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A NOVEL METHOD FOR EXAMINING TEMPERATURE SENSOR NOISE: HOW CAN THE OPTIMAL DEVICE BE SELECTED USING THE CORRELATION OF IMPORTANT PARAMETERS?

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Abstract. By comparing ten important parameters, the authors of this work present a novel method for determining which test measuring device is most similar to a particular reference sample: the comparative analysis of positive and negative fluctuations (CAPoNeF). In the absence of any potential outside influences, the output signals recorded from the available set of temperature sensors were used as the original data. Choosing the optimal sensor is not possible with the current treatment approaches. All the same, the issue can be resolved using the CAPoNeF approach, which makes it possible to choose the optimal element according to its features of fluctuation and noise.
The distribution of the "prizes" and selection of the best sensor among the suggested ones were made possible by the analysis of the reduced matrix N (number of local minima) $\geqq M$ (number of relevant parameters). When compared to the reference sample, which is the average of all recorded values across the temperature scale, analysis of the noise of temperature sensors across the manufacturer's specified temperature range revealed high data processing accuracy. As this method is developed further, it will be possible to analyze electronic components automatically and put in place as traffic light system.

Keywords: temperature, noise of measurements, optimal selection of sensor type, correlation of important parameters, comparative analysis of positive and negative fluctuations.

Section 1: Introduction and problem statement

The widespread use of electronic components and a wide range of measurement tools, which enable connectivity with the outside world, greatly simplifies the lives of modern people. Technologies that were unheard of and uncontrolled a short time ago are now actively developing, widely used in many facets of human endeavor, and producing both good and bad outcomes. The advancement of technology in the modern world, which involves automating present activities and leaving just control functions for humans, has both advantages and disadvantages.

The second aspect is the economic viability of automating manufacturing, both during the design and planning stages and throughout production. Even though the first stage was well planned by engineers, the second stage is more susceptible to the impact of negative factors, both internal and external. To be sure, there are a ton of methods, approaches, and tools out there that can be used to monitor the overall technical health of a system or just a particular part of it. The vast majority of them rely on examining the output signal from the sensor and contrasting it with an acceptable threshold value that has been predetermined. Papers [1-23] contain the main methods for data processing.

The existing probabilistic techniques are capable of solving most issues, however they become unsatisfactory when data analysis is applied to noise processing [24] Conversely, since the proposed method is not based on any model assumptions, it does not include uncontrolled error. Unfortunately, there are currently extremely limited methods for studying noise spectroscopy [25-31]. Digital signal processing researchers often ignore the noise track since it is widely accepted to contain no useful information [19]. We were able to create a generic methodology that allows us to assess the technical state of the electronic component in comparison to the reference sample based on a few crucial factors that are generated from the trend-free noise sequences after a careful and comprehensive analysis. We were able to ascertain the existence of a vehicle system node malfunction in addition to the high degree of accuracy of the findings obtained from a previous study [32] that employed the statistics of *complex moments* approach to process pressure sensor noise. We were able to advance from the study of electrical engineering and electronics to the study of sea noises (silent, calm, furious/strongly agitated) thanks to the discoveries from [33].

The current work aims to apply the comparative analysis of positive and negative fluctuations (CAPoNeF) approach to select a temperature sensor whose noise parameters are closest to a specific reference sample. The structure of the work is as follows. The second section includes a description of the setup and the specifics of the experiment. The third section contains an explanation of the recommended course of action. The fourth section presents the suggested processing of the acquired experimental data. In the fifth section of the report, the authors provide the main conclusions derived from the data and lay the groundwork for future investigations.

Section 2: Experimental details

The experiment was carried out at the KNRTU-KAI Institute of Radio Electronics, Photonics and Digital Technologies' Department of Radio Electronics and Information and Measuring Technology. Fig. 1 depicts the experiment's layout. The measuring apparatus was an Elvis II breadboard that was connected to a personal computer that had drivers pre-installed for data reading and processing. Let's talk a little bit about the reasoning behind choosing this particular kind of measuring equipment and the assigned kind of measuring apparatus.

The automated Elvis workstation from National Instruments features an integrated reference voltage source, a high-bit analog to digital converter (ADC), and Windows-compatible software. USB connections are among the most affordable solutions available today. They allow you to provide quick data transfer speeds, minimize the effects of external interference, and interfere. Investigating various measuring devices, whose working principles are derived from various physical events, is certainly fascinating and a lot of fun.

Thus, in previous work, we examined photodiodes and transistors to study their intrinsic noise, pressure sensors to assess the efficiency of the vehicle's fuel system, and so on. Temperature sensors were selected as the study's subject due to their relative availability, low cost, easy analysis, and extensive market availability. This is especially important because our study has received very little outside funding.

