IET Science, Measurement & Technology

Research Article

T–S fuzzy-based multi-LAE approach for sensor linearisation

ISSN 1751-8822
Received on 25th July 2017
Revised 17th May 2018
Accepted on 18th June 2018
E-First on 18th September 2018
doi: 10.1049/iet-smt.2018.5228
www.ietdl.org

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Abstract: Most sensors exhibit a non-linear input–output relationship. Sensor linearity is essential for the true representation of measurand in modern instrumentation systems. Although several linearisation techniques (LTs) have been proposed in recent years, they incur common problems of scalability, reliability, flexibility, complexity and cost. Hence, an effective software lineariser is needed to overcome these difficulties. This study presents a Takagi–Sugeno (T–S) fuzzy-based sensor LT using piecewise linearisation. The non-linear static relationship splits into '*N*' multiple linear algebraic equations, which are combined using T–S fuzzy logic to ensure a smooth transfer from one region to another. The linearity (mean square error) of 0.1663 is obtained for negative temperature coefficient thermistor in simulation over a temperature range of 307 to 373 K, and of 0.0255 is achieved for infrared sensor in real time over a distance range of 12–30 cm. The performance of the proposed LT is compared with popular curve fitting, a look-up table and soft computing approaches. The results show that the proposed LT outperforms other approaches regarding performance indices. This technique eliminates hardware complexity rendering better accuracy over the span of measurement.

1 Introduction

The sensor is a fundamental element of a measurement system that comes in direct contact with the measurand. Sensors possess undesirable characteristics due to which the output deviates from the ideal value, and it is known as non-linearity. The sources of non-linearity are the ageing effect, hardware constraints in the signal conditioning circuit (SCC), environmental changes in temperature, humidity and pressure. The non-linearity compensation is a real challenge for the true representation of the measurand. The linearity describes the closeness between the calibration curve and the specified straight line. It enhances the ease of interpretation in the sensor's output data [1]. The methods of linearisation include hardware, software and hybrid (hardware- and software-based approaches together) linearisation. In the literature, different techniques have been reported based on the hardware method to linearise the non-linear characteristics.

The non-linear thermistor is connected to resistors either in series or parallel combination, which linearises the different segments. It is a simple technique, suitable for a limited temperature range and sensitivity [2]. The various SCCs are devised using operational amplifier (op-amp)-based circuit configurations for thermistor linearisation. These techniques are suitable for the specified temperature range [3–5]. Later, researchers have designed linearisers to produce frequency and/or digital output directly. The frequency output is advantageous, as it can be transmitted over long cables; it provides high noise immunity and digital compatibility. The different electronic circuits such as multivibrator, sigma–delta modulator, IC-555 timer and dual slope digital converter are used to produce digital output [6–8]. The accuracy is limited in hardware method due to component tolerances, the lower flexibility of electronic circuits and hardware complexity. However, hardware complexity introduces temperature drift leading to non-linearity and lack of reliability in the circuit [9, 10].

The software-based approach is popular due to simplicity and flexibility, and it is proposed for different sensors in [11, 12]. The curve fitting techniques using interpolation, least mean square (LMS) polynomial and artificial neural network (ANN) are reported. ANN–LMS is more accurate compared with polynomial interpolation for optical displacement sensor application [13]. The software techniques for infrared (IR) sensor linearisation using low-cost microcontrollers are reported in [14]. It is concluded that look-up table (LUT)-based approach is accurate at the expense of large memory size and processing time. The conventional fuzzy logic (FL) utilises the heuristic approach to linearise the input–output relationship. However, the FL approach gives less accuracy due to the lack of expert knowledge. It can be improved using an ANN or the genetic algorithm. It is reported that the programmable gain amplifier-based algorithm has better performance as compared with other methods.

Later, researchers have attempted the hybrid approach to achieve better results. Recently, Kumar and Lakshmi Narayana [9] have proposed a hybrid approach for the thermistor by combining hardware and ANN-based technique. This work has used two-stage circuit using (NE/SE566) voltage-controlled oscillator SCC, OP07-based SCC and LM555 integrated timer circuit [9, 10] in the first stage and heuristic techniques such as ANN in the second stage. This method is accurate and suitable for the entire range of the sensor. The drawbacks of ANN-based approach are complex network architecture, large memory requirement and training–validation problem. ANN is not suitable for low-end microcontroller environment such as 8051 [5, 15].

On the basis of ample literature survey, it is concluded that the end user always prefers a simpler software approach such as a lower-order linear algebraic equation (LAE) to linearise the non-linear sensor input–output relationship. However, one algebraic equation is not sufficient to represent the entire operating range. The coefficients of the LAE changes as per the change in operating point. So, there is a need for an adaptive mechanism to compute these coefficients at each operating point. Whenever the operating point range changes, these coefficients are calculated online which leads to computational complexity. It forces to rely on the fixed adaptive mechanism to solve this problem. The multimodel approach is the most suitable technique in the process control application for developing non-linear control. This method is quite popular in the control field, due to its simplicity, flexibility in tuning linear models, and it can act as a fixed adaptive controller [16, 17]. Thus, an efficient lineariser based on multimodel approach is essential for sensor linearisation.

