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# Prospects for using Chromel-Alumel Thermocouples TChA (Type K) with Normalizing Converters Based on Neural Network Methods of Linearization and Compensation of ThermoEMF Instabilities. Short Review

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## Abstract

The object of study is implementation of normalizing converters based on neural network methods to increase the accuracy of temperature measurements with Chromel-Alumel thermocouples (Type K). Detailed analysis of physical and technical limitations of Type K thermocouples is conducted including non-linearity of characteristic curve, irreversible parameters drift during high-temperature exploitation, reversible instability (hysteresis), as well as influence of cold junction temperature. Traditional linearization and error compensation methods are compared with innovative approaches based on artificial neural networks. Multilayer perceptrons (MLPs) for static error compensation and recurrent networks with long short-term memory (LSTM) for dynamic effects accounting are validated as the most effective architectures for solving the stated problems. The study demonstrates that neural network methods enable complex adaptive error compensation that can not be achieved by traditional methods, which paves the way for the development of a new generation of intelligent temperature sensors. It is concluded that type K thermocouples are highly competitive and promising in modern industrial systems in an Industry 4.0 environment, provided they are equipped with intelligent neural network converters.

**Keywords:** type K thermocouple, neural network, error compensation, intellectual sensors, machine learning

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# Перспективы применения термопар хромель-алюмель ТХА (тип К) с нормирующими преобразователями, основанными на нейросетевых методах линеаризации и компенсации нестабильностей термоЭДС. Краткий обзор

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Представлен комплексный анализ перспектив применения термопар хромель-алюмель (тип К) в сочетании с нормирующими преобразователями на основе нейронных сетей для повышения точности температурных измерений. Проведён детальный анализ физических и технических ограничений термопар типа К, включая нелинейность статической характеристики, необратимый дрейф параметров при высокотемпературной эксплуатации, обратимую нестабильность (гистерезис), а также влияние температуры холодных спаев. Осуществляется сравнительный анализ традиционных методов линеаризации и компенсации погрешностей с инновационными подходами, основанными на искусственных нейронных сетях. В качестве наиболее эффективных архитектур для решения поставленных задач обоснованы многослойный перцептрон (MLP) для компенсации статических погрешностей и рекуррентные сети с долгой краткосрочной памятью (LSTM) для учёта динамических эффектов. Показано, что нейросетевые методы позволяют осуществлять комплексную адаптивную компенсацию погрешностей, недостижимую для классических методов, и открывают путь к созданию нового поколения интеллектуальных датчиков температуры. Делается вывод о высокой конкурентоспособности и перспективности термопар типа К в современных промышленных системах в условиях Industry 4.0 при условии оснащения их интеллектуальными нейросетевыми преобразователями.

**Ключевые слова:** термопара типа К, нейронные сети, компенсация погрешностей, интеллектуальные датчики, машинное обучение

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## Introduction

Chromel-Alumel thermocouple (TchA, type K) is the most common temperature transducer in industry. Its popularity is defined by wide operating temperature range (from -200 °C to 1260 °C), optimal combination of performance characteristics, and high reliability at a relatively low cost. Key advantages of these thermocouples include high mechanical strength and vibration resistance, which are critical for operation in industrial environments, transport systems, and power plants. They demonstrate stability and durability when operating in oxygen-containing atmospheres, and, with appropriate protective sleeves, even in aggressive environments.

An important factor is the low cost of type K thermocouples compared to thermocouples made of noble metals (types S, R, B) and high-precision platinum resistor thermometers. Furthermore, their output characteristics are regulated by international (IEC 60584)[1] and national (ASTM E230, GOST R 8.585-2001)[2,3] standards [1], which ensures exceptional interchangeability of sensors. Because of this, the areas of application of type K thermocouples cover virtually all industrial sectors: metallurgy (furnaces, heating lines), oil and gas and chemical industries (reactors, synthesis columns), power engineering (boilers, turbines, cogeneration systems), automotive and aircraft manufacturing, as well as scientific research.