One of the most important requirements for performing measurements is making sure that the measurement is uniform and that the outcomes can be reproduced in the future. However, it is also critical to remember that all measuring instruments have to be in same conditions and exposed to identical external forces in order to minimize the effect of the intrinsic randomness of the external leads. One method of compensating for the presence of a systematic component is the filtration process. The two primary types of measurements are parallel and sequential measurements. In previous work [32-33], we measured components successively (one after the other) utilizing one channel of an analog-to-digital converter. This has the advantages of simplifying the measurement process, requiring less energy consumption, and eliminating the need for a multi-channel ADC. As for ensuring the consistency of measurements in this case, there is a major problem. Firstly, in order to minimize the effect of extra thermal noise, a longer cooling time is required if a soldering installation method is used due to the solder location's continuous heating. Second, when using mounted mounting, it is common to experience contact rattle when changing out a measurement element (sensor). This might lead to additional random error. Thirdly, the influence of external factors like temperature, humidity, and light will fluctuate randomly over time, albeit not significantly. Nevertheless, after a great deal of effort, we obtained measurement data that were highly reproducible. For this investigation, we selected a parallel data collection strategy in which each measuring device (temperature sensor) was linked to a separate channel of the multichannel ADC of the Elvis workstation and assessed simultaneously. This method allows the precise assurance of measurement unity because it allows the transient capacitances and resistances of each contact of the measuring devices to be leveled by directly measuring them prior to the experiment. Furthermore, every sensor will simultaneously be exposed to systematic external impacts, which enables the application of filters or the disregard of this effect as required. Consequently, the measurement device itself will be the only source of random noise, which is merely necessary to solve the current issue. Any measuring channel circuit can actually be represented by a sensor, an analog-to-digital converter, a unified measuring converter, and a key. A potential user is aware that the accuracy of the next block shouldn't be worse than the accuracy of the previous blocks if we are unable to initially collect a high-precision useful or noisy signal. Using a high-bit ADC is not necessary in this situation.

Therefore, processing the data using high precision methods is not necessary if the data were initially acquired with a low level of accuracy. Therefore, present methodologies can be used to a wide range of problems involving useable signals, as was said in the previous section, but where noise data analysis is concerned and a great processing sensitivity is necessary. This is particularly true when the signal-to-noise ratio (SNR) parameter value is less than one, or when interference is present and the useful one is virtually absent. The main drawback of most currently employed methods in this context is that the signal type in issue is not amenable to processing.

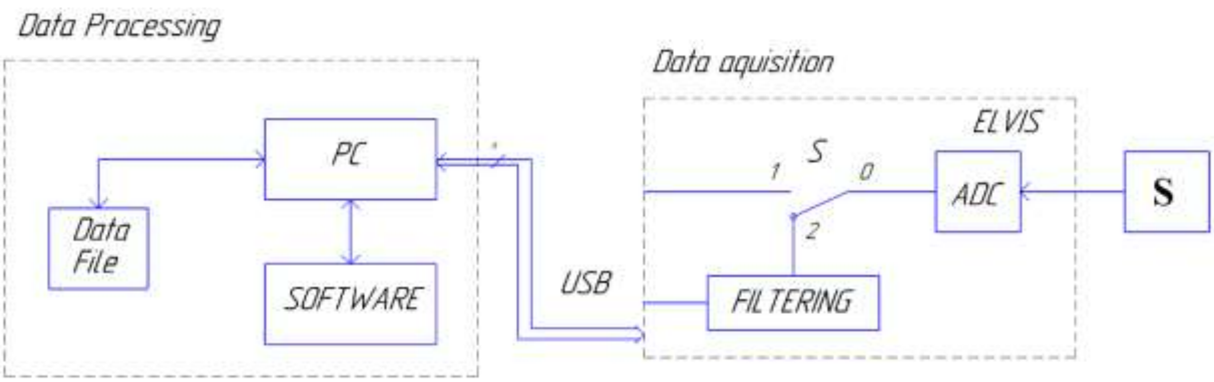


Fig. 1. Diagram of the experimental setup

The data processing and data removal procedures make up the two blocks that make up the scheme depicted in Fig. 1. The first unit is made up of sensors connected to Elvis II measurement apparatus, whose working principle depends on the output voltage's relationship to the surrounding temperature. This device can connect up to 14 devices simultaneously, has a bit depth of 16 bits, and a sampling rate of 1.25 MS/s, making it ideal for completing the assignment. Measurements were conducted in parallel while all sensors were simultaneously connected to the measuring apparatus at the same ambient temperature to guarantee the experiment's unity.

Reducing the impact of outside noise and interference, particularly random noise, and looking at each device's solely internal settings are equally crucial. Filtering is recommended in order to eliminate the effects of systematic mistakes and the analysis of low-frequency noise (S). The integrity of the final image is taken into consideration when choosing the filtering range through experimentation. A personal computer (PC) connected to the Elvis breadboard via a USB data exchange bus serves as the data processing unit's representation. This protocol's market availability, fast data processing speed, adaptability, and relative simplicity define it. Data is written to a file (specified as DataFile) at all times, and it is always possible to quickly access the data if needed.

To facilitate data processing, the software block is represented by a software product that is written in the relevant programming language and implemented in MathCad. This software allows for the application of novel mathematical algorithms that evaluate the technical state of an electronic component by comparing its positive and negative fluctuations to a reference sample. The device that most closely resembles the reference in terms of total value key correlation parameters is chosen. The following section has a thorough explanation of these settings. Since we are self-funded and do not get outside money, measuring devices need to be exceedingly affordable in order to comply with the price-quality principle. Thirdly, the notion of supplying either locally made or imported sensors through local merchants was considered because of the restricted availability of goods. After a careful analysis of the market, we decided on LM335Z type sensors because they were fully competent of finishing the tasks.