This research work proposes the design and development of the LT for the non-linear sensor using multi-LAE approach. The

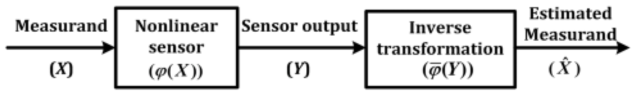

Fig. 1 *Schematic representation of inverse transformation*

simpler piecewise linearisation is used to find out the multi-LAE. These local LAEs are combined using the T–S FL to ensure a smooth transition. The contribution and organisation of this paper is as follows: the mathematical model formulation, T–S fuzzy-based multi-LAE approach implementation (block diagram and flowchart) and merits of the proposed LT are discussed in Section 2. In Section 3, the proposed LT is demonstrated via thermistor linearisation in simulation and real-time platform and the performance is compared with other popular approaches as reported in the literature. In Section 4, the experimental setup and the results regarding performance metrics with linearity and graphical analysis for microcontroller-based IR sensor linearisation are reported. The conclusion is presented in Section 5.

2 Design and development of sensor linearisation using T–S fuzzy-based multiple model approach

In this section, the mathematical model formulation, block diagram and flowchart representations are discussed. The introduced section highlights the merits of the proposed LT as compared with other approaches.

2.1 Mathematical model formulation

The non-linear sensor characteristic is represented as

$$Y = \varphi(X) \tag{1}$$

where X is the measurand, Y is the sensor output and $\varphi(.)$ is the non-linear function which relates X and Y.

In the real-time process measurement, only the sensor output (Y) is available. On the basis of the sensor output, the measurand is to be estimated as shown in Fig. 1. The estimated measurand ($\hat{X}$) is represented as

$$\hat{X} = \bar{\varphi}(Y) \tag{2}$$

The sensor linearisation is to find out the reciprocal or inverse transformation function as per (2).

The T–S fuzzy-based multi-LAE technique is proposed in this work as per (4)–(10). The entire operating range of the sensor static characteristic is divided into 'N' operating ranges by applying the piecewise linearisation technique (LT). The $\bar{\varphi}_j(Y)$ is represented as 'N' LAEs as given below:

$$\overline{\varphi}_j(Y) = a_j + b_{\,j}Y \tag{3}$$

where a_j and b_j are the LAE coefficients of every 'jth' operating region.

T–S fuzzy is described by IF–THEN rules, for one premise variable which has the following form of fuzzy rules [18].

R_j: If z is A_j then

$$\hat{X}_j = \bar{\varphi}_j(Y), \quad (j = 1, 2, 3, \ldots, P) \tag{4}$$

where 'P' is the number of rules, i.e. equal to the number of local LAE. In general, $P = N$ and A_j is the fuzzy set. z is the premise variable and w_j is the weighted value of fuzzy membership function.

The output of the T–S fuzzy model is the estimated measurand and it is represented as follows:

$$\hat{X} = \sum_{j=1}^{N} [h_j(z)]\hat{X}_j \tag{5}$$

where the membership grade $h_j(z)$ is defined as follows:

$$h_j(z) = \frac{\mu_j(z)}{\mu(z)} \tag{6}$$

$$\mu_j(z) = w_j \tag{7}$$

$$\mu(z) = \sum_{j=1}^{N} w_j \tag{8}$$

It should be noted that the grade of membership should be

$$h_j(z) \in [0, 1] \tag{9}$$

and

$$\sum_{j=1}^{N} h_j(z) = 1 \tag{10}$$

2.2 Block diagram and flowchart representation

The block diagram of the proposed LT is shown in Fig. 2. The static characteristic of the non-linear sensor is obtained from the measurand and the sensor output. Subsequently, the static characteristic is divided into local regions using the piecewise LT. The local regions are fitted with 'N' number of LAE based on the range and accuracy. The coefficients of LAEs are obtained from static characteristic using linear regression procedure. The sensor linearisation is an inverse transformation and the sensor output is selected as a scheduling variable to combine the multi-LAE.

The proponent's firmware is developed in the MATLAB editor. In real-time implementation, this algorithm is fused into Arduino integrated development environment (IDE) to perform system online. In the last stage, the T–S fuzzy-based scheduler is used to combine multi-LAE and to evaluate the performance. The type and shape of the membership function are problem dependent and the preferred membership function is triangular or trapezoidal to maintain simplicity [18, 19]. The flowchart for the implementation of the proposed LT as described above is shown in Fig. 3 to validate the performance of negative temperature coefficient (NTC) thermistor and IR sensor in the following section.

2.3 Merits of the proposed LT

The merits of the proposed LT are discussed regarding the best features of different approaches. The proposed LT has several benefits than other approaches as per the designer and end user viewpoint. It is a fixed adaptive mechanism in which defuzzification is not required. In many practical applications, finding the inverse model is challenging, time-consuming and sometimes inverse never exists [20]. In the proposed LT, multi-LAE based on the inverse transformation is designed for sensor output. The proposed LT incorporates flexible tuning of these LAEs so that the inverse model can be easily developed, tested and realised. It is a simple software approach that overcomes hardware and architecture complexity. Scalability is referred to as the ease with which the system can be sized or modified over the non-linear range. The proposed LT provides ease in the modification which overcomes the limitations of hardware-based linearisation. Reliability describes the failure free operation over the non-linear range. The salient features of the proposed LT are compared with other methods which are reported in the literature as summarised in Table 1.

