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A neural network developed in a Foundation Fieldbus environment to calculate flow rates for compressible fluid

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ABSTRACT

This paper proposes the development of an artificial neural network multilayer perceptron, implemented in a Foundation Fieldbus environment, to calculate the flow rate of natural gas by using an orifice plate in a closed pipe. The principal benefit of using neural networks lies in their low computational cost and simplicity of implementation, which allows just standard blocks to be used, making the technology independent of the Foundation Fieldbus system manufacturer. To perform the calculation, the proposed methodology relies on static pressure, temperature and differential pressure measurements, which are typically available in industrial plants. The developed methodology generates highly accurate results, and this approach can be implemented at a relatively low cost for Foundation Fieldbus system users.

1. Introduction

Multivariable transmitters are commonly used for flow measurements in a large number of industrial applications, such as fuel and air flows for general combustion systems, air measurement in painting systems for the automobile industry, steam injection in dryers for food and beverage manufacturing, as well as boiler systems [1,2].

Results from recent studies and simulations in industrial plants show an increasing use of intelligent systems as a soft sensor, that may have several practical applications as shown in [3–6,13,14].

Reference papers [7–12] show an effective utilization of ANN (Artificial Neural Network).

Refs. [15] proposed an architectural multi-agent-based artificial neural network (ANN), which allows applications of intelligent systems based only on standard function blocks (blocks not customized by a specific manufacturer) of the field devices in Industrial Foundation Fieldbus networks. This architecture enables the allocation of resources (algorithms) in sensors or transmitters and actuators that allow plant operators to perform certain tasks to assist supervisors in detecting and resolving network problems such as noise filtering, prediction and calibration. Consequently, this leads to an improvement in decision support in terms of plant operation and allows less human intervention.

In Refs. [4–15–22], soft-sensors, or systems where ANNs or Fuzzy techniques were successfully used to infer variables or to deal with non-linear systems, all have some similarity with the work presented herein. This article differs from Refs. [16,17] because it is related to monophasic flowing fluids and a lower flow measurement uncertainty is reached.

It is important to point that in Ref. [18], choked flow equations are considered. However, for most of industrial applications with orifice plate, the speeds are typically subsonic (non-choked). For this reason, choked flow equations are not considered.

This paper presents a methodology for calculating flow rates of compressible fluid in closed ducts, based on measured values of differential pressure, static pressure and temperature. These measurements use neural networks techniques whose training parameters and topology of the network are transported to function blocks in a Foundation Fieldbus environment.

Although the flow calculation can be performed by a multivariable transmitter, it is performed at a lower cost by using the developed methodology.

2. Flow measurement

Multivariable transmitters are well-known devices for measuring compressible fluids in industrial applications. They can be configured with numerous flow primary elements and process fluids.

Fig. 1 illustrates the correlation between a multivariable transmitter and its equivalence to a set of mono-variable transmitters.

The application of these transmitters to flow measurement using orifice plates emerged in the late twentieth century. Basically, the

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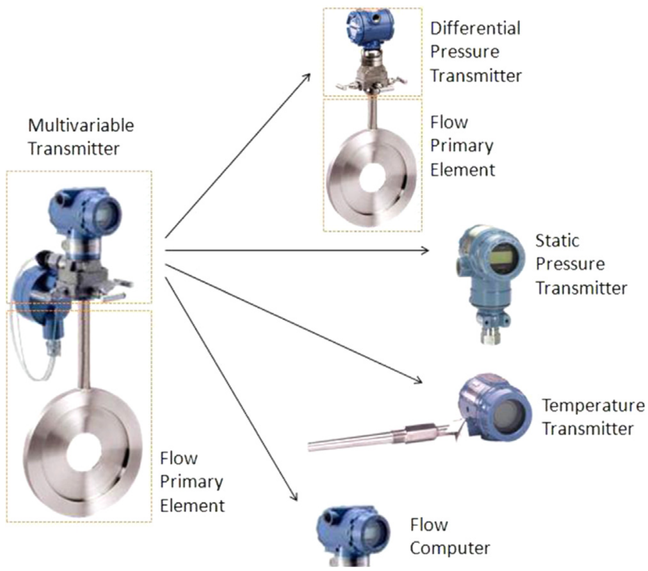

Fig. 1. Multivariable transmitter and mono-variable transmitters [2].

transmitters measure differential pressure and have an internal static pressure transducer.