However, despite these advantages, one should take into account the accuracy limitations. According to NIST data and published studies of common standard converters, the measurement error of type K thermocouples in industrial settings can reach 5–10 % of the range [2, 3]. This is critical for modern manufacturing processes that require sub-degree accuracy, such as in the semiconductor industry or chemical reaction control. The main sources of error are nonlinearity of the thermoelectric voltage output, temperature hysteresis, drift of characteristic curve over time, and the dependence of the measurement result on the temperature of the cold junction.

## 1. Prospects for the use of K-type thermocouples in the context of Industry 4.0

In the context of the Fourth Industrial revolution (Industry 4.0), the requirements for measuring systems are undergoing significant changes. The focus is shifting from a single measurement to reliability, scalability, repeatability of the result, integration into digital ecosystems, and the total cost of ownership of the entire measurement system. It is in this context that K-type thermocouples are discovering new perspectives based on their fundamental advantages of low cost and reliability in the range from -100 to +1000 °C, which covers most of the needs of industrial production.

One of the key prospects is economic efficiency of distributed measuring systems and the Internet of Things (IoT). In scenarios that require the deployment of a large number of sensors, the cost of a single element becomes decisive. Research shows that the use of machine learning algorithms makes it possible to compensate for the systematic error of inexpensive sensors, providing accuracy sufficient for trend monitoring and predictive analytics tasks, while the total cost of the system is 50–70 % lower than when using more expensive analogues [4].

In addition, K-type thermocouples are indispensable for multipoint monitoring in extreme conditions. For modern technological processes, for example, in petrochemistry or pharmaceuticals, monitoring of the temperature field throughout the entire volume of the device is critically important. Multipoint thermocouples that combine several measuring junctions in one housing radically reduce the cost of installation, cable routing and subsequent maintenance compared to installing an array of single sensors [5]. At the same time, they demonstrate high reliability in conditions of vibrations and aggressive environments, and the development of new protective shells based on ceramic and metal-ceramic composites continues to expand the limits of their application [6].

An important advantage for Industry 4.0 is the low thermal inertia of type K thermocouples. Due to the low mass and compact size of the measuring junction, they have a minimum time constant, which allows them to instantly respond to temperature changes in gas and liquid flows [7]. This proper-

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[1] IEC 60584-1:2013 Thermocouples – Part 1: EMF specifications and tolerances. International Electrotechnical Commission.

[2] GOST R 8.85-2001 Gosudarstvennaya Sistema obespecheniya jedinstva izmerenij. Termopreobrazovateli soprotivleniya iz platiny, medi i nikelya. Nominalnyje staticheskiye harakteristiki preobrazovaniya [State System for Ensuring the Uniformity of Measurements. Resistance Temperature Transducers Made of Platinum, Copper, and Nickel. Nominal Static Conversion Characteristics] (in Russian).

[3] ASTM E230/E230M-17. Standard Specification for Temperature-Electromotive Force (emf) Tables.

ty makes them ideal for real-time control tasks such as exhaust gas temperature control in engines, steam monitoring in turbines, and temperature control in fast-flowing chemical processes [7, 8].

K-type thermocouples are becoming a key element for building Digital Twins. Creating accurate digital copies of physical assets requires dense sensor networks. The low cost and reliability of K-type thermocouples makes it economically feasible to deploy such networks for monitoring large-scale equipment. Data from a variety of sensors, after statistical processing and analysis using neural networks, make it possible to detect anomalies with high reliability, predict wear and optimize operating modes, ensuring long-term and stable operation of equipment.

Thus, the niche of K-type thermocouples in modern industry is clearly defined: this is the field of large-scale, reliable and cost-effective measurements over a wide temperature range, where cost of ownership, resistance to external influences and the ability to be integrated into digital systems are crucial.

## 2. Measurement problems with thermocouples of the THA type: physical and technical aspects

The nonlinearity of the thermo-EMF of type K thermocouples varies greatly among different units each described by a separate pronounced polynomial curve: the deviation from ideal linearity could reach 4 % at 1000 °C. It complicates the operational use of this type of thermocouple comparing to other types of thermocouples that have almost linear dependences of thermal EMF on temperature.