3 Thermistor linearisation using T–S fuzzy-based multi-LAE approach

In this section, the systematic way of thermistor linearisation using T–S fuzzy-based multi-LAE approach is demonstrated in both simulation and real-time environment.

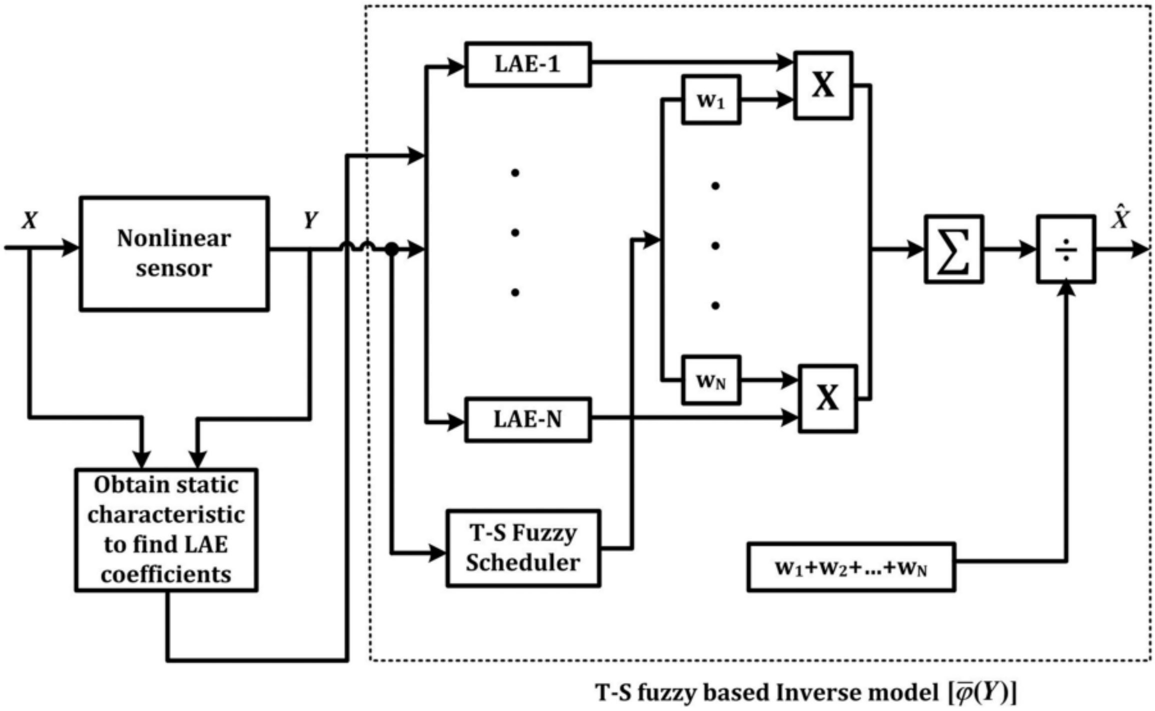

Fig. 2 *Block diagram of the proposed LT*

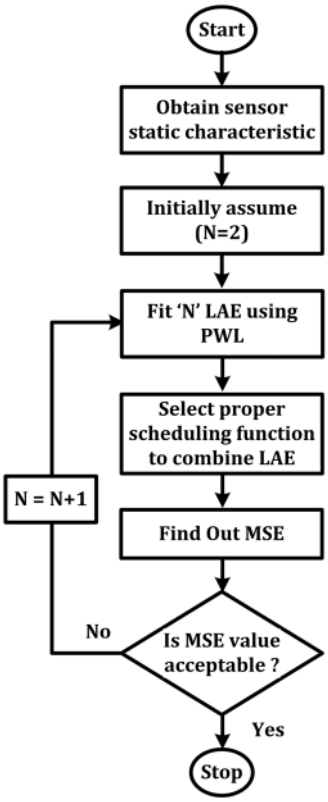

Fig. 3 *Flowchart of proposed LT*

3.1 Simulation environment

The standard NTC thermistor characteristic equation which relates temperature and resistance is given below [9]:

$$R_t = R_o \exp\left[\beta\left(\frac{1}{T_t} - \frac{1}{T_o}\right)\right] \tag{11}$$

where R_t is the thermistor resistance at input temperature (Ω), R_o is the resistance at the reference temperature (Ω), T_t is the input temperature (K), T_o is the reference temperature (K) and β is the thermistor material constant (K).

The static characteristic of the NTC thermistor is obtained by simulating the non-linear (11) and by using the value of parameters as reported in Table 2. The proper LT is required to get the linear relationship between the temperature and resistance as shown in Fig. 4.