Eleven pressure sensors of the LM335Z type were employed as measuring devices, and each sensor's measurements were done in the same settings at room temperature. The data for processing was the arithmetic mean, and the experiment was repeated three times. Selecting a reference sample was a particularly pressing problem. The manufacturer's supplied output values for the sensor parameters are the best choice. Still, no manufacturer will divulge this knowledge openly; it is without a doubt at least a trade secret. Consequently, it is wise to use the arithmetic mean of all sensors at a particular moment as a reference value. Fig. 2 below provides suggestions for choosing a reference sample.

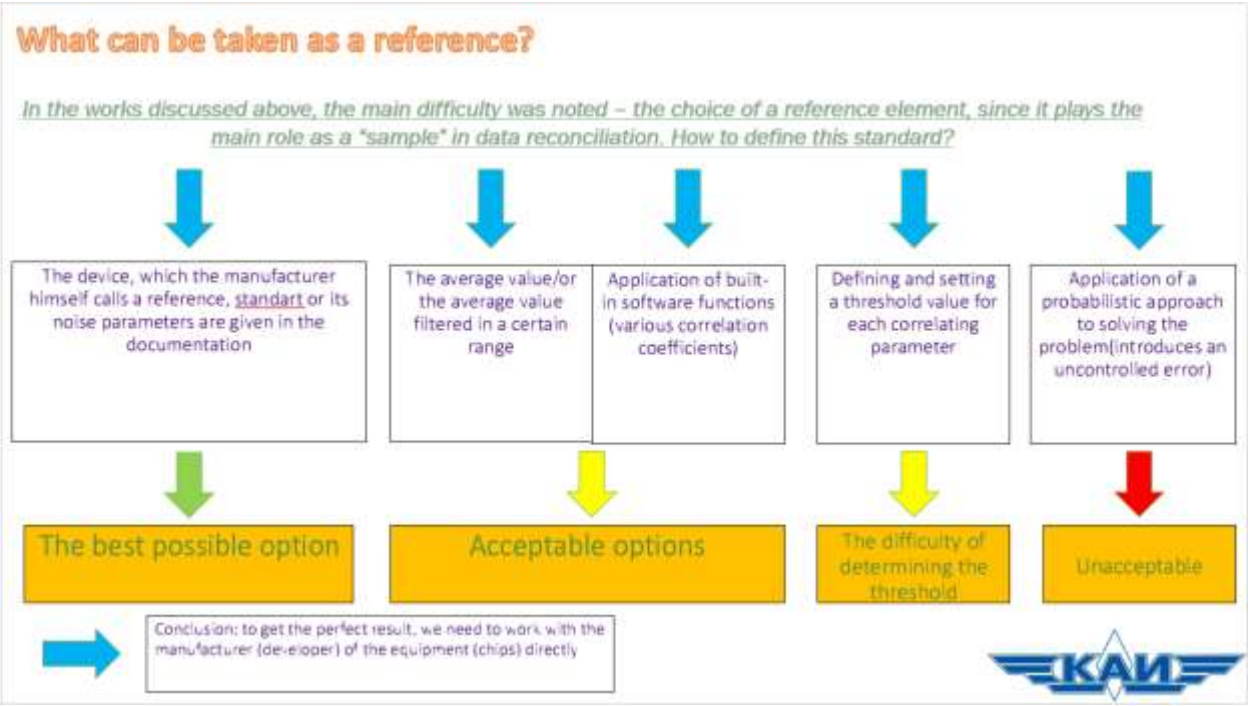
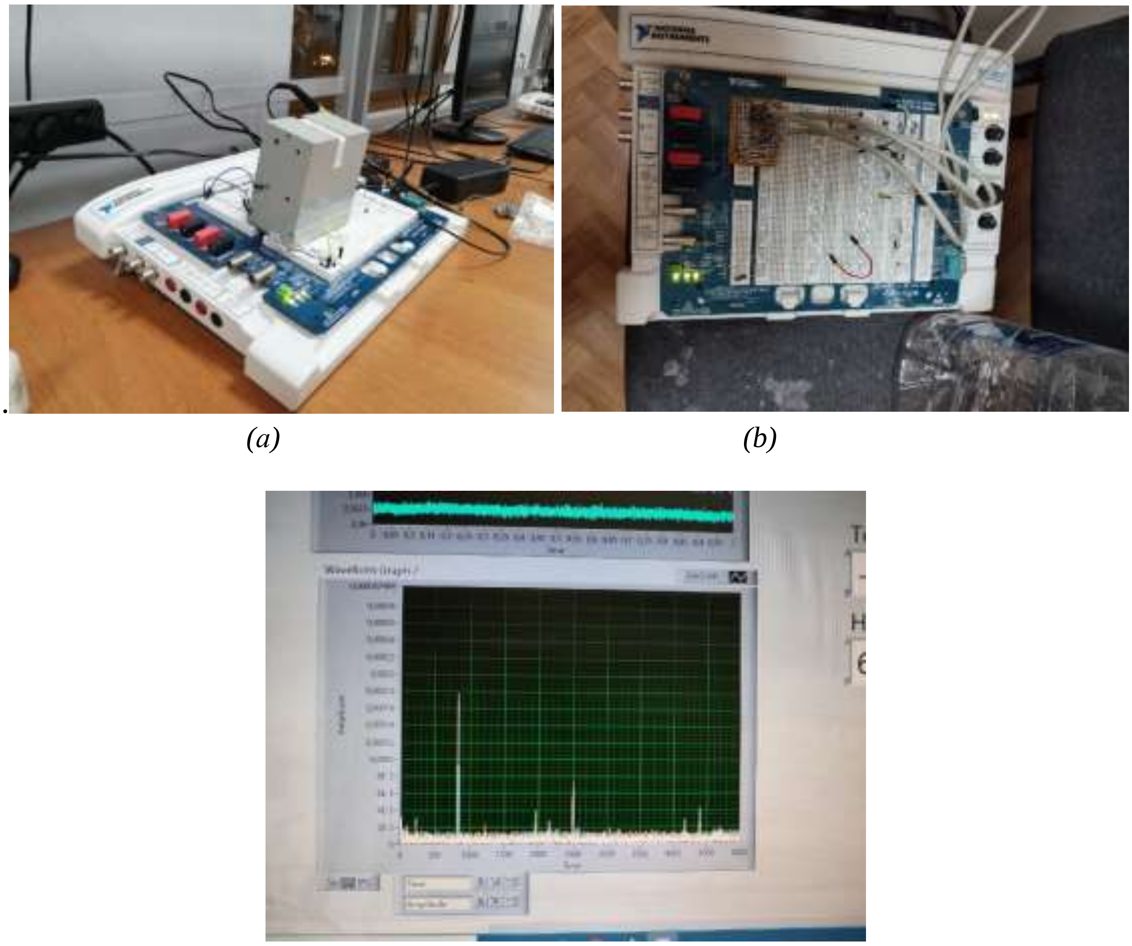