For the type K thermocouple, the reference function in the temperature range from 0 °C to 1300 °C [2] is defined by the following equation (1).

$$E=\sum_{i=0}^{n} a_i \times (t_{90})^i \times c_0 \times \exp[c_1 \times (t_{90}-126.9686)^2], \qquad (1)$$

where $E$ is EMF expressed in microvolts (μV); $t_{90}$ is ITS-90 temperature expressed in degrees Celsius (°C); $a_i$ is the $i$-th coefficient of the polynomial; $n$ is the order of the polynomial; $c_0$, $c_1$ are constants given in IEC 60584-1.

This nonlinearity of the thermo-EMF of a type K thermocouple is fully demonstrated by the dependence of the Seebeck coefficient of this type of metal junction on temperature (Figure 1) caused by the heterogeneity and behavior of the thermocouple materials.

To convert the measured value of the thermal EMF, the standard dependence of the thermocouple voltage on temperature is described by a power series (2):

$$E(T) = a_0 + a_1 T + a_2 T^2 + ... + a_n T^n, \qquad (2)$$

where the coefficients $a_i$ are determined by the electrode materials (for example, chromel-alumel for type K) [2].

Approximation of the initial temperature to thermo-EMF dependence for type K thermocouples using a polynomial function (1) and coefficients given in standards IEC 60584, ASTM E230, ITS-90 and GOST R 8.585-2001 demonstrates high accuracy. However, numerical modelling shows that the normalization curve is divided into three temperature sections, each of which has a characteristic error in mathematical approximation: in the range from -200 °C to 0 °C the error ranges from -0.02 °C to 0.04 °C; in the range from 0 °C to 500 °C the error ranges from -0.05 °C to 0.04 °C; and in the high-temperature range from 500 °C to 1372 °C the error increases to values from -0.05 °C to 0.06 °C.

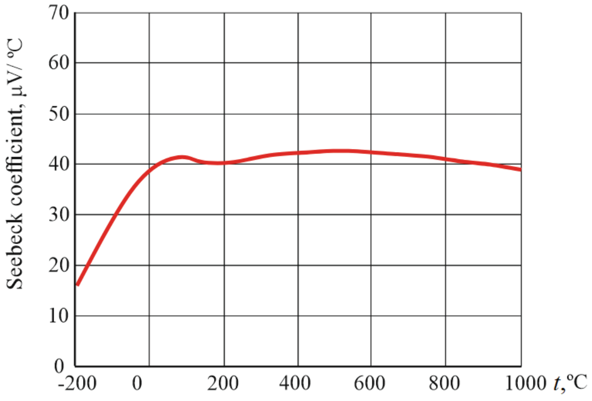

**Figure 1** – Seebeck coefficient for thermocouple type K

Despite the quite high accuracy of the polynomial model, many industrial measuring devices for linearization and normalization of the output thermo-EMF use standard IEC 60584 tables, approximating the dependence with ready-made piecewise linear tabular segments. This approach, dictated primarily by the limited computing power or hardware limitations of outdated measuring instruments, leads to additional calculation errors. Its value can reach 0.2…2 °C, which is especially noticeable in the areas of the approximating curve break where the linear segments cannot accurately reproduce the initial nonlinear dependence. Thus, the total measurement error consists of the intrinsic approximation error of the standard and the methodological error introduced by simplified calculation algorithms used in measuring equipment.

Two types of thermo-EMF instability are also observed in K-type thermocouples: irreversible instability that gradually accumulates over time (long-term, cumulative), and reversible instability (cyclic, short-term) [9].

The irreversible instability of the K-type thermocouple is mainly due to its interaction with the environment at high temperatures. The change in thermo-EMF is especially noticeable when operating K-type thermocouples at temperatures starting from ≈600 °C for ≈1000 hours. When operating a K-type thermocouple in air and in other oxidizing environments (especially with high oxygen content), an irreversible increase in its thermo-EMF is observed. Only in some cases, at 500 °C, there is no thermo-EMF drift. The magnitude of the thermo-EMF drift increases with increasing temperature and operating time. The graph of thermo-EMF changes is shown in Figure 2 [1]. Similar studies have also been conducted by several authors [10], [11], [12].