In this work, the LT is implemented using the T–S fuzzy-based multi-LAE approach as reported in Section 2. The static characteristic is presented in Fig. 5*a*. It is evident from Fig. 5*a* that operating range (307–373 K) of NTC thermistor is highly non-linear. One LAE is not sufficient to represent the entire operating region. Mean square error (MSE) performance criterion is used for selecting the number of LAEs. Initially, the number of LAEs is assumed as two, and the corresponding MSE value is large as shown in Fig. 5*b*. It indicates that as the number of LAEs increases, MSE decreases rapidly. It is explicitly clear that, up to seven LAEs, the error decreases rapidly and when it approaches eighth LAE, the level of MSE variation is minimal. Hence the number of LAEs is selected as seven, and its corresponding coefficients are obtained using linear regression procedure as reported in Table 3. These LAEs are combined using thermistor output resistance as the scheduler. At first, these LAEs are combined using the crisp-based scheduler. It exhibits sudden bumping action during the transition from one region to another. To achieve a smooth transition, these LAEs are combined using the T–S fuzzy-based scheduler with a membership function as shown in Fig. 6*a*. The multi-LAEs are combined using T–S fuzzy-based scheduler outperforms, crisp scheduler and other approaches excluding LUT method as shown in Fig. 6*b*. The performance of both the schedulers is compared with other approaches (as reported in [14, 15]) using performance indices (as reported in the Appendix). It is inferred from Fig. 6*c* that the linear fit is not accurate due to non-linear thermistor characteristic. The polynomial fitting has improved performance concerning MSE and standard deviation (STDV). The seventh-order polynomial is used to fit the thermistor data. LUT method is highly accurate due to the replica of input and stored data sets. However, in real-time accuracy depends on many factors such as LUT size and analogue-to-digital converter (ADC) resolution. The backpropagation neural network (BPN) shows better performance in training the data set. An independent test is carried out for testing and validation and its performance deteriorates at some of the data points which affects overall accuracy. The proposed LT

Table 1 Comparative features of different LTs

Features	Hardware method [3–8]	Software method [11–14]	Hybrid method [9, 10]	Proposed LT
scalability and expandability	low due to hardware limitations	low due to hindrance nature	low due to limitations in hardware parts	high due to modularity. no need to re-estimate entire characteristics
reliability	low due to chances in the component's failure	high due to robust software operation	medium due to failure in a hardware circuit	high due to robust software operation
flexibility and ease of modification	low due to a limited operating range of components	moderate	low	high due to modularity, homogeneous and heterogeneous models can be combined
complexity and maintenance	high due to hardware components	low due to the absence of hardware components	moderate due to an integrated approach	low due to the absence of hardware components

Table 2 Parameters used for NTC thermistor

Parameter	Specified value
R_o	5000 Ω
T_o	298 K
β	4282 K

Table 3 LAE coefficients for NTC thermistor

Resistance, Ω	Temperature, K	a_j, K	b_j, K/Ω
(3281–1941)	(305.40–318.92)	338.21	–0.0100
(1941–1398)	(318.92–326.53)	346.09	–0.0140
(1398–1022)	(326.53–334.51)	356.16	–0.0212
(1022–732)	(334.51–343.59)	366.49	–0.0313
(732–552)	(343.59–351.78)	376.89	–0.0455
(552–407)	(351.78–360.58)	385.23	–0.0606
(407–278)	(360.58–371.65)	395.50	–0.0858

surmounts the linearfit, polynomial fit (polyfit), BPN and crisp-based scheduler regarding the performance metrics.

3.2 Real-time environment

The experimental setup for temperature measurement is shown in Fig. 7*a*. The standard FLUKE 9009 model dual well dry block temperature calibrator with an accuracy of ±0.2°C is used as the temperature bath. The RS components make 151221 NTC thermistor (5 kΩ) is used as a sensor for temperature measurement. FLUKE make 115 true root mean square digital multimeter is used for resistance measurement with resolution 0.001 kΩ and accuracy of 0.9% during calibration. The standard op-amp IC741-based SCC is used to convert input temperature of 307–373 K into an output voltage 3.99–0.33 V. The voltage output from the SCC is fed to the Arduino Mega ADK 2560 microcontroller as shown in Fig. 7*b*.

The static characteristic of the NTC thermistor is obtained by conducting a real-time experiment. The number of LAE models is identified as seven which results in lowest MSE as per the procedure described in Section 2 and the corresponding coefficients are reported in Table 4. These LAEs are combined using thermistor output voltage as a scheduler. The proposed T–S fuzzy-based LT is compared with the linearfit, polyfit, BPN and crisp-based scheduler in real-time environment and the experimental linearity representation is shown in Fig. 7*c*.

4 IR sensor linearisation using T–S fuzzy-based multi-LAE approach

4.1 Experimental setup

The schematic representation of the experimental environment and the experimental setup for real-time implementation of the proposed LT is shown in Figs. 8*a* and *b*. The experimental setup consists of an IR distance sensor (Sharp 2Y0A21), Arduino Mega ADK, reflector, universal serial bus connector, Arduino IDE and ruler. The IR sensor is used for the distance measurement due to a compact size and low cost. It consists of an IR emitting diode

