Intelligent Information-Measuring System for Scanning Liquid Flows

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Abstract. This study presents the development and validation of an Automated Liquid Flow Scanning and Intelligent Measurement System (ALFSS) designed to provide high-accuracy, adaptive, and real-time monitoring of liquid flow processes in complex industrial and scientific environments. Traditional liquid flow measurement systems, including mechanical flow meters, analog sensors, and conventional digital measurement platforms, often suffer from limitations such as low adaptability, high sensitivity to noise, calibration drift, and reduced reliability in nonlinear and dynamically changing flow conditions. These limitations significantly affect the stability, accuracy, and robustness of measurement results, particularly in large-scale industrial infrastructures and safety-critical systems.

To address these challenges, the proposed system integrates multisensor measurement architectures, adaptive filtering techniques, intelligent data processing and real-time decision-making algorithms into a unified intelligent measurement platform. The system architecture is based on a layered structure consisting of a sensor layer, signal conditioning layer, data acquisition layer, processing unit, intelligent analysis layer, decision system, and visualization and control interface. This modular design ensures scalability, flexibility, and compatibility with different industrial and laboratory environments.

A comprehensive mathematical modeling framework is developed, including fluid flow dynamics models, state-space representations, measurement equations, and integrated error models. The system incorporates stochastic modeling approaches to represent uncertainties, sensor noise, calibration errors, and environmental disturbances. Adaptive estimation is achieved through Kalman filtering and extended data fusion techniques, enabling optimal state estimation under noisy and uncertain conditions. Multisensor data fusion strategies are implemented to enhance measurement reliability, improve accuracy, and provide redundancy against sensor failures.

An intelligent algorithmic framework is proposed, including automated flow scanning, adaptive filtering, sensor fusion, fault detection, anomaly analysis, and intelligent decision generation. The system is capable of detecting abnormal flow behaviors, identifying system faults, and generating corrective control actions in real time. Simulation models are developed using MATLAB/Simulink environments to validate system performance, stability, and robustness. Performance evaluation is carried out using quantitative metrics such as root mean square error (RMSE), accuracy indices, response time, and stability criteria based on Lyapunov theory.

The obtained results demonstrate that the proposed ALFSS significantly outperforms classical measurement systems in terms of accuracy, adaptability, robustness, and reliability. The system shows strong resistance to noise, high sensitivity to dynamic flow variations, and stable performance under nonlinear operating conditions. The developed framework is suitable for applications in water supply systems, oil and gas pipelines, chemical process industries, energy systems, hydraulic infrastructures, laboratory measurement platforms, and aerospace fluid systems.

The proposed smart measurement system provides a scalable, adaptive, and future-oriented solution for next-generation automated fluid flow monitoring and control technologies, providing higher accuracy, stability, and adaptability compared to classical measurement methods [1–5].

Keywords: Intelligent, measurement system, fluid flow, scanning, multisensor, test measurement, Kalman filter, adaptive control

1.Introduction

Real-time measurement and control of fluid flows in modern industrial and technological systems is an important scientific and technical problem. Classical measurement systems (mechanical flowmeters, analog sensors, differential pressure measurement methods) show low accuracy, high noise effect and poor adaptability in nonlinear dynamic environments [6–9].

For this reason, the concept of intelligent measurement systems (IMS) has been developed [1, 3, 10]. The Automated Liquid Flow Scanning (ALFS) approach forms a complex system approach that provides not only measurement, but also structural analysis of the flow, tracking of change trajectories, anomaly detection and prediction [2, 4, 11].

Accurate, reliable and real-time measurement of fluid flows in modern industry, energy, water management, chemistry, oil and gas and hydraulic systems remains one of the important scientific and technical problems. Nonlinear variability of flow parameters, turbulent regimes, influence of environmental factors, sensor errors and noise components seriously limit the capabilities of classical measurement systems [6–9]. Traditional mechanical flowmeters, analog sensor platforms and simple digital measuring devices do not provide stable results in complex dynamic environments, create high calibration errors and reveal long-term reliability problems [22].