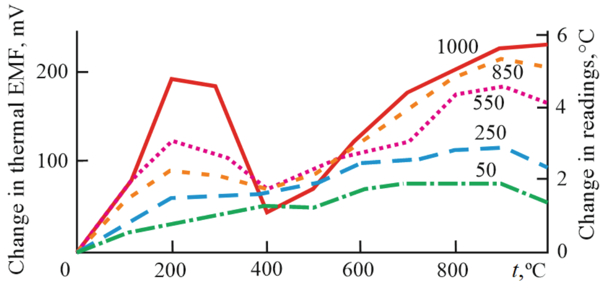

**Figure 2** – Change in the calibration characteristics of a type K thermocouple and its thermoelectrodes as a result of heating in air at 1000 °C (diameter of the electrodes 3.2 mm). The initial calibration is the abscissa axis. Figures over the curves indicate operational time in hours [4]

The reversible instability of a K-type thermocouple is mainly due to the occurrence of short-range transformations in chromel in the temperature range of 250–550 °C [9]. Graphs of the thermo-EMF readings for this range are shown in Figure 3.

The magnitude of the reversible drift depends on the previous history of the thermoelectrodes, the graduation temperatures, the cooling rate, and the gradient of the temperature field in which the thermocouple is located. Reversible drift is very difficult to distinguish from irreversible thermo-EMF instability. When using classical methods of measuring and normalizing thermo-EMF values, it is impossible to exclude reversible drift which produces deviation equivalent to 3…5 °C in the output signal readings [9].

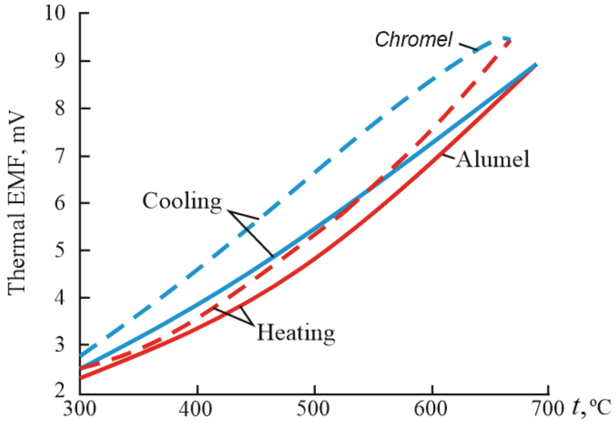

**Figure 3** – Measured reversible instability of thermoelectrodes of a type K thermocouple during the heating and cooling cycle [4]

The measurement accuracy of type K thermocouples is limited by a combination of physical, technical, and operational factors. The systematic errors inherent to the method include several key aspects. First, the nonlinearity of the thermo-EMF of a type K thermocouple has a pronounced polynomial curve: the deviation from ideal linearity reaches 4 % at 1000 °C. Secondly, the fundamental problem is the influence of the temperature of the free ends (cold junctions) of a thermocouple. Since thermo-EMF develops in proportion to the temperature difference between the working and free ends, any inaccuracy in their measurement or compensation introduces a non-linear error in the result.

Instability phenomena make a significant contribution to the total measurement error. The irreversible instability of the type K thermocouple is mainly due to the interaction with the environment at high temperatures, which causes irreversible changes in the materials of thermoelectrodes (chromel and alumel). These include oxidation, changes in chemical composition at grain boundaries, diffusion of impurities, and evaporation of alloying additives during vacuum measurements. Studies show that the drift can reach several degrees per year during prolonged operation in such conditions. Reversible instability, in turn, is mainly due to the occurrence of short-range transformations in chromel in the temperature range of 250–550 °C. In addition, the calibration can change due to mechanical stresses and vibrations leading to plastic deformation and a change in the crystal structure of the conductors.