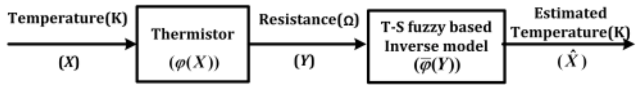

Fig. 4 *Schematic representation of thermistor linearisation*

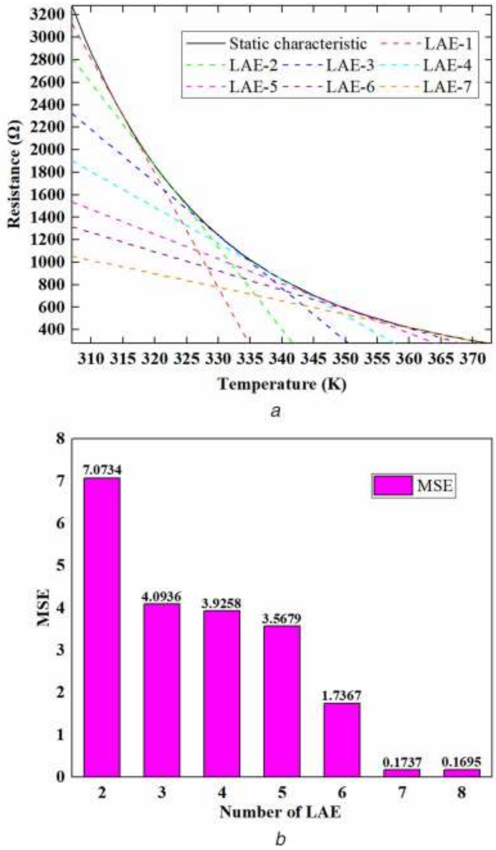

Fig. 5 *Static characteristic*
(a) Thermistor static characteristic, *(b)* MSE for the number of LAE

(IRED), position sensitive detector and signals conditioning unit. The output of IRED is the modulated beam, which hits an object, and the SCC assesses the reflected light. The object position is determined using the triangulation method. These sensors are used for different applications such as energy saving equipment in automated teller machines (ATM), vending machines and robot cleaner [21].

Arduino Mega ADK is the Arduino board based on 8 bit ATMega 2560 microcontroller. ATMega 2560 operates at a maximum frequency of 16 MHz. It is a high-performance, low-power, low-cost microcontroller with the reduced instruction set computer architecture. Successive approximation type 10 bit ADC is used in ATMega 2560 microcontroller, which has input resolution of 4.88 mV with a supplied voltage of 5 V. The digitisation error in ADC is 23.79 mV with a spread of 2.1%. The analogue input pin of the microcontroller is connected directly to the output of the IR sensor.

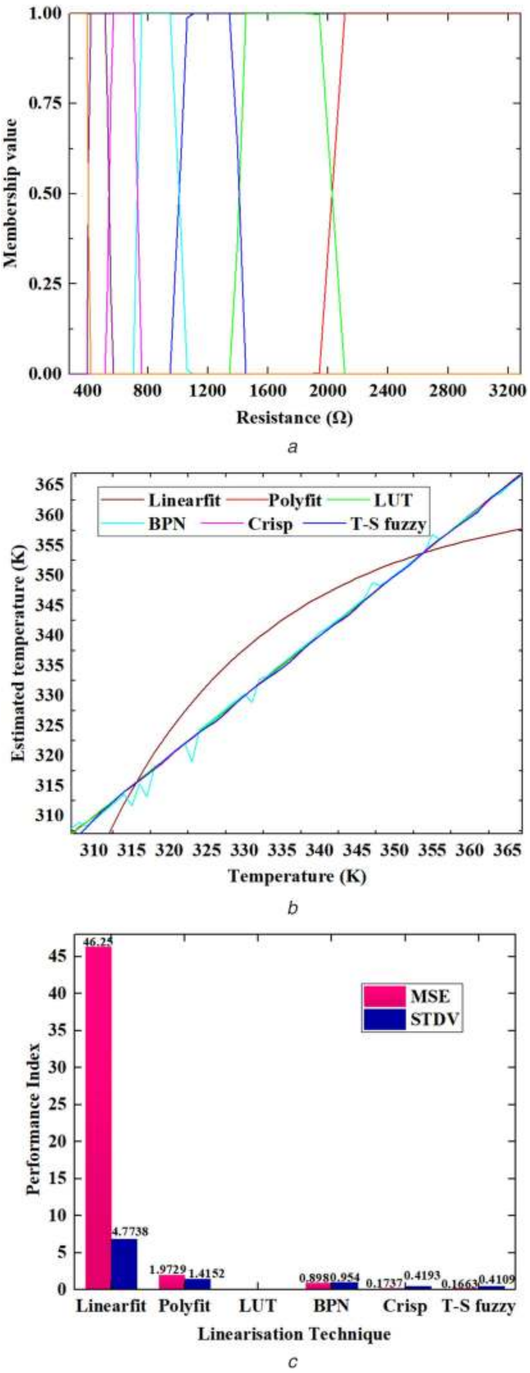

Fig. 6 *Performance comparison using different LTs for thermistor linearisation*
(a) Membership function for the thermistor, ***(b)*** Linearity analysis of applied LT, ***(c)*** Graphical error analysis of thermistor

Table 4 LAE coefficients for RS151221 NTC thermistor

Voltage, V	Temperature, K	a_j, K	b_j, K/V
(3.99–2.56)	(307–319)	40.466	–0.1191
(2.56–1.90)	(319–327)	28.83	–0.0825
(1.90 –1.41)	(327–335)	21.887	–0.0612
(1.41–1.01)	(335–344)	16.253	–0.0444
(1.01–0.76)	(344–352)	11.727	–0.0312
(0.76–0.55)	(352–361)	8.9537	–0.0233
(0.55–0.33)	(361–373)	7.1495	–0.0183

To reflect the true industrial environment, the measurement noise is introduced from thermal and electromagnetic sources, which are present in the vicinity of the experimental setup. In addition to the reasons cited, the noises occur due to unknown factors present in the environment. In the real-time experiment, Arduino is interfaced with LabVIEW, and it is observed that the output voltage changes randomly due to the presence of noise with a sampling of 0.1 s. Random voltage data values are considered for every calibration point using the averaging method for noise analysis [22]. The spread of each measurand data point is estimated and it is observed that STDV which varies from 2.3 to 6.4%.