2.The physical basis of the flow measurement process

The physical basis of the flow measurement process is based on the laws of classical hydrodynamics and is presented in a simple form by the following expression [6,7]:

$$Q = A \cdot v, \tag{1}$$

where $Q -$ is the flow rate, $A -$ is the cross-sectional area, and $v -$ is the flow velocity. However, in real industrial systems, this simple model is not sufficient, and the process is described by more complex dynamic structures based on the Navier–Stokes equations [17,18]:

$$\rho \left(\frac{\partial v}{\partial t} + v \cdot \nabla v \right) = - \nabla p + \mu \nabla^2 v + f, \tag{2}$$

This shows that the measurement process requires not only physical, but also mathematical modeling, computational methods, and intellectual analysis mechanisms.

Therefore, the multi-sensor intelligent information-measuring system we propose will provide high accuracy and reliability through the dual information it collects from sensors, special calculation methods and intelligent analysis mechanisms based on mathematical models [36].

Intelligent Measurement Systems

As a result of the transformation in measurement technologies in recent decades, the concept of Intelligent Measurement Systems (IMS) has been formed [1–5]. Unlike classical measurement structures, these systems not only integrate the measurement function, but also functions such as:

– adaptive analysis,
– self-calibration,
– noise immunity,
– decision-making,
– prediction,
– risk analysis,
– security mechanisms [10–15].

Automated Liquid Flow Scanning

In this context, the concept of Automated Liquid Flow Scanning (ALFS) is emerging as a new generation of measurement technology. The ALFS approach represents a complex intelligent system approach that integrates not only flow measurement, but also flow structure scanning, dynamic behavior modeling, anomaly detection, and adaptive control [11, 13].

In modern measurement systems, the measurement process is no longer limited to simple sensor readings and is expressed by the following mathematical structure [19–21]:

$$z(t) = h\big(x(t)\big) + \varepsilon(t), \tag{3}$$

where $z(t)$ - the measured signal, $x(t)$ - the real state, $h(\cdot)$ - the measurement function, $\varepsilon(t)$ - the measurement error. This model shows that the measurement process is uncertain and stochastic.

Therefore, state-space models are used in modern systems [20, 21]:

$$\dot{x}(t) = Ax(t) + Bu(t) + w(t), \tag{4}$$

$$y(t) = Cx(t) + v(t), \tag{5}$$

This approach allows for an integrated modeling of the dynamic behavior of the system, external influences, and measurement errors.

In addition, the Kalman filter and its extended forms form the main mathematical basis of adaptive measurement systems [1, 25, 26]. These filtering mechanisms provide optimal situation assessment in noisy conditions and significantly increase measurement accuracy.

In modern approaches, sensor fusion technologies are widely used [13, 27, 28]. This approach is expressed by the following model:

$$\hat{x}_{fusion} = \sum_{i=1}^{n} w_i x_i\,,\ \ \sum_{i=1}^{n} w_i = 1, \tag{6}$$

This model increases the reliability of measurements, provides resistance to sensor failures, and increases the stability of the measurement system.

Thus, modern measurement systems are no longer simple measurement platforms, but are formed as intelligent information systems. In these systems, measurement, analysis, decision-making, and control are combined into a single integrated platform [12–15].

The purpose of this research is to develop a scientifically based, adaptive, multi-sensor and intelligent measurement architecture for Automated Liquid Flow Scanning / Intelligent Measurement System (ALFSS), mathematical modeling, construction of algorithmic structures, verification in a simulation environment and scientific justification of application possibilities. The proposed system, unlike classical measurement approaches, aims to ensure not only measurement accuracy, but also system adaptability, stability, security and intelligent decision-making capabilities.

This approach elevates ALFSS to the level of an intelligent technological platform, not just a technical measurement device, and forms it as a scientific model of the next generation of automated measurement and control systems.