Thermoelectric heterogeneity stands out among the operational errors. Different sections of thermoelectrodes may have minor deviations in composition or structure, and in the presence of a temperature gradient along such an inhomogeneous electrode, a parasitic thermo-EMF occurs, distorting the measurement result. This error is one of the most difficult to eliminate. Electrical interference also has a significant impact. The low signal level of the thermocouple (odds to few dozens of mV) makes it extremely sensitive to interference from power equipment. Also, with a large length of conductors, especially small diameter ones, the difference in their resistance can lead to an additional error due to the flow of direct current producing uneven voltage drops in two conductors. Finally, significant errors could be caused by heat dissipation through the electrodes and the protective cover of the thermocouple, which is especially critical when measuring the temperatures of small objects or in environments with low thermal conductivity, such as gases or vacuum.

The accuracy of the type K (chromel-alumel) thermocouple is regulated by a number of international and national standards.

According to ASTM E230 standard, the standard accuracy class is ±2.2 °C or ±0.75 % of |T| in the range 0…1260 °C, and the special class is ±1.1 °C or ±0.4 % of |T| in the same range. For negative temperatures (extended range), the accuracy class according to ASTM E230 is ±1.1 °C or ±0.4 % of |T| in the range of minus 200…0 °C.

The IEC 60584-2 standard (GOST R 8.85-2001) establishes accuracy classes "1", "2" and "3". Class "1" ranges from minus 40 °C to +375 °C with the error of ±1.5 °C and from +375 °C to +1200 °C with the error of ±0.004 × |T|. Class "2" establishes the error of ±2.5 °C in the temperature range from minus 40 °C to +333 °C and ±0.0075 × |T| in the temperature range from +333 °C to +1200 °C. Class "3" establishes the error of ±2.5 °C in the temperature range from minus 167 °C to +40 °C and ±0.015 × |T| in the temperature range from minus 200 °C to minus 167 °C.

Thorough accounting and compensation for the described errors using traditional methods poses significant difficulty, which results in a significant deterioration of measurement accuracy. It is apparently possible to obtain much more accurate values than the standards regulate, compensating for the main instability of the behavior of chromelalumel alloys.

## 3. Standard methods and means of converting thermo-EMF readings to temperature

Traditional thermocouple signal processing methods are based on hardware and software implementation of standard algorithms [13]. The accuracy of these methods strongly depends on the hardware and software used for signal processing. For the analysis below the best and average achievable parameters where selected.

1) Hardware cold junction compensation is the most common method of reducing the measurement error. It is generally implemented by usage of precision semiconductor temperature sensors (for example, integrated circuits of the AD59x or LM35 series) installed in the terminal block of the measuring instrument. The temperature of the cold junctions measured by these sensors is used to create a compensating bias voltage, which is added to the amplified thermocouple signal using analog circuits. This method has low accuracy with the resulting errors up to 5–20 °C and requires periodic monitoring and verification.

2) Software linearization could be described as a more accurate method than the hardware compensation. In microprocessor converters, the digitized values of the thermo-EMF and cold junction temperature are generally processed according to the standard polynomial equations given in IEC 60584, ASTM E230, ITS-90, GOST R 8.585-2001. These high-degree equations in the form of up to the 8th to 9th degree polynomials for type K thermocouples make it possible to approximate the characteristic curve with high accuracy. However, such calculations are extremely computationally expensive so much simpler approximation using standard tabular values is mainly used instead. The accuracy of software linearization usually ranges from 0.5 °C to 5 °C.

3) The combined hardware and software solution assumes the use of specialized microchips (ASICs). Ready-made solutions such as Analog Devices MAX31856 have become widespread [14]. These chips integrate an instrument amplifier, a cold junction compensation circuit and a linearizer on a single chip, providing an output voltage that linearly depends on the temperature of the working junction. The accuracy of normalization and linearization is however quite poor consisting about 2...15 °C.