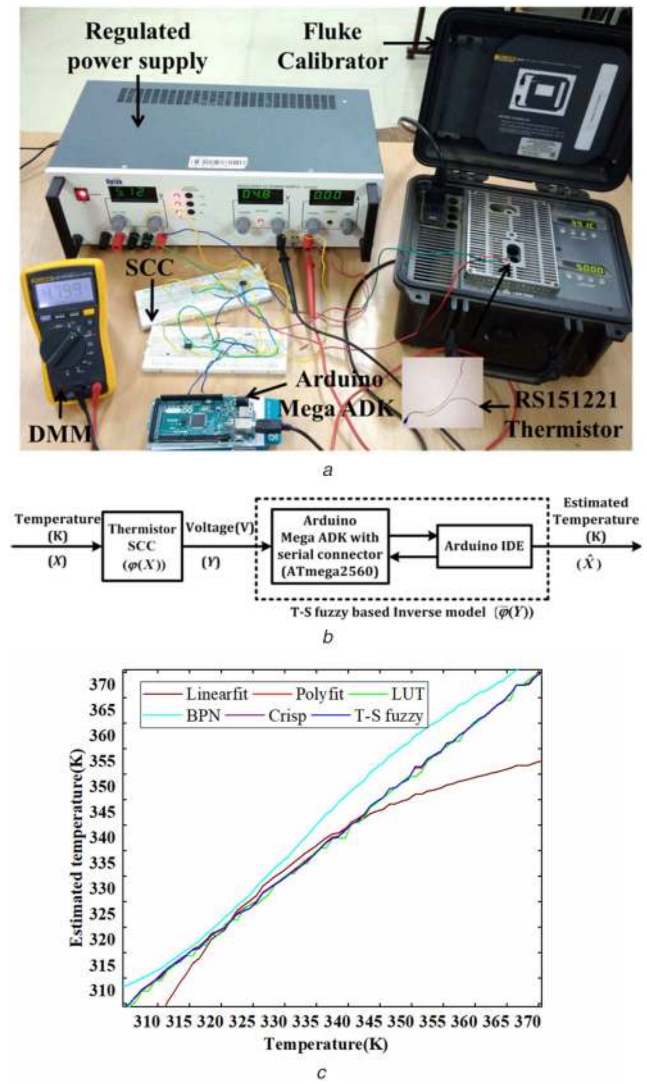

Fig. 7 *Real-time environment of NTC thermistor*
(a) Experimental setup for temperature measurement, ***(b)*** Schematic representation of real-time environment, ***(c)*** Experimental linearity representation

4.2 Experimental results

The real-time implementation of the proposed LT and other popular approaches is carried out using the experimental setup as shown in Fig. 8*b*. The IR sensor is calibrated for input distance 12–30 cm and the output voltage 2.0616–1.0069 V. The input–output (distance–voltage) characteristic is shown in Fig. 9.

It is interpreted from Fig. 9 that the relationship is non-linear and more LAEs are required to represent the entire measurement range. As reported in Section 2, initially the number of LAEs is assumed as two and MSE is very large as shown in Fig. 10*a*. As the number of LAEs is increased, MSE is decreased. When the LAE approaches six, MSE attains optimum value. The number of LAEs is selected as six and the corresponding coefficients are listed in Table 5. The proponent's firmware is fused in the Arduino IDE to achieve piecewise linearisation using the crisp-based scheduler, and the performance is evaluated in real-time environment. To achieve a smooth transition, the same number of LAEs are combined using the T–S fuzzy-based scheduler. It is fused in the Arduino IDE and the performance is shown in

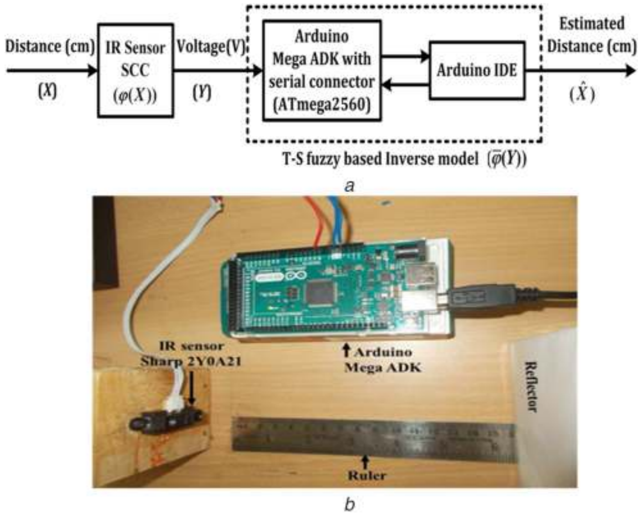

Fig. 8 *Real-time environment of IR sensor*
(a) Schematic representation of the experimental environment, ***(b)*** Experimental setup for distance measurement