3. System Architecture

The system is built on a multi-layered intellectual structure [12–14]:

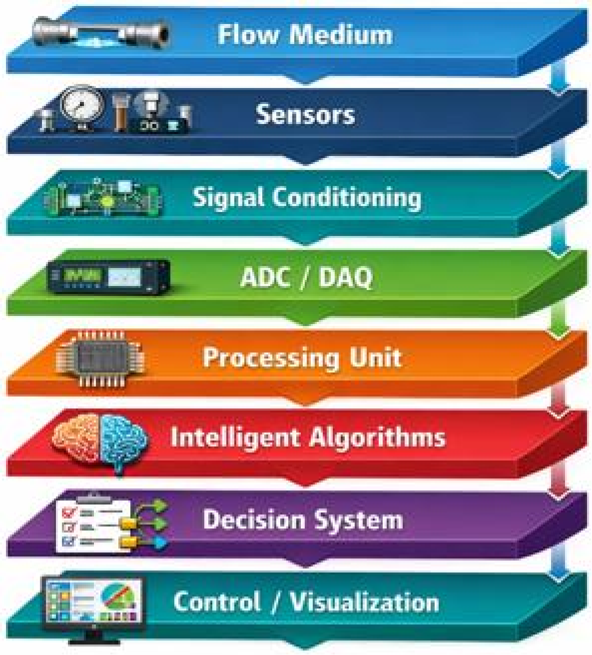


Fig. 1. Multi-level system architecture

This structure is based on the integration of sensor networks, real-time processing, and decision-making systems [13,15].

Thus, the total error as a result of complex measurements will be equal to the sum of all errors that must be taken into account and will be calculated by the following formula:

$$E_{total} = E_{sensor} + E_{noise} + E_{calibration} + E_{quantizion}, \quad (7)$$

This model reflects the integration of error components in complex measurement systems [22].

E_{sensor} – Sensor Error: This error arises from the non-ideality of the physical sensor that directly performs the measurement. Causes:

- Sensor sensitivity is not ideal;
- Temperature effect;
- Nonlinearity;
- Hysteresis effect;
- Drift (change in parameters over time).

Mathematically, the real output of a sensor with a linear characteristic is expressed as:

$$y = kx + b + \varepsilon_s \quad , \quad (8)$$

where: k – sensitivity error,
b – offset,
ε_s – sensor error.

Practical example: If the pressure sensor shows 102 kPa instead of 100 kPa → this is E_{sensor} sensor.

E_{noise} – Noise Error: This error is the random electrical or environmental effects added to the measurement signal. Sources:

- electromagnetic interference (EMI);
- thermal noise;
- internal fluctuations of electronic components;
- parasitic effects on transmission lines.

Characteristic:

- is random;
- its average value is usually close to zero:

$$E_{noise} \sim N(0, \sigma^2).$$

Noise reduction methods include:

- filtering (Kalman, low-pass filter);
- shielding;
- averaging.

$E_{calibration}$ – Calibration Error: Arise as a result of the sensor or measurement system not being properly adjusted to the reference values. Causes:

- incorrect calibration factor;
- outdated calibration;
- reference device error;
- environmental change.

Mathematical expression - If the real conversion is as follows:

$$y = k_{true}x,$$

but the system:

$$y = k_{cal}x,$$

then the system will function with the following expression :

$$E_{calibration} = \left(k_{cal} - k_{true}\right)x$$

Conclusion: This error is a systematic error and affects all measurements in the same direction.

$E_{quantizion}$ – Quantization Error: This error occurs when an analog signal is converted to discrete levels by an ADC (Analog-to-Digital Converter).

Cause: The ADC only accepts a limited number of levels: 2^N – where N is the number of bits.

The quantization step is defined as follows:

$$\Delta = \frac{V_{max} - V_{min}}{2^N}$$

The maximum error will be determined by the following formula:

$$E_{quantizion} \leq \frac{\Delta}{2}$$

Example: 10-bit ADC → 1024 levels. The signal is rounded to the nearest digit → information loss occurs.

