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Research Article

Evaluation and Compensation of Temperature Effects on Ultrasonic Flow Measurement

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Abstract

This paper presents an evaluation of temperature effects on ultrasonic piezoelectric transducers for electronic flow measurement devices. Transducers generates ultrasonic wave against electrical signals and electrical signals against ultrasonic waves due to their bidirectional characteristics. Temperature dynamics of the physical environment is one of the most crucial parameters which affects the electrical dynamics of the ultrasonic transducers. Due to the temperature related false sensor readings, flow measurement process for different temperature causes calibration errors. In order to identify the temperature effects on transducers characteristics and constitute a generalized solution, a test procedure and data collection process are developed. Initially, two identical transducers are located reciprocally on a flow meter body. Secondly, bodies are located on a test bench to get signal measurements for different flows. A wireless communication data acquisition card is employed to collect ultrasonic signal measurements. Test procedure is repeated for 5 different temperatures and 13 flow rates. The created dataset is evaluated and visualized in MATLAB environment. A temperature effect compensation process, which is based on machine learning algorithms, is proposed. This method considers time domain information of transducer elements. Experiment temperature value and average values of Time-of-Flight (TOF) signals for each transducers are considered to predict actual flow velocity. In this manner, machine learning algorithms linear regression, suppor vector regression (SVR), Gaussian process regression (GPR) and artificial neural networks (ANN) are employed to construct the relation between temperature variation and flow measurement. Compensation performance is investigated by considering the R^2, root mean square error ($RMSE$), mean absolute error (MAE) and mean square error (MSE) model evaluation metrics. According to the results, neual network based compensation algorithm gives the best result with $R^2 = 0.95$.

Keywords: Ultrasonic transducers, Flow metering, Compensation, Time-of-Flight Measurement.

Ultrasonik Akış Ölçümünde Sıcaklık Etkisinin İncelenmesi ve Kompenzasyonu

Öz

Bu makale, elektronik akış ölçüm cihazları için ultrasonik piezoelektrik dönüştürücüler üzerindeki sıcaklık etkilerinin bir değerlendirmesini sunar. Dönüştürücüler, çift yönlü özelliklerinden dolayı elektrik sinyallerine karşı ultrasonik dalga ve ultrasonik dalgalara karşı elektrik sinyalleri üretir. Fiziksel ortamın sıcaklık dinamiği, ultrasonik dönüştürücülerin elektrik dinamiklerini etkileyen en önemli parametrelerden biridir. Sıcaklık değişimi kaynaklı yanlış sensör okumaları, farklı sıcaklıklar için akış ölçüm işlemi sırasında kalibrasyon hatalarına neden olur. Bu nedenle, dönüştürücü özellikleri üzerindeki sıcaklık etkilerini belirlemek ve genelleştirilmiş bir çözüm oluşturmak için bir test prosedürü ve veri toplama süreci geliştirilmiştir. Başlangıçta, bir akış ölçer gövdesi üzerinde karşılıklı olarak iki özdeş dönüştürücü konumlandırılmıştır. İkinci olarak, gövdeler, farklı akışlar için sinyal ölçümleri almak

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üzere bir test masasına yerleştirilmiştir. Ultrasonik sinyal ölçümlerini toplamak için bir kablosuz iletişim veri toplama kartı kullanılmıştır. Test işlemi 5 farklı sıcaklık ve 13 debi için tekrarlanmıştır. Veri toplama sonucu elde edilen veri seti MATLAB ortamında değerlendirilip, çalışma koşulları belirlenmiştir ve makine öğrenmesi algoritmalarına dayalı bir sıcaklık etkisi kompenzasyon modeli önerilmiştir. Bu yöntem, dönüştürücü elemanlarının zaman ekseni bilgilerini dikkate almaktadır. Gerçek akış hızını tahmin etmek için her deney sıcaklık değeri ve Uçuş Süresi (TOF) sinyallerinin ortalama değerleri dikkate alınmaktadır. Böylece, sıcaklık değişimi ve akış ölçümü arasındaki ilişkiyi oluşturmak için makine öğrenmesi algoritmalarından doğrusal regresyon, destek vektör regresyonu (SVR), Gaussian süreç regresyonu (GPR) ve yapay sinir ağları (YSA) kullanılmıştır. Önerilen modelin kompenzasyon performansı R^2, ortalama kare-kök hata ($RMSE$), ortalama mutlak hata (MAE) ve ortalama kare hata (MSE), gibi hata metriklerinin hesaplanması ile incelenmiştir. Sonuçlara göre, YSA tabanlı kompenzasyon algoritmasının $R^2 = 0.95$ metriği ile en iyi sonucu verdiği görülmüştür.