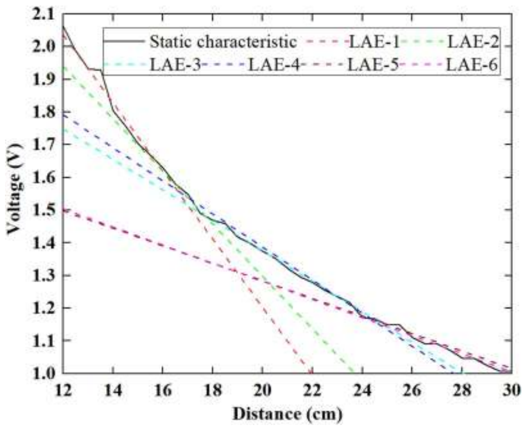

Fig. 9 *IR sensor static characteristic*

Figs. 10*b* and *c*. The performance of the proposed LT is compared with other popular techniques such as linearfit, polyfit of the fourth-order, LUT- and BPN-based approach, which are implemented in Arduino IDE. The performances are evaluated for all the approaches using performance indices. The linearity analysis of the proposed LT with other approaches is reported in Fig. 10*c*. The fitting error as per MSE (12) and mean absolute deviation [MAD – (13)] is calculated. The graphical interpretation of the experimental result is reported in Figs. 11*a–c*. A comparison of all the applied approaches regarding MSE and MAD shows that the proposed LT has the lowest fitting error. The uncertainty in the estimated output of all applied LT is calculated using STDV (15). The uncertainty analysis in output data is reported for all the techniques in Fig. 11*c*. The least dispersion spread of estimated output data is achieved using the proposed LT compared with other approaches.

5 Conclusion

The linearisation of the non-linear sensor using a multi-LAE approach is demonstrated for the thermistor in simulation and real-time platform and IR sensor using a real-time environment. The non-linear sensor output is divided into '*N*' number of LAEs, and the outputs are combined using the crisp and T–S fuzzy-based scheduler. The crisp-based scheduler performance is compared with the T–S fuzzy-based scheduler. Furthermore, the performance of both schedulers is compared with other popular approaches. It is apparent from the results that the T–S fuzzy-based scheduler renders a smooth response and the lowest fitting error compared with the crisp-based scheduler and other popular approaches. This multi-LAE-based approach is simple and straightforward, and it can be extended to any non-linear sensor characteristic to be linearised. This method is based on software linearisation. It is easily implementable using the microcontroller-based system. The main features of the proposed LT are as follows: (i) eliminates hardware complexity, (ii) suitable for homogeneous and heterogeneous LAEs, and (iii) due to ageing and other reasons, if the LAE coefficients are changed in one operating regions, the affected region is needed to be re-identified. There is no need for identifying the entire operation regions, as long as no changes occurred in other operating regions. Similarly, if the range/span is increased due to the operating requirements, there is no need to re-identify entire operating regions in the proposed approach. From this, it is concluded that the proposed approach is highly scalable and flexible in nature. This feature is not available in other software linearisation approaches. (iv) The proposed LT is based on the data-driven approach.