Physical meaning: The measurement process is the following chain process:

Sensor → Electronics → ADC → Processing → Result

Each stage of the functional modules adds its error and the result is E_{total}.

Table 1. Short comparison table

Error type	Character	Source	Reduction method
(E_{sensor})	Systematic	Sensor physical property	High quality sensor
(E_{noise})	Random	Electrical noise	Filtration
$(E_{calibration})$	Systematic	Miscalibration	Periodic calibration
$(E_{quantization}$	Discretization	ADC bit limitation	High bit ADC

4. Algorithms

4.1. Flow scanning algorithm

$$x_k = f(x_{k-1}, u_k) + \omega_k$$
$$y_k = h(x_k) + v_k \tag{9}$$

This model forms the basis of discrete adaptive measurement systems [23, 24].

Kalman filtering

$$K_k = P_k H^T (H P_k H^T + R)^{-1}$$
$$\hat{x}_k = \hat{x}_{k-1} + K_k (y_k - H\hat{x}_{k-1}) \tag{10}$$
$$P_k = (1 - K_k H) P_{k-1}$$

The Kalman filter is considered an optimal filtering method in adaptive measurement systems [1, 25, 26].

Sensor fusion

$$\hat{x}_{fusion} = \sum_{i=1}^{n} \omega_i x_i$$

$$\sum_{i=1}^{n} \omega_i = 1$$

This approach is used to increase accuracy in multisensor systems [27, 28].

Fault detection$r_k = y_k - \hat{y}_k$

$$|r_k| > \delta \Rightarrow \text{Fault detected}$$

Anomaly detection is a key component of security-based systems [29, 30].

4.2. Modeling and Statistical Estimation

The root mean square error (RMSE) formula is a widely used measure of the residual standard deviations and also a measure of forecasting error. It estimates the average difference between the values predicted by a model and the actual observed values. It is a measure of confounding factors, meaning smaller values indicate a better fit between the model and the data. RMSE is very sensitive to outliers because it squares the deviations before averaging. Performance indicators [31-33]:

$$RMSE = \sqrt{\frac{1}{N}\sum_{k=1}^{N} (x_k - \hat{x}_k)^2}$$

$$Accuracy = 1 - \frac{|x - \hat{x}_k|}{x}$$

Lyapunov Stability Criterion [21,34]

$$V(x) > 0,\ \dot{V}(x) < 0$$

4.3. Test measurement algorithm for scanning parameter values

A test measurement method is proposed to determine the measurement errors of sensors with linear or nonlinear conversion characteristics, thanks to which additive and multiplicative tests are of particular importance [35,36].

As an example, simultaneous measurement of flow rate, volume, and temperature in a pipeline is considered. With the help of the system we offer, it is possible to read the current readings of smart sensors installed on any pipeline. If we assume a quadratic transformation function:

$$f_x = b_0 + b_1\rho_x + b_2\rho_x^2, \tag{12}$$

where f – the output quantity of the transmitter, frequency;

ρ_x – the input quantity of the transmitter, measurement parameter, density;

b_0, b_1, b_2– the parameters, coefficients of the transmitter's TF.

This algorithm, consisting of four measurement cycles, allows for highly accurate determination of the coefficients of the conversion characteristic. The generalized result of measurements performed with combined multiplicative and additive tests is determined by the following formula:

$$\rho_x = \frac{(f_0 - f_3) + (f_1 - f_2)}{(f_0 - f_3) - (f_1 - f_2)} \rho_{et}, \tag{13}$$

Since the errors of the measurement cycles are taken into account, the difference of these expressions will give the error (Δ_T) of the tested MS:

$$\Delta_T = (\rho_x + \rho_{et})(\Delta_1 - \Delta_2) + (\rho_1 - \rho_{et})(\Delta_3 - \Delta_0), \tag{14}$$