Fig. 2. Recommendations for the selection of a reference sample

A metal cover was placed over the board, and the entire installation—including the metal box—was grounded to reduce the impact of outside electromagnetic radiation and lighting (Fig. 3a). Fig. 3b depicts the Elvis breadboard in general view with a printed circuit board mounted on it and a harness connecting the sensors. Fig. 3c displays the noise spectrum that is being studied.

It is important to note that in the noise spectrum there is no frequency that is a multiple of the power supply frequency. The current bursts, which are systematic in nature and can be eliminated if needed, are present in all measured signals [20]. The cutoff frequency of the program filter is selected based on the requirements for ensuring the precision of the results and the lack of data loss. However, it is important to remember that, as we are investigating thermal noise, it is imperative to ensure that the room temperature stays consistent throughout the whole measurement procedure.



(a) (b)

(c)

Fig. 3. Using a metal box to reduce outside interference and grounding it like the installation, the experiment was conducted as follows: *a)* a general view of the Elvis breadboard with a printed circuit board mounted on it and a wiring harness connecting the sensors; *b)* the noise spectrum was examined; *c)* the noise spectrum is demonstrated

Fig. 4 depicts the experimental setup's layout. Let's go over how it works in general and some suggestions for selecting the denominations that make up its components.

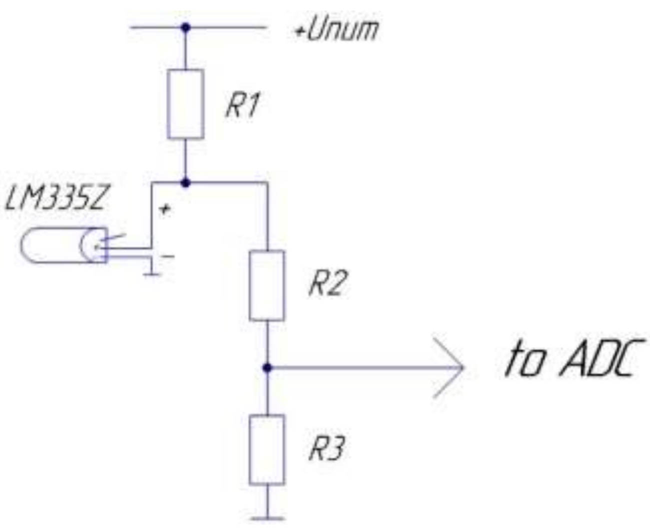


Fig. 4. Electrical schematic diagram of the installation

Since every temperature sensor was measured concurrently, or in parallel, it was anticipated that the Elvis system noise could not have a significant impact because it affected every sensor in the same way. As a result, we take the temperature sensor's noise into consideration.