Anahtar Kelimeler: Ultrasonik transduser, Akış ölçümü, Kompanzasyon, Uçuş süresi ölçümü.

1. Introduction

Parameter change caused by temperature effect is a widely countered disturbance phenomenon in the sensor and measurement fields including biomedical (Sarjova et al., 2005), process control (Mehta et al., 2022), measurement devices (Fang et al., 2022) and embedded system designs (Rudnicki, 2020). Transducers are commonly used cheap and easy to use sensor elements to measure distance (Balasubramanian et al., 2022), liquid flow (Yao et al., 2021), gas flow (Chen et al., 2021) and pressure (MacAskill et al., 2021). However, change of temperature has a significant role on transducer electrical characteristics which causes false sensor readings and measurement errors (Zibitsker et al., 2021). Calibration process, due to the underlying problem, is underwhelmed to converge to actual measurement. Identifying the behavior of the problem and developing a method to eliminate temperature effects is a crucially significant for the sake of true measurement process. Related literature is investigated to study on different perspectives on the problem. Huang and Young (2009) employed an external sensor to measure the temperature of a distance measurement system to compensate the ultrasound velocity during the measurement process. Wang and Zhang (2010) proposed to use a neural network model which considers the temperatre sensor data and ultrasonic flow measurements to both calibrate and compensate the measurements, and proved that the measurement error decreased to 3% from 5.2%. Scale transform and cross-correlation methods are employed by Harley and Moura (2012) to find phase delay caused by the temperature variations. Herein, they can find the optimal time domain information of the ultrasonic waves. A methodology, that aims to model temperature effects on signal amplitute and waveform of the ultrasound to understand that how temperature affects the measurement, is proposed by Jia et al. (2021). Huang et al. (2021) employed the transducers to predict temperature value of a specific medium where the ultrasound velocity is known and used to extract temperature.

In this study, transducer complex dynamics are investigated under certain temperature and flow conditions with a data acquisition process. The problems defined in the literature focus on the temperature change of the water however we focus on the temperature effect on the transducer and its electrical characteristics. Upstream and downstream signals, which represents the electrical signals on transducers caused by ultrasonic wave transmitted from other transducer, might be evaluated to determine the working conditions. Thus, transducers are placed inside of a brass flow meter body to measure the stream signals during the flow. Through the instrument of heat test bench, flow and temperature test conditions are satisfied. Flow measurements, temperature measurements, Time Of Flight (TOF) values representing the time domain features of stream signals and actual flow measurements are collected using a data acquisition card. During the test process, data are collected for different water temperatures ($10^o\ C$, $20^o\ C$, $30^o\ C$, $40^o\ C$, $50^o\ C$) and 13 flow rates between 16 L/h and 5000 L/h.

Remaining parts of the paper is organized as follows: In Section 2. transducer element and its mathematical dynamics are explained. Problem is detailly defined, collected data are given and proposed compensation method is explained. In Section 3. the results of the experiment and compensation work are presented. Conclusion and the future work of the study are presented in the Section 4.

2. Material and Method

2.1. Ultrasonic Transducer and Flow Metering

Ultrasonic transducers are piezoelectric components used to generate and/or receive the ultrasonic sound waves (Jaffe et al., 1965). Pulsed ultrasonic transducers use electrical energy to generate ultrasonic wave trains into the water medium. Reflected waves, which might be called echo, are transformed into electrical energy back by the ultrasonic transducers. The total time during the transmission and reflection is considered to compute distance or depth in a water medium. Based upon this principle, ultrasonic transducers might be employed for flow measurement process. Initially, reciprocal transducers are located on a body (or transducer paths are connected with the mirror reflecting the waves) to generate and receive waves (Figure 1). Transducers are pulsed with a pre-determined specific period of time. Received signals by the transducers are employed to compute wave transmission time measure Time-of-Flight (TOF). These waves are called Upstream (In the direction of flow) and/or Downstream (In the reverse direction of flow) signals. This transmission/receiving operation might be performed with an ultrasonic Time-to-Digital Conversion (TDC) integrated circuit chip. TOF difference value, which might be computed considering the time difference between downstream and upstream signals, is considered to measure both direction and amplitute of the flow with an offset compensation and calibration process.

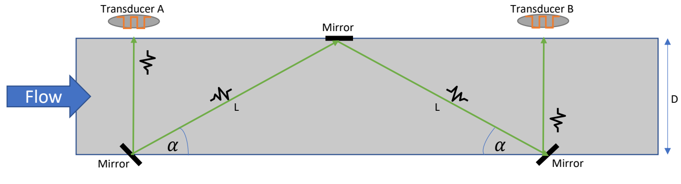


Figure 1. Visual representation of an ultrasonic flow meter.

