4876216901117;
21	32	0.23203125	23.203125	1.000361524	33.00036152	793.3006402	770.1296619306949;
22	32	0.22734375	22.734375	1.000377907	33.00037791	793.3010391	756.5269699652767;
23	38	0.230859375	23.0859375	1.000364924	39.00036492	942.0791923	749.9054062167986;
24	36	0.2390625	23.90625	1.000348945	37.00034895	891.869065	759.9135013047973;
25	32	0.22734375	22.734375	1.000377907	33.00037791	793.3010391	759.3700485839255;
26	33	0.230859375	23.0859375	1.000364924	34.00036492	817.7207947	748.4393776817659;
27	37	0.23671875	23.671875	1.000351831	38.00035183	916.8943077	745.329269730873;
28	33	0.23671875	23.671875	1.000351831	34.00035183	817.7204741	750.9285452371995;
29	38	0.2296875	22.96875	1.00036877	39.00036877	942.0792894	748.1043015907187;
30	32	0.230859375	23.0859375	1.000364924	33.00036492	793.300723	755.3756975975416;
31	37	0.2390625	23.90625	1.000348945	38.00034895	916.8942353	748.1390786636111;
32	32	0.2390625	23.90625	1.000348945	33.00034895	793.3003339	752.4789614544908;
33	33	0.23203125	23.203125	1.000361524	34.00036152	817.7207115	742.6605394844013;
34	33	0.237890625	23.7890625	1.000350247	34.00035025	817.7204353	737.4027345897357;
35	32	0.235546875	23.5546875	1.000353723	33.00035372	793.3004502	732.2967855205094;
36	35	0.228515625	22.8515625	1.000373088	36.00037309	867.0005527	727.5182571220097;
37	32	0.23671875	23.671875	1.000351831	33.00035183	793.3004041	729.7527942508078;
38	32	0.2296875	22.96875	1.00036877	33.00036877	793.3008166	723.1290107527977;

Fig. 20. Screenshot for the CSV (comma separated value) file, generated by the desktop application to save the system data in real time. This format is the industry standard for "Big data applications". This makes it very easy to use this data to be analysed using Big Data and data science algorithms such as map Reduce.

X. CONCLUSION

The objective of this paper was to hypothesize or create a wireless sensor network that was capable of taking very high temperature measurements using temperature sensors, such as the thermocouple. The system was to allow all types of thermocouples (Type-E, Type-J, Type-K, Type-N, Type-R, Type-S, Type-T and Type-B) in any number and configuration. This was to be achieved without the use of any interfacing / amplifier ICs as is the current trend. As most thermocouples in use today, do not provide cold junction compensation, the proposed system was to incorporate that as well. Cold junction temperature reduces errors in measurements by providing accurate temperature readings. We also wanted to plot the temperature-cold junction voltage characteristic graphs of all the thermocouples. The system was able to monitor the data from the connected thermocouples and also provide predictive analysis to remove any errors from the cold junction compensated sensor network data. Finally, we wanted to present the sensor network data as a graph, using a rich graphic user interface, and save the data to disk.

Through our research, we were able to achieve all of these objectives. In section IV and VIII, we have talked about the system workflow and underlying algorithm that allows the wireless sensor network to be set up with any configuration of thermocouples, without the use of interfacing hardware circuits. in section VII, we have talked about cold junction temperature compensation for the various types of thermocouples. In section IX, part (d), we have plotted the temperature-cold junction voltage characteristic graphs of the various types of thermocouples. During our research, we were not able to find these graphs in any online resource or book. In sections V, VI, we have talked about the need for predictive filtering and explained how one of the predictive algorithm works. Predictive filters are used in many aerospace and defense applications to provide accurate sensor information. In section IX, part (a), we have shown a screenshot from the desktop application that we wrote for this system. in part (b), (c) we are able to see the system working - measuring cold junction temperature, thermocouple voltage, performing cold junction compensation. In part (g), we have shown how the system data is saved as .csv (comma separated value) file. Finally, in part (f), we have compared filtered/unfiltered system data to help the reader better understand the need for using a predictive filtering algorithm.

The significance of our research can be summarized as follows:

1) We were able to create a modular and scalable wireless sensor network capable of interfacing with any configuration and number of thermocouples without hardware dependencies. This makes the system cheaper than the current counter-parts and makes it 'Plug-And-Play', allowing it to be reconfigured easily.

2) We were able to plot the temperature-cold junction voltage characteristics of the various types of thermocouples, to help better understand why cold junction temperature compensation is necessary.

3) We were able to implement predictive filtering algorithm in a wireless sensor network capable of measuring high temperatures. We have graphically compared unfiltered and Kalman filtered data of better understand their requirement and performance.

We were able to find a number of limitations in the proposed system as well. The first limitation is that the process of calculating the Kalman filter coefficients for the various batches, models and manufacturers of thermocouples can be a long, tedious and time consuming process. The quality of the data collected also influences the performance of the Kalman filter. Tuning the filter for optimal performance has to be done carefully. Another limitation of the system is that Xbee has only released the API and API documentation for Java. Even though Java is a platform independent programming language and the program can be run on any platform/OS, we cannot create a similar system using C, C++ or Python for example.

Through our research, we have successfully synthesised a new paradigm for implementing wireless sensor networks capable of performing high temperature measurements. The proposed paradigm is radically different from the one in use in the industry or scientific equipment, laboratories or institutions. We have talked about the shortcomings of the old paradigm, while explaining how our paradigm not only overcomes these, but also provides its unique features which have never been implemented in such temperature measurement systems. The proposed system is also cheaper and easier to implement and reconfigure because of its hardware independence. As accurate temperature measurement is the basis of controlling a number of processes, we believe that adopting this system can be of great use to the field of manufacturing and scientific research.

XI. FUTURE SCOPE

In this section, the future scope and associated topics of research are discussed.

The predictive filtering algorithm can be optimized further to increase overall speed and performance of the system. Algorithms such as extended Kalman and scented Kalman filters can be used if required.

The data gathered by the system can be used for probabilistic and stochastic analysis to study trends. This data can be used for machine learning and data analysis using map reduce algorithms.

A multi-node system consisting of an array of thermocouples can be created as well, depending on the application requirements. A system with multiple nodes can be created to demonstrate scalability and modularity.

As an example, a system with multiple K, B, E type of thermocouples can be made. This makes the process of data collection, processing, visualization and logging uniform. The system can also be adopted to accommodate other sensors, such as pressure and gas sensors to detect leaks, pressure changes or other failures in the workspace. The system can be extended to act as a control system with incorporated actuators.

The data from the system can be used by data scientists to optimize the associated process. The data can be presented in the form of an online dashboard. The system can we made compliant with the latest Industry 4,0 standard or integrated into the Internet of Things (IoT) framework to create connected systems.

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