The manufacturer's specifications state that the ELM335Z type sensor under investigation has three outputs and is intended to function at temperatures between -40 and +80 degrees Celsius. The power supply circuit is connected to pin number one (+), and ground is connected to pin number two (-). The third pin is not used; it is used for calibration. The supply voltage is taken from the built-in Elvis +5V power supply. The manufacturer states that the current that passes through the sensor is between 0.4 and 5 milliamperes. The nominal values of the voltage divider resistors from the sensor are selected so that, while the current flowing through them has minimal effect on the current flowing through the sensor, their decreased resistance is still substantially less than the Elvis II ADC's input resistance. The sensor operates in two critical phases: its minimum voltage at -40C and its maximum voltage at 80C. In light of the aforementioned, the component rating values shown below are the most suitable ones, at which the manufacturer's requirements are fulfilled and the permitted current limits are not exceeded: Resistance values were chosen using the E24 series as a guide: R1 = 1K, R2 = 9.1 kOhm, and R3 = 27K. We presume that the temperature of the sensors stays the same because they were placed in close proximity to one another on the same printed circuit board and the measurements were taken after the elements had cooled and the ambient temperature had been established.

Section 3. Description of the CAPoNeF – method

What makes the oscillations of random fluctuations known as "noise" so popular in science these days? Any arbitrary trend was considered to be a reaction to an applied external field before fluctuations were taken into consideration. This field could be electromagnetic, mechanical, etc. After that, the theory tries to explain the observed reaction. The fitting curve's coincidence with the observed trend gives us some specific knowledge, which helps us understand the outside world better. There's another trend going on right now. Once dismissed as useless "noise" and uninteresting, scientists are now trying to extract information from random fluctuations.

Many academics decide not to pursue noise exploration because it initially seems worthless. Through a thorough analysis of the nature of noise and a thorough study of the mathematical machinery, it was actually possible to lift the mystery surrounding noise analysis, to be able to "read" it quantitatively, to identify the key components, and to reduce them to a minimal set of the most statistically significant parameters. As previously mentioned, a common issue among all current approaches is the existence of an uncontrolled error that hinders us from checking the accuracy of the data acquired, especially when processing noisy data. There are two types of statistical decision-making errors that we are aware of [34]: first-kind errors, which cause false alarms, and second-kind errors, which cause a target to be missed. When configuring any system, the total of these errors needs to offer a minimum value and ideally tend to zero. This leads to an uncontrollable error known as skew since it is hard to choose the right threshold value at which the desired amount is small. Which is a better option, to put in more time and effort to repeat a signal check or to simply overlook it, figuring it's just a signal that can be ignored? Both situations' risks lead to an uncontrollable error that the measurement results are unable to account for. When processing noisy data, this cannot be allowed to continue. Is it feasible to propose a general strategy devoid of these errors and model assumptions? This approach [35] describes a particular "competition" between positive and negative amplitudes/fluctuations of the provided trendless sequence (TLS) using ten parameters. For the convenience of a possible reader, they are reproduced here in an instructional manner. Ten parameters can be proposed to provide a quantitative explanation of these fluctuations:

1. $p_1 = \langle y \rangle = N^{-1}\sum_{j=1}^{N} y_j$, the mean value of the TLS that determines to a specific balance between positive and negative fluctuations.
2. $p_2 = Rg(Dy) = \max(Dy_+) - \min(Dy_-)$, which defines the range of the given sequence for amplitudes that are located in the opposite sites of the TLS, namely $Dy_j = y_j - \langle y \rangle, j = 1, 2, ..., N$. This value is always positive and corresponds to the maximal intensity of the given TLS. For stable TLS it tends to the minimal deviations.
3. $p_3 = Rg\,|Dy| = \max(Dy_+) - |\min(Dy_-)|$, which defines the relative contribution of amplitudes that are in the opposite sides of the TLS, where Dy_+ stands for the positive values of the TLS and Dy_- gives the negative values of the TLS. $p_3 \cong 0$ corresponds to an “ideal” balance between positive and negative amplitudes. In the opposite case, when $p_3 > 0, p_3 < 0$, one can detect a set of specific “spikes/outliers” of positive (negative) amplitudes in the given TLS relatively to each other.
4. $p_4 = Rg(S) = \max(Sm_+) - \min(Sm_-)$, with $Sm_\pm = \sum_{j=1}^{N_+, N_-} Dy_{j,\pm}$ which defines the range of sums that evaluates the cumulative effect of the given fluctuations. It is proved to be very effective together with the independent parameter p_2. For "ideal" TLS it tends to its minimal value.
5. $p_5 = mean(y) - 0.5 \cdot (\max(y) + \min(y))$, which reflects a possible asymmetry between positive and negative fluctuations with respect to their mean value. For "ideal" TLS $p_5 \cong 0$ and it tends to zero. Therefore, one concludes that the TLS is completely symmetric, in other cases, when ($p_5 < 0,\ p_5 > 0$) it is possible to estimate the value of asymmetry.
6. $p_6 = DN = N(x_+) - N(x_-)$, which determines the number of amplitudes located in the opposite sides of the TLS. If $p_6 < 0,\ p_6 > 0$ then the number of positive amplitudes exceeds the number of negative amplitudes or vice versa. In "ideal" completely symmetric case $p_6 \cong 0$.
7. $p_7 = \max(Bd)$. If all amplitudes are put in descending order $y_1 > y_2 > ... > y_N$ and the obtained sequence of these ranged amplitudes is integrated, then one receives the bell-like curve defined by the fitting function $Bd(x) = A(x - x_0)^\alpha (x_N - x)^\beta + B$ and the maximum of this integrated curve clearly indicates the boundary between positive and negative fluctuations. This maximal value tends to minimal value for "ideal" TLS.
8. $p_8 = Range(JDy) = \max(JDy) - \min(JDy)$, which reflects the range of the cumulative/summarized fluctuations that are obtained after summation of positive and negative fluctuations, where $JDy_j = JDy_{j-1} + 0.5 \cdot (x_j - x_{j-1})(Dy_j + Dy_{j-1}),\ Dy_j = y_j - \langle y \rangle$, $JD_1 = 0$ and j=1,2,…,N is the sampling volume of the considered TLS. The minimal value of this parameter signifies about the minimal range/stability of the given fluctuations. For stable TLS this parameter should accept minimal value.
9. $p_9 = \langle JDy \rangle$, which is the mean value of JDy_j, is also important for evaluating the contribution of the cumulative fluctuations.
10. p_{10} = <ω>, which is an important parameter to determine the mean frequency of the fluctuations that cross the horizontal axis. In the most cases, the distribution of the roots can be approximated by a segment of the straight line $r_k = a \cdot k + b$, where the integer value k determines the number of the calculated roots. In this simple case, the mean frequency <ω> and the corresponding phase <φ> can be found from the condition: cos(ωr_k - φ) or, equivalently, $\omega r_k - \varphi = \frac{\pi}{2} + \pi k$. This parameter reflects the intensity of fluctuations crossing