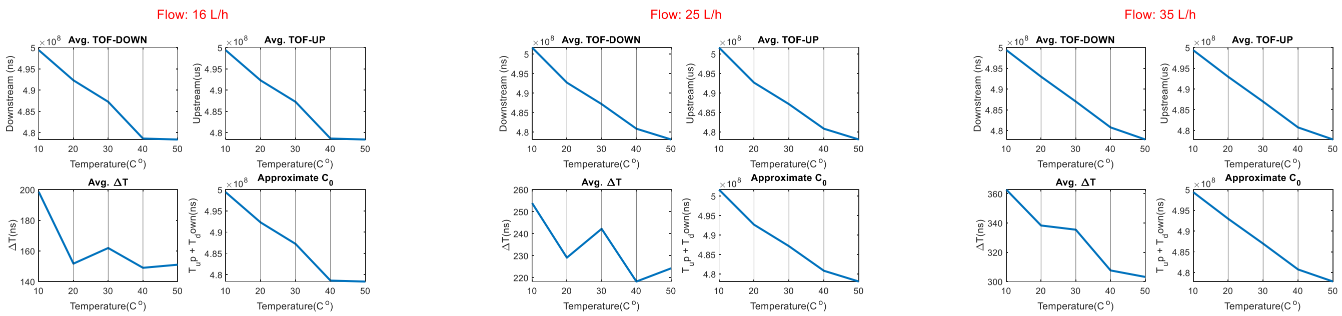
2.2. Time of Flight Measurement and Data Collection

TOF of an ultrasonic wave in the direction of downstream might be given as:

$$t_{(B>A)} = \frac{D}{C_0} + \frac{L}{C_0 + vcos(\alpha)} + \frac{L}{C_0 + vcos(\alpha)} + \frac{D}{C_0} \quad (1)$$

where L is the distance between transducers, D is the diameter of the pipe, α is the degree between pipe and mirror, C_0 is the speed of ultrasonic wave in water, v is the flow velocity, and $t_{(B>A)}$ is the downstream TOF value. In the same manner, upstream TOF migh be calculated as:

$$t_{(A>B)} = \frac{D}{C_0} + \frac{L}{C_0 - vcos(\alpha)} + \frac{L}{C_0 - vcos(\alpha)} + \frac{D}{C_0} \quad (2)$$



where $t_{(B>A)}$ is the upstream TOF value. Due to the TOF value is reverse proportional to the flow velocity, TOF Difference (TOF DIFF) value migh be computed as:

$$\Delta T = t_{(B>A)} - t_{(A>B)} = \frac{2L}{C_0 - vcos(\alpha)} - \frac{2L}{C_0 + vcos(\alpha)} = \frac{4Lvcos(\alpha)}{C_0^2 - v^2\cos^2(\alpha)} \quad (3)$$

Computing the flow velocity is directly affected by the change of water temperature due to the sound velocity C_0 is affected by temperature. To eliminate this dependency:

$$t_{(B>A)} * t_{(A>B)} = \frac{4(L+D)^2}{\big(C_0 - vcos(\alpha)\big)\big(C_0 + vcos(\alpha)\big)} + \frac{4Dcos(\alpha)\big(L - C_0L - Dvcos(\alpha)\big)}{C_0^2\big(C_0 - vcos(\alpha)\big)\big(C_0 + vcos(\alpha)\big)} \quad (4)$$

Left side of the Eq. (4) may be assumed as zero, and substituting (4) in (3) for $C_0^2 - v^2\cos^2(\alpha)$ gives temperature independent flow velocity as:

$$v = \frac{\Delta T}{t_{(B>A)} * t_{(A>B)}} * \frac{(L+D)^2}{Lcos(\alpha)} \quad (5)$$

Due to the flow calculation is not dependent on C_0 variations, measurement is not affected by temperature variation. However, the aim of this study is to eliminate temperature effects on transducer electrical characteristics. To understand the temperature related measurement behaviors and dynamics of the transducer, flow measurements are performed for different temperatures and velocities (Figure 2). TOF values for both upstream and downstream, temperature readings, flow measurements and actual flow velocities are recorded to perform a calibration process which eliminates the temperature variation effects.