By substituting the calculated values of the additive and multiplicative tests, as well as the measurement errors, into the function that determines the final error of the test MS, we obtain the following mathematical model for the total (total) error:

$$\Delta_T = \rho_{et}[(\Delta_1 - \Delta_2) - (\Delta_3 - \Delta_0)] + \rho_x[(\Delta_1 - \Delta_2) + (\Delta_3 - \Delta_0)]. \tag{15}$$

We obtain the following expression for the absolute error $\Delta_{inp.}$ introduced into the input of the tested MS:

$$\Delta_{inp.} = f_T^{-1}[f_T(x) + \Delta_T] - x = \frac{\Delta_T}{f(x)_T^{-1}}, \tag{16}$$

where, $f_T(x) = (y_3 - y_0)(\rho_x - \rho_{et}) + (y_2 - y_1)(\rho_x + \rho_{et})$,

If we differentiate expression with respect to x, we get the following value for

$$f'_T(x) = (y_0 - y_3) - (y_1 - y_2), \tag{17}$$

If we substitute expressions (15) and (18) into (17), we get the following expression:

$$\Delta_{inp.} = \frac{\rho_{et}[(\Delta_1 - \Delta_2) - (\Delta_3 - \Delta_0)] + \rho_x[(\Delta_1 - \Delta_2) + (\Delta_3 - \Delta_0)].}{2\rho_{et}\big(b_2 + b_3(\rho_x + \rho_{et})\big)}, \tag{18}$$

If the real transfer function of the initial MS is in the form of a third-degree polynomial, then its identification as a result of piecewise nonlinear approximation is also realized by the appropriate algorithm.

Thus, all error components are random variables, and the distribution laws of Δ_i are defined as the sum of the distributions of random variables and, therefore, can be considered normal. Therefore, for their complete description, it is enough to know the MΔ -mathematical expectation and DΔ -variance.

From this we can conclude that under the mentioned conditions, the main characteristics of the errors of the tested measurement, which implement the algorithms for increasing the measurement accuracy of the MS based on simple additive and multiplicative tests, are justified for the tested IMS operating on the basis of the optimal set of additive, multiplicative and combination tests.

When the errors of the measurement cycles are independent of each other, due to the application of the combined test algorithm, we obtain the following expression for the variances of the errors of the tested MS:

$$\sigma_{\Delta_T}^2 = \sigma_{\Delta_0}^2[x(k-1)-\theta)]2 + \sigma_{\Delta_1}^2[x(k-1)+\theta] + \sigma_{\Delta_2}^2[x(k-1)+\theta] + \sigma_{\Delta_0}^2[x(k-1)-\theta)], \qquad (19)$$

As can be seen from the expressions obtained above, the dispersion of the Δ_T error of the main test equations of the MS tested in the algorithmic-test method of increasing measurement accuracy is increased compared to the dispersion of a single-step measurement.

As can be seen, the uncorrelated components of the additive error generally prevail, so the coefficient $K^*_{\sigma_{ad.}}$ depends on the values of the additive and multiplicative tests.

Clarify, the dependence of the coefficient $K^*_{\sigma_{ad.}}$ on the values of additive and multiplicative tests: as can be seen from expression, the detected correlation relation (CR) between the measured value, additive, and multiplicative test parameters is visually reflected by the presence of their values in the area A_0.

As a result of the application of algorithm, the uncorrelated components of the additive error of the TMS measurement result do not increase, at least because of the interrelation of the same error components. Graph 1 describes the dependence of $K^*_{\sigma_{ad.}}(\theta,k)$ in case of $x=x_0$.

As can be seen from the Graph, the dependence $K^*_{\sigma_{ad.}}(\theta,k)$, a given range of values of additive and multiplicative tests, is located behind the line intersecting with the points A^*A^* on the the single-level plane $K^*_{\sigma_{ad.}}$.