the horizontal axis. If p_{10} accepts maximal values then one concludes that TLS does not contain the statistically significant low-frequency components.

A keen reader may inquire of the authors whether or not the collection of suggested parameters is comprehensive. The following are the fundamental standards by which these parameters are chosen: Three requirements must be met: (a) there must be no treatment errors (no integral/wavelet transformation is performed), (b) there must be no model assumptions (no fitting function is used for regression analysis), and (c) the parameters must be almost independent of one another and uncorrelated. Interestingly, all suggested parameters for the "ideal" TLS tend to their smallest values (p_1 and p_{10} parameters are excluded).

These parameters with their sensitivity to external factors can be divided on three groups: (a) p_2, p_3, p_4, p_7, p_8; (b) p_5, p_6, p_9; (c) p_1, p_{10}. The second group (b) suggests departures from symmetry in both vertical and horizontal directions, while the first group (a) is the most sensitive. Two additional parameters from the (c) group describe the degree of potential "uniform" oscillations inside the specified TLS as well as the stability of the mean value.

If we consider the list of parameters in detail, it is possible to adjust them a little, which will be very interesting to a potential reader. If, instead of a range, we consider the specific minimum and maximum values of the sequence, we get the parameters p_8 and p_9, respectively. The parameter p_{10} can be replaced for the average value of the specified sequence

$$p_8 = \min(JDy)\,;\;\; p_9 = \max(JDy)\,;\;\; p_{10} = mean(JDy)\;.$$

The needed task and the quality of the source data dictate whether to utilize the first or second set of parameters, and each unique case requires a different strategy for selecting the most useful values. The first set of parameters may be crucial for a prospective researcher to consider while delving into the noise of some periodic signals, particularly when analyzing the role of cumulative oscillations. You can select an average value from a range of groupings of criteria, such as arithmetic, harmonic, modal, and median, depending on the type of problem you're looking at.

For clarification, a graph of their distribution is provided below in Fig. 5 for the second group of parameters, which illustrates the function of invariant points in the data sequence.

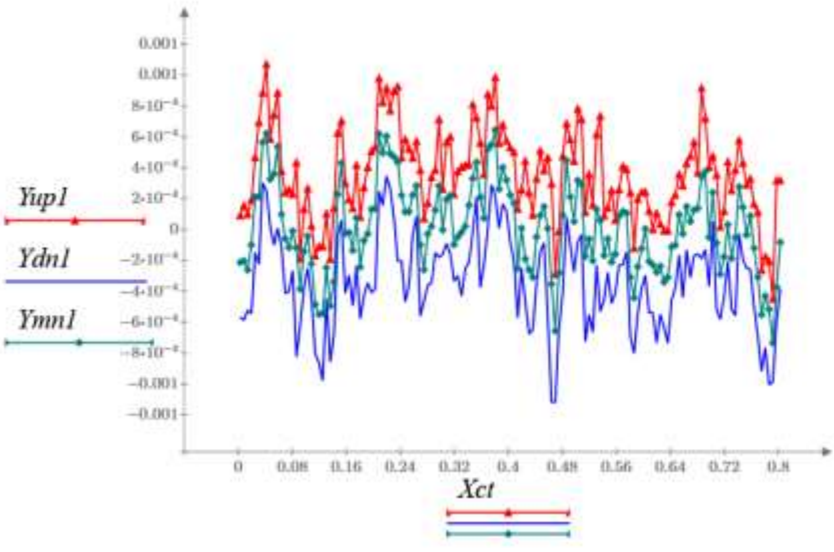


Fig. 5. Distribution of maximum, minimum and average values that remain invariant. Along the abscissa axis, the counts reduced to the normalized value are postponed. Along the ordinate axis, the voltage values ae given in volts (V)