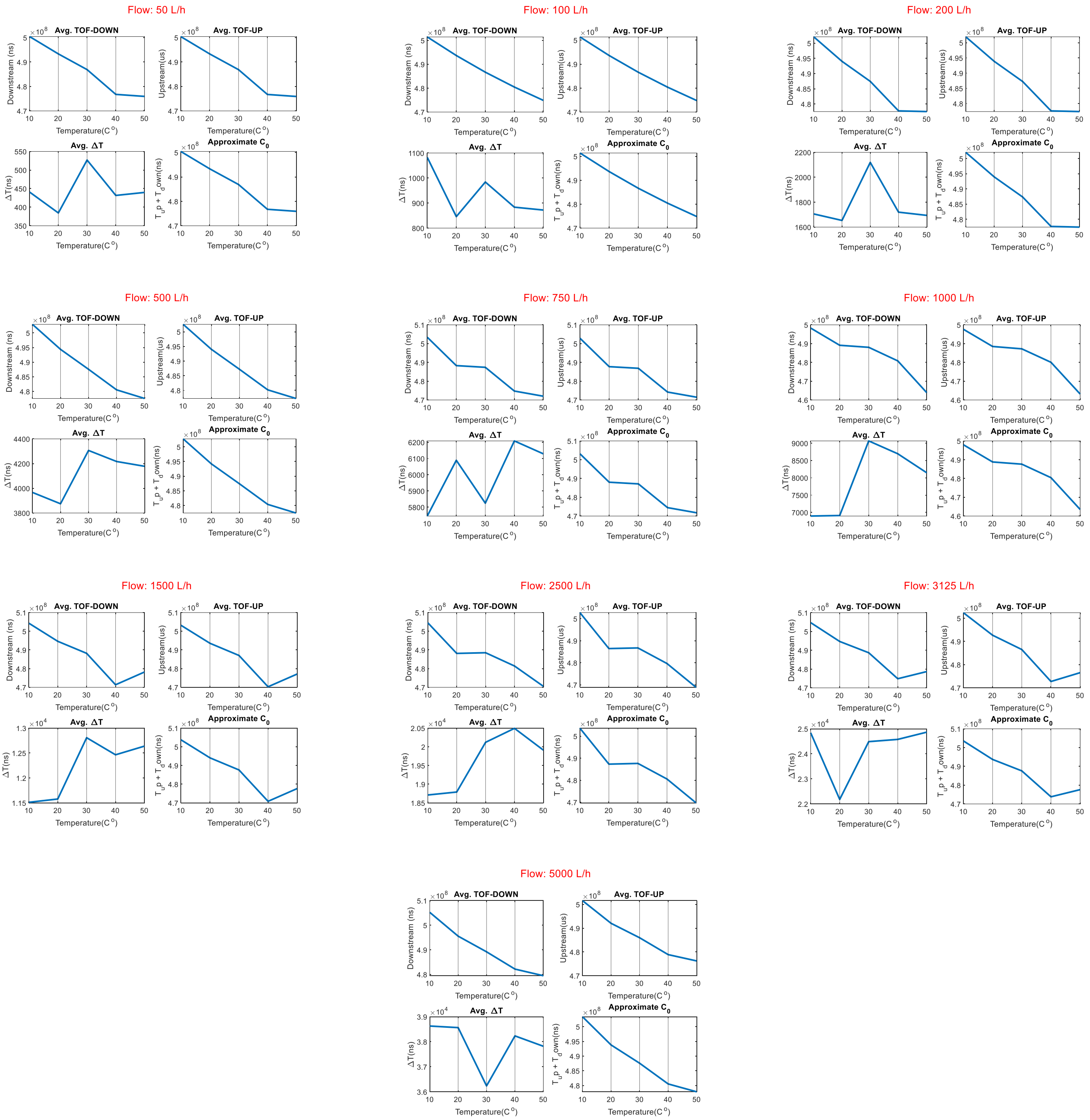


Figure 2. TOF signal evaluation of collected data during experiments.

2.3. Temperature Compensation Process

Temperature parameter must be know to eliminate its effects on transducer. Due to the C_0 parameter has a known correlation with temperature, it migh be employed to estimate temperature value. C_0 might be computed as:

$$t_{(B>A)} + t_{(A>B)} = \frac{4LC_0}{C_0^2 - v^2\cos^2(\alpha)} \qquad (6)$$

due to the $C_0^2 \gg v^2\cos^2(\alpha)$, equation (6) becomes:

$$C_0 = \frac{4L}{t_{(B>A)} + t_{(A>B)}} \qquad (7)$$

Proposed compensation method is based on a machine learning model which considers the water temperature correlated parameter C_0, flow measurement v to estimate actual velocity $\hat{v}$ (Figure 3).

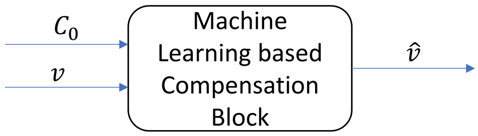


Figure 3. Block representation of proposed machine learning model.