An RTD (resistance temperature detector) is connected directly to the electronic board of the transmitter, which consists of a flow computer able to perform the calculations in accordance with international standards such as AGA3 and ISO5167 [1].

The transmission of the calculated value of the flow rate is performed through analog or digital communication, which also allows the transmission of values of other variables such as differential pressure, static pressure and temperature [1].

Multivariable instruments are highly accurate in computing the value of the flow, whose error is approximately 1.0% of the mass flow [2].

These models are used in flow rate measurements including custody transfers with natural gas, evaluating consumption of industrial or hospital gas, or in mass balance applications in many different industries. However, the cost of the multivariable instrument is relatively high.

2.1. The orifice plate

Used for over one hundred years, the orifice plate is the most well-known primary element that generates differential pressure in order to measure flow rate. As presented in Table 1, the orifice plate is an element that allows the flow measurement of gases, liquids and steam. The operating principle of plate is well known, while its cost is relatively low compared to other technologies.

The formula used for massic flow rate when considering multivariable transmitter is:

$$Q_m = \frac{\pi}{4} C_d Y_1 d^2 \sqrt{\frac{2\Delta P \rho}{1 - \frac{d^4}{D^4}}} \tag{1}$$

where C_d and Y_1 are empirical values.

The contracted equation is shown in multivariable manual [1], actually it is (1) rewritten:

$$Q_m = N C_d E Y_1 d^2 \sqrt{\Delta P(\rho)} \tag{2}$$

where Q_m is the mass flow rate (mass per unit of time); N is the unit conversion (dimensionless); C_d is the discharge coefficient (dimensionless); E is the approach speed factor (dimensionless); Y_1 is the gas expansion factor (dimensionless); d is the diameter of the orifice (length dimension); ρ is the density of the fluid (mass per unit volume); ΔP is the differential pressure (dimension of force per area, typically given in inches or millimeters of water at a specific temperature).

$$E = \frac{1}{\sqrt{1 - \frac{d^4}{D^4}}} \tag{3}$$

and N summarizes all the constants.

Note that Eq. (1) illustrates the complexity of the flow calculations due to the interlocking between the variables.

The value of the diameter of the orifice plate changes according to variations in the temperature and thermal expansion coefficient of the plate that is related to the material from which the plate is made (usually 316 stainless steel). Temperature variation also affects the diameter of the piping; consequently, it causes a change in the value of beta (ratio between the diameters of the orifice plate and the orifice pipe).

The variation in temperature and pressure values results in modifications in fluid density and viscosity, which causes a variation in the Reynolds number and which will consequently modify the discharge coefficient. The variation in fluid velocity causes changes in the differential pressure value measured by the multivariable transmitter sensor. The approach speed factor and the discharge coefficient have non-linear terms.

3. Neural network

ANNs are computational models inspired by the functioning of biological nervous systems. They consist of processing units associated with certain weights representing the neurons and synaptic connections in biological neural networks. All the knowledge acquired is propagated to the neurons by modifying their synaptic weights. The training or learning is performed to adjust the synaptic weights along the neural network until its output provides the response which is compatible with a set of predetermined stimuli (inputs). Accordingly, the ANN synaptic weights are balanced in order to obtain the response patterns for the stimuli, which are consistent with those desired values [19,20].

ANNs are able to deal with problems which contain large amounts of variables and data sets. They also have the ability to map nonlinear and time-varying systems, and require minimal information about analytic models that govern the process.

3.1. The artificial neuron

The first artificial model for a biological neuron was proposed in 1943 by Warren McCulloch, a psychiatrist and neuron-anatomist, and Walter Pitts, a mathematician [19]. Their work presented the concepts of the neuron as a basic processing unit that could receive several inputs [19,20].

3.2. Multilayer perceptron networks

The topology of a multilayer perceptron network consists of a system of neurons interconnected by synaptic linkages. Neurons in this type of network are essentially organized in three types of neural layers: the input layer, the hidden layer and the output layer. The input layer is responsible for receiving stimuli or patterns of the system to which the network is connected. The first layer is also responsible for transmitting these stimuli to the hidden layer.

As mentioned in the literature [3–5,7–12,15,16,18,19,22], ANNs are an excellent tool for dealing with complex and nonlinear calculations, and are a growing trend in networks applications using communication among field devices, such as a Foundation Fieldbus.