Section 4. Data processing procedure

By the original program written in the simplest soft as Mathcad 15 we prepared 11 triangle matrices N(3 rows) × M(10 columns) coinciding with number of parameters p_1-p_{10} defined in the previous section. Then taking the mean value and the ranges for each column we obtain two matrices showing the distribution of mean values and ranges for each fixed parameter p. The further simplification of these two matrices N(10 rows, coinciding with 11 LM335Z) × M(10 columns, coinciding with number of parameters p_1-p_{10}). The further reduction becomes possible if we multiply mean value depending on the fixed parameter p on the given range from another matrix for the same parameter p, i.e M_k =mean(p_k)·Range(p_k). (k=1,2,…,10) In the result of this multiplication the following matrix is obtained. We select 3 minimal values in each column. They highlighted by purple (1-st place), yellow (the 2-nd place) and bronze (the 3-rd place) colors, correspondingly. This matrix (except parameters belonging to the group (c) p_1, p_{10})) is shown below. The temperature sensor number 1 with its recorded noise sequence is shown in Figure 5; other measuring devices show a similar pattern. The graph indicates that there is no discernible signal and that all that is seen is a regular noise sequence that does not first seem to have any information. It is important to remember that the recommended approach can only be applied to trend-free sequences in which the research graph's curve lacks a law of change. As a result, if a trend appears in the series, it needs to be either removed or an alternative data processing technique needs to be applied, like the three exponents method [36].

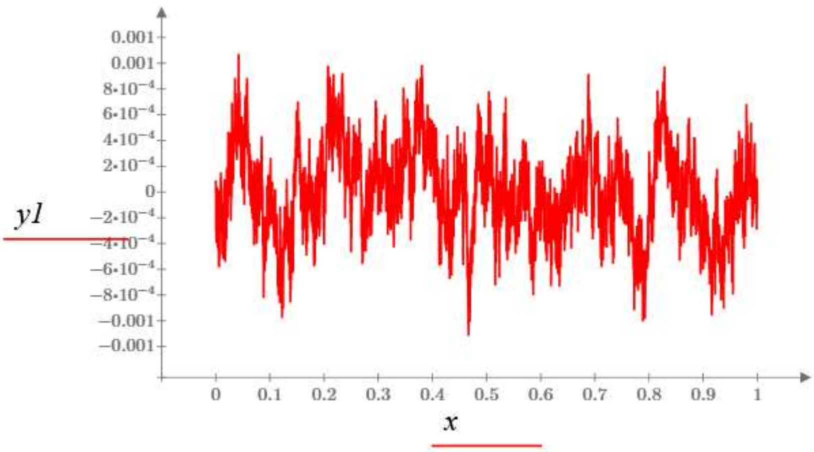


Fig.6 Initial noise sequence of the temperature sensor number 1. Along the ordinate axis, the voltage value are given in volts.

The distribution of the maximum, minimum, and average values is shown in Fig. 5. Why is it so important to think about these things? According to the theoretical and actual investigations of one of the authors (RRN), they remain invariant, meaning that their values do not alter in response to permutations of other points in a set sequence. Curious readers and future researchers may question if there is a way to increase processing accuracy because the noise sequence graph in Figure 6 is pure noise and cannot be examined visually. This gives you the ability to do an integration operation that improves the sensitivity and accuracy of data processing, two major issues. Figure 7 shows the integrated data from sensor No. 1 (red) and the reference sample (blue).

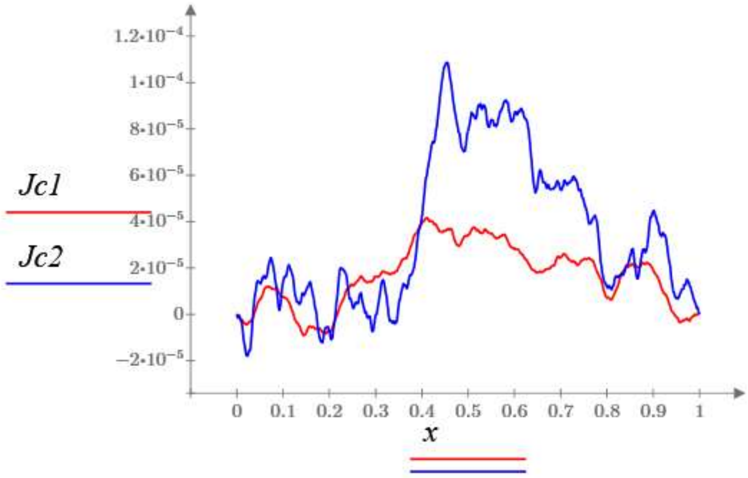


Fig.7 Application of integration operation leads to increasing of sensitivity and accuracy. As is has been mentioned above, the ordinate axis is given in the the voltage value (V)

The values of key parameters (Pr1-Pr10) for experimental sensors (S0-S10), the reference sample SE with the distribution of "prizes" are shown in Table 2.