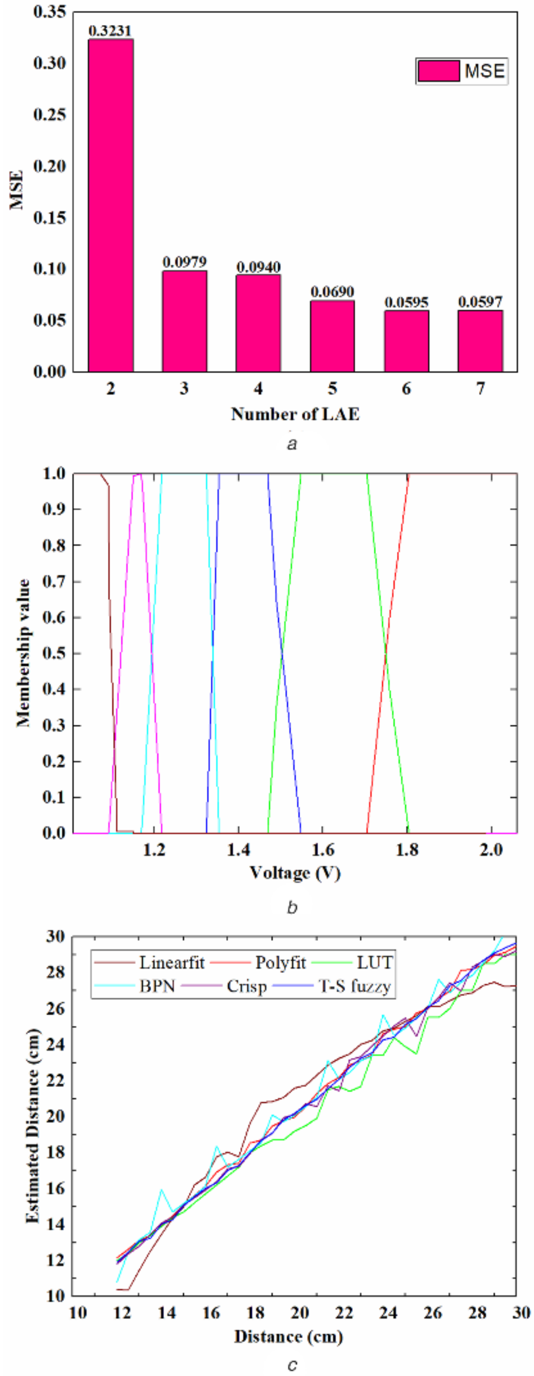

Fig. 10 *Membership function and linearity analysis*
(a) MSE for the number of LAEs, ***(b)*** Membership function for IR sensor, ***(c)*** Linearity analysis of applied LT

Table 5 LAE coefficients for IR sensor

Voltage, V	Distance, cm	a_j, cm	b_j, cm/V
(2.0616–1.7032)	(11.75–14.94)	30.09	–8.90
(1.7032–1.4620)	(14.94–18.00)	36.57	–12.68
(1.4620–1.3223)	(18.00–21.28)	52.31	–23.47
(1.3223–1.1706)	(21.28–24.21)	46.81	–19.31
(1.1706–1.0901)	(24.21–26.92)	63.61	–33.66
(1.0901–1.0069)	(26.92–29.92)	66.21	–36.05

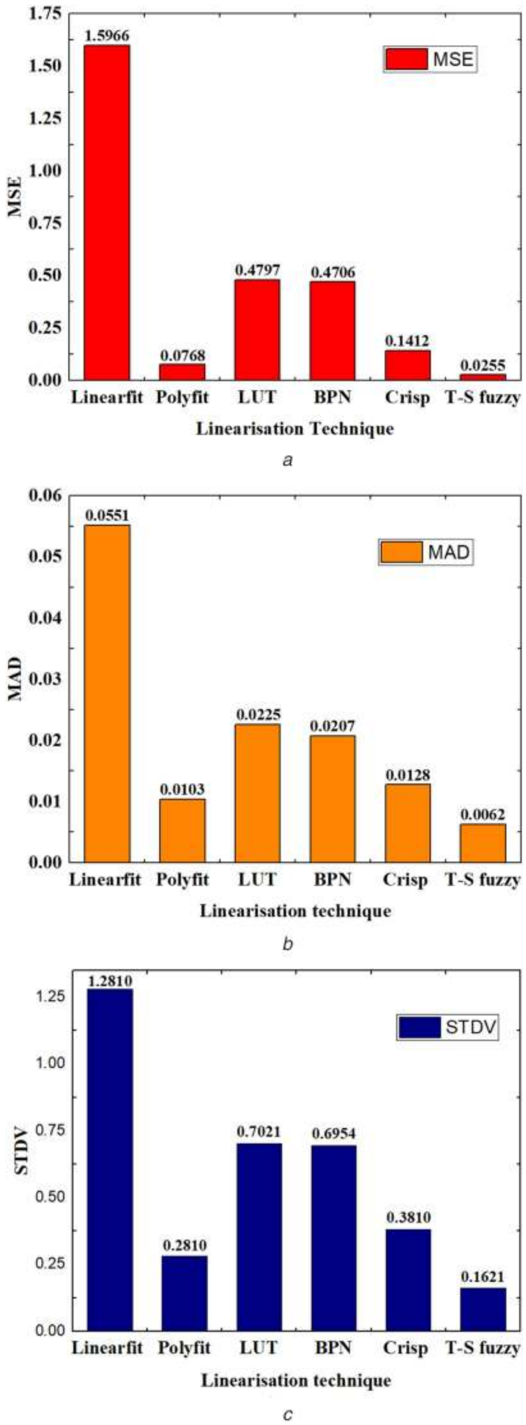

Fig. 11 *Graphical error analysis of IR sensor using*
(a) MSE, ***(b)*** MAD, ***(c)*** STDV

6 Acknowledgments

This publication is an outcome of the R&D work undertaken in the project under the Visvesvaraya Ph.D. scheme of Ministry of Electronics & Information Technology, Government of India, being implemented by the Digital India Corporation (formerly Media Lab Asia).

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8 Appendix

The linearisation accuracy is obtained by calculating MSE, MAD and STDV as statistical performance indices. The magnitude of MSE accounts for a fitting error of LT. It is given by

$$\text{MSE} = \sum_{i=1}^{N} \frac{(\text{IV} - \text{EV})^2}{N} \tag{12}$$

The comparison of different LT regarding fitting accuracy is expressed using MAD. It is given by

$$\text{MAD} = \frac{\sum_1^n |\text{relative error}|}{n} \tag{13}$$

where

$$\text{relative error} = \frac{\mathrm{IV} - \mathrm{ES}}{\mathrm{IV}} \quad (14)$$

The dispersion spread of linearised output data is obtained using STDV and is given by

$$\mathrm{STDV} = \sqrt{\sum \frac{(\mathrm{IV} - \mathrm{EV})^2}{N - 1}} \quad (15)$$

where IV is the ideal value, EV is the estimated value and 'N' is the number of data points in the non-linear range.