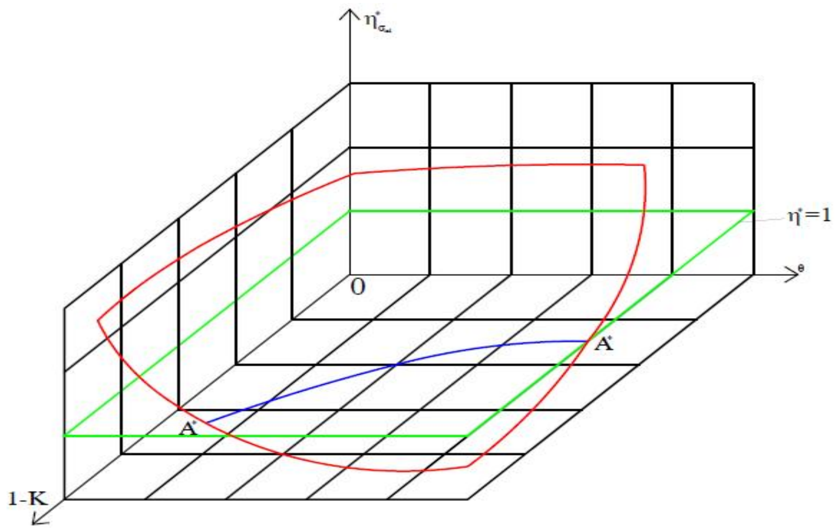
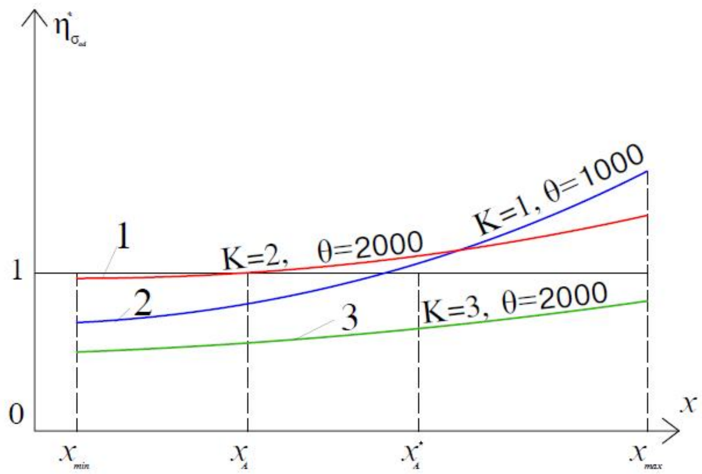


Fig. 2. Dependency graph $K^*_{\sigma_{ad.}}(\theta,k)$

Fig. 3 illustrates the dependence of $K^*_{\sigma_{ad.}}(x)$ on the given values of the additive and multiplicative tests selected from area A_0 . When the x values of areas θ and k are given, the additive components of the measurement error occurring during the execution of algorithm (90) do not increase compared to the analogous IMS error, are limited to values x_A, x^*_A and .The curve 3 corresponding to the θ and k values define the all IMS measurement range in this area.



Graph 2. Dependency graph $K^*_{\sigma_{ad.}}(x)$

here, 1 – dependency $K^*_{\sigma_{ad.}}(x)$, in case of $k = 2, \quad \theta = 2000$; 2 – dependency $K^*_{\sigma_{ad.}}(x)$, in case of $k = 3, \quad \theta = 1000$; 3 – dependency $K^*_{\sigma_{ad.}}(x)$, in case of $k = 3, \quad \theta = 2000$

Conclusion. Thus, the study of the metrological characteristics of the tested MS shows that the following factors most affect the resulting measurement error of this type of systems:

– the factor of the error arising from the use of fixed factors of additive and multiplicative tests;

– the uncorrelated factor of the static error of the tested MS;

– the factor of the dynamic error of the tested MS;

– the factor of the error arising from the inadequacy of the adopted mathematical model of the real conversion characteristic of the tested MS.

The developed test algorithms were tested on a real automatic density measuring (ADM-2M) device sample, the measurement errors were evaluated, and a decrease in the total error by several times was confirmed.

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