To perform this process, machine learning models are employed. Linear regression is method which defines a linear mathematical expression between dependent and independent variables to perform a prediction process of the independent variable (Weisberg, 2005). This model might be defined as:

$$\hat{y} = \theta^T X \tag{9}$$

where $\hat{y}$ is the model prediction, θ represents model regression parameters, and X represents model inputs.

Support Vector Regression (SVR) method employees a mapping kernel function which projects feature space into a higher dimensional hyperplane (Awad and Khanna, 2015). The objective of constructing a Support Vector Machine (SVM) is to map features into a higher dimensional space (F) by employing a kernel function. Estimation function of a general SVR might be defined as:

$$\hat{y} = \alpha_i K(x_i, x_j) + b \tag{10}$$

where α_i represents the support vectors with i samples, and b represents the bias term. Mapping function K is employed as linear, quadratic and cubic, respectively.

Gaussian process regression is a non-parametric regression method based on optimizing the distribution kernel function hyper parameters (Wilson et al., 2011). Kernel function with optimal parameters define a regression fit which maximize the negative log-marginal-likelihood (NLML) of the training set.

In this framework, probabilistic approach to regression between input-output relation might be defined as:

$$\hat{y} = f(x) + \epsilon \tag{11}$$

where ϵ term represents a Gaussian distribution.

Fundamentals of ANN is based on learning brain neuron cells, and hypostatized in machine learning framework (Eskov et al., 2019). This model consists of an input layer, hidden layers, an output layer and processing elements known as neurons. Each neuron node receives its input from previous neuron nodes. Neurons passes linearly weighted sum of the signal to another neuron over an activation function. Activation functions within the hidden layers gain the model its dynamics, and are selected considering the complexity of the dataset. Multi-Layer Perceptron (MLP) type of ANN has known number of input and output layer neurons, and equals to the number of independent and dependent variables, respectively. MLP might be defined as:

$$\hat{y} = h_o\left(W_o^T * h_i\left(W_{in}^T * X\right)\right) \tag{12}$$

where W_{in} represents the hidden-layer neuron parameters, $h_i(\cdot)$ represents the hidden-layer activation function, W_o represents the output-layer neuron parameters, and $h_o(\cdot)$ is the output-layer activation function. In this work, a single hidden-layer MLP type ANN is employed for compensation process.

3. Results and Discussion

MATLAB environment is employed to study on the collected dataset. Firstly, C_0 and v values are computed for each temperature value. Linear regression, SVR, GPR and ANN are employed to perform compensation process. Model performances are investigated by considering the metrics $R^2, RMSE, MSE, MAE$ values (Table 1).

Table 1. Model performance metric evaluations.

	Linear Regression	Linear Kernel SVR	Quadratic Kernel SVR	Cubic Kernel SVR	GPR	ANN
R^2	0.82	0.81	0.81	0.84	0.92	0.95
$RMSE$	0.09876	0.1009	0.1007	0.0932	0.0374	0.0707
MSE	0.0097	0.0101	0.0101	0.0086	0.0014	0.0050
MAE	0.0414	0.0315	0.0352	0.0220	0.0076	0.0065

According to the results, linear models have close performance in terms of R^2 and error metrics. Although the quadratic kernel SVR is a nonlinear model, it is understood that it provides close performance to linear models in terms of R^2 and error metrics. Cubic kernel SVR gives slightly better performance on R^2, $RMSE$ and MSE metrics, but it is successful in terms of MAE metric compare to previous models. Thus, it is observed that solving the problem with quadratic or qubic approaches is not appropriate in terms of a trade-off between model complexity and model performance. GPR, as a probablistic distribution based model, gives the best performance in terms of $RMSE$ and MSE metrics due to its stochastic behavior. ANN, which gives the best performance in terms of R^2, also is successful in terms of MAE compare to all proposed models on predictin the actual flow velocity.

4. Conclusions and Recommendations

This study presents a machine learning based calibration method for temperature effects on transducer dynamics on flow measurement devices. Herein, the problem is identified and related works are given. Initially, transducer component and flow measurement process are defined. The data collection process for understanding the nature of the problem and adapting the proposed method parameters are explained. Afterward, temperature effect and proposed method are explained. Machine learning models and machine learning based compensation process are detailly explained. Finally, model performances on compensation process are investigated via performance indexes. According to the results, neural network based compensation block gives the better performance compare to other models in terms of performance metrix. In the future direction of the study, a reinforcement learning based compensation method may be considered to eliminate disturbance effects.

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