The limitations of standard methods for compensating for thermocouple errors are fundamental, which renders the achievement of the highest possible accuracy with these methods impossible. One of the key disadvantages is the lack of adaptability of existing algorithms. They are not able to take into account the individual drift and aging of a particular thermocouple, as well as its deviation from the average standard characteristic curve. Long-term instability is associated with fundamental physicochemical processes such as impurity diffusion, corrosion, and mechanical deformations. For example, oxidation of an aluminum electrode above 800 °C leads to a thermo-EMF drift of up to 0.1 °C/hour, and when working in vacuum furnaces, the drift can reach 1 °C per year due to evaporation of materials. This phenomenon requires frequent calibration and verification, which is expensive and often considered economically unjustified. As a result, thermocouples are often used with a greater than nominal error.

Another significant disadvantage is the disparate error compensation. Each type of error, such as cold junction temperature, thermal inertia of the compensation unit, or uneven heating of the printed circuit board, is compensated by a separate unit or algorithm. This approach does not take into account the mutual influence of factors and can lead to the accumulation of errors, reducing the overall effectiveness of compensation.

Standard methods also demonstrate an inability to account for complex effects. These include, for example, reversible instability and hysteresis, the effects of which are not described by standard polynomials. A special type of hysteresis occurs due to irreversible microstructural changes in the thermocouple materials during cyclic heating and cooling. In type K (nickel-chromium/nickel-aluminum) thermocouples at temperatures above 500 °C, there is a discrepancy between the readings during heating and cooling reaching sometimes 6 °C due to the oxidation of chromium and the formation of oxide films. This effect is not linear and depends on the rate of temperature change, which excludes the possibility of its compensation by simple correction factors.

Finally, the classical cold junction temperature compensation using thermistors or integrated sensor chips has a dynamic error in the range of 0.1…1 °C. This error is caused by thermal lag and uneven heating of the measuring unit. In conditions of frequent and unpredictable changes in ambient temperature, this limitation becomes critical.

The combination of these fundamental limitations encourages an active search for more flexible and adaptive signal processing methods based on machine learning principles that are able to adapt to changing conditions and take into account the complex nature of errors that arise.

## 4. The use of neural networks for characteristic curve normalization and error compensation

Artificial neural networks offer a fundamentally different approach to solving the problem of error compensation of thermocouples. Instead of using a cascade of disparate algorithms, it is proposed to implement a single nonlinear model that maps the input data directly into the exact temperature value, taking into account all the main sources of errors in a comprehensive manner.

Three neural network architectures are considered to be the most promising for this task.

1) The multilayer perceptron (MLP) is a classical feed-forward network architecture, ideally suited for approximating complex nonlinear static dependencies which is the standard problem of temperature measurements using a type K thermocouple [15], [16]. Its key advantage in this context is the ability to approximate any continuous nonlinear function with any given accuracy.

The MLP network structure consists of an input layer, one or more hidden layers with nonlinear activation functions, and an output layer. It is easy to implement, demonstrates high-speed operation, and has excellent ability to approximate static characteristics. Thus MLP could effectively for non-linearity, cold junction error, and systematic deviations of a particular thermocouple from a standard curve.

2) Recurrent Neural Networks (RNN), and, in particular, their improved version, Long Short-Term Memory networks (LSTM), are designed to process sequences of data. This makes them an ideal tool for compensating for the temporal instabilities of type K thermocouples’ thermo-EMF (hysteresis), which by its nature is a dynamic effect dependent on the history of temperature changes [17], [18], [19].

LSTM building blocks contain internal memory (state) and mechanisms for "forgetting" and "remembering" information, which allows them to take into account the context, that is, the previous states of the system. Unlike MLPs, RNNs/LSTMs have internal feedback that allows them to store and update contextual information. A time series of recent measurements is fed to the network input. The network is trained to identify patterns in this sequence corresponding to the heating or cooling phase, and predict the adjusted output temperature value basing on this information. It makes LSTM networks ideal for error compensation in conditions of dynamic temperature change when the inertia of the sensor and measuring circuit introduces significant dynamic error. The network could be trained to predict the current true temperature, taking into account the history of its change. The ability to simulate dynamic processes, compensate for phase shift caused by inertia, and filter high-frequency noise is especially important for managing fast-pacing processes.

3) Hybrid architectures represent a combination of convolutional layers and a perceptron (CNN + MLP) for noise filtering, and fully connected layers for regression. In systems operating under conditions of electromagnetic interference (induction heating systems, induction furnaces, powerful electric generators or motors), such networks reduce the root-mean-square (RMS) error by comprehensive filtering of high-level noise and subsequent compensation of static and dynamic errors. However, such networks are extremely difficult to learn and introduce difficult-to-compensate unpredictable errors when operating conditions differ from training conditions.

A hybrid network usually consists of two main parts:

1) A convolutional part (CNN).

One or more one-dimensional convolutional layers act as an adaptive digital filter. These layers do not have full connections and process just local parts (segments) of the signal, extracting features and effectively suppressing high-frequency interference. The parameters of this "filter" are not set manually, but are trained using the sample data.

2) A fully connected part (MLP).

After filtering the features extracted by CNN layers, the data is transferred to the input of a classical multilayer perceptron. Its task is to perform the final regression and compensation of the remaining errors based on the noise-free signal.

In tasks where flexible and diverse filtering of measurement results and signal recovery is required, the hybrid (CNN + MLP) architecture reduces the RMS error, which indicates the powerful filtering potential of this hybrid bundle of different neural networks. This bundle is used to filter noise during temperature measurement in other studies, similar works are presented in [20], [21].

The main problem with such complex architectures is their extremely high propensity for overfitting. The network becomes highly specialized for specific learning conditions (noise level and type, process dynamics). When operating conditions change (for example, the emergence of a new source of interference, a change in the frequency of the stray signal), the network may begin to introduce an unpredictable error that is difficult to compensate for, as its behavior becomes difficult to interpret and correct. This requires a very extensive and diverse training dataset, and complex weighting methods. At the same time, the problem of dynamic instability of thermo-EMF of type K thermocouples (thermo-EMF hysteresis) remains unresolved.

The implementation of artificial neural networks for normalization and compensation of thermocouple errors is a fundamentally new and promising approach that overcomes the key disadvantages of traditional methods. Its main advantage lies in the transition from disparate compensation of individual errors to the creation of a single nonlinear model that comprehensively takes into account all major sources of errors and directly maps the input data into an accurate temperature value.

The analysis showed that specific neural network architectures are most effective for solving various types of errors, and choosing a specific one is a compromise between the complexity of the task, data availability, computing resources, and system stability requirements. The Multilayer Perceptron (MLP) has exceptional efficiency in compensating for static errors such as non-linearity of the thermo-EMF and systematic deviations from the standard characteristic curve due to its ability to approximate any continuous nonlinear functions. To account for dynamic effects such as hysteresis, which depends on the history of temperature changes, recurrent networks with LSTM blocks capable of storing time dependencies are an ideal tool. In conditions of strong electromagnetic interference, hybrid architectures (CNN + MLP) are promising, where convolutional layers act as an adaptive filter and the perceptron performs the final refining and compensation, although such models require extensive training dataset due to their tendency to overfitting.

Different architectures of neural networks represent a compromise between the complexity of the problem being solved, the availability of representative data for training, computational resources, and the required stability of the information measurement system in the realities of operating conditions [22].

## Conclusions

The analysis demonstrates that the combination of reliable and cost-effective type K thermocouples with modern machine learning methods would eventually achieve accuracy exceeding standard requirements thus highlighting the high prospects of type K thermocouples in the context of industrial digitalization. Machine learning approaches, in particular multilayer perceptrons (MLP) for compensating static and LSTM networks for dynamic errors, allow us to overcome the fundamental limitations of traditional compensation methods. Instead of disparate algorithms, a single adaptive model is proposed that comprehensively takes into account nonlinearity, hysteresis, and sensor aging. This paves the way for the creation of a new generation of "intelligent" temperature sensors capable of self-tuning and operating as part of information and measurement control systems and "digital twins" within the framework of the Industry 4.0 concept.

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