Table 2. Distribution of "prizes"

	S0	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	SE
Pr1	1,938	1,936	1,933	1,92	1,877	1,858	1,89	1,88	1,935	1,926	1,935	1,912
Pr2	0,003382	0,003221	0,003221	0,003705	0,003544	0,003866	0,004188	0,003383	0,00306	0,00306	0,003383	0,002153
Pr3	-0,000146	0,0001867	-0,000119	0,0003391	9,13E-05	0,0004587	-0,0002154	-8,91E-05	0,0002236	4,29E-05	-0,000147	-7,48E-05
Pr4	3,387	3,523	3,473	3,467	3,684	3,695	4,381	3,809	3,506	3,49	3,339	2,424
Pr5	0,9172	1,123	0,929	1,202	1,053	1,269	0,9022	0,9487	1,158	1,028	0,9168	0,9328
Pr6	1447	-261	-501	-283	473	247	475	889	825	-419	1361	-69
Pr7	0,0001694	0,0001763	0,0001738	0,0001735	0,0001843	0,0001849	0,0002192	0,0001906	0,0001754	0,0001746	0,0001671	0,0001213
Pr8	-15,64	-68,56	-13,2	-130,8	-37,61	-61,02	-23,9	-73,05	-37,52	-39,84	-34,79	-78,56
Pr9	43,8	16,35	43,69	2,887	17,82	11	22,38	16,19	32,54	23,23	23,33	26,76
Pr10	10,64	-25,92	10,94	-70,95	-9,631	-26,98	-0,5674	-28,47	-1,149	-5,874	-3,042	-22,98
		2nd place	3st place	3st place				3st place	3st place	2nd place	WINNER	

Now let's look at the data in Table 2. Using the formulas presented in section 3, the values of the parameters Pr1–Pr10 were ascertained for every sensor S0-S10 as well as the reference sample. For the ease of data processing, an additional table was used, listing the values of the relevant parameters in ascending order. The value that, after taking the sign into account, is closest to the reference sample for each of the ten parameters was shown in green. As we can see, most of the parameters have values that are close to one other, but there are clearly differences. Theoretically, two parameters could have the same value, in which case choosing the winner could be difficult.

What is a person to do in this situation? Please remember that we discussed two possible parameter groups in the previous section that may be used when applying this method to the evaluation of noise data. Comparing the winner to the reference sample, it should be feasible to identify the winner with clarity using a different set of criteria. Here, the test was conducted using both sets of parameters, and the outcomes were the same. It is important to understand that all of the diversity in the world arises from the fact that everything has a unique noise nature. The greatest coincidence between the parameters indicates the closest the test sample can be to the reference. After examining the data in Table 1, we determine that test sample number 10 (three maximum likelihood matches) is the "winner". The second spot, which is shared by test samples 1 and 9, is explained by two coincidences each. Three, seven, and eight sensors are tied for third position. Though the prize distribution is conditional, it does enable the visual identification of the best sensor, akin to what happens in sporting events. In addition to choosing the best element from the list of suggestions, it is possible to determine which sensor values are within the acceptable range and pinpoint the issue provided the manufacturer supplies the reference data. In this case, the manufacturer determines the threshold value for each of the linked qualities by considering the technical specifications needed to create and maintain electronic equipment. The procedure for processing data will be the same in this case.

Section 5. Discussion of the obtained results

In this research, the noise of temperature sensors was analyzed and contrasted with the reference sample. A novel approach to data processing is presented, which is based on a comparison of positive and negative fluctuations. Assessing both internal and exterior correlations is necessary to ascertain which test sample most closely resembles a given standard. The suggested method does not contain uncontrolled errors because it does not make any model assumptions, in contrast to earlier approaches based on the probabilistic method. The procedure's application showed that the results were quite accurate, allowing us to conclude that sensor number 10 is the "winner" of this group of sensors because it replicates the reference sample's parameters the best.

With additional investigation into this sort of sensor across the complete temperature range using an appropriate temperature chamber, we can evaluate the parameters provided by the manufacturer and establish that these sensors can be employed and preserve their operational properties in crucial working situations. This is especially important in a number of hazardous sectors and bad climates. Moreover, the proposed technique allows you to analyze only the noise properties of measurement devices, highlighting two benefits: firstly, noise data is regarded as "garbage" and is neither proprietary nor confidential, so it can be shared freely for scientific purposes. Second, by conducting data analysis inside the non-destructive testing framework—that is, without taking the measurement devices out of the blocks—you can save manufacturing cycles.

As long as the electrical component meets the manufacturer's criteria, it will be able to track its current state in real time if the "traffic light" system is further deployed. The device is completely operational when the light is green; when it is yellow, there are deviations that do not affect the consumer or operational characteristics of the item. A red light indicates a malfunction and the device should be thrown away. Here, there are tight limitations on the quality of the reference sample.

This study's specifics closely match the publication's theme because the methodology offered is versatile and may be applied to any type of data processing, including that of artificial and natural data. By analyzing the noise of any electronic component—including sensors, optical devices, wireless systems, low-power and low-noise devices, and optical devices—monitoring and diagnostics will be enhanced without requiring the components to be taken out of the control object. The lifespan of the electronic component will be extended by the extended application of the mathematical technique in the form of "hardware," which is built with low energy consumption in mind. When the system is incorporated directly into the control object, real-time system performance monitoring is possible with an operator-specified polling frequency. This would make it possible to monitor energy characteristics in real time, such as leakage current and energy consumption, and to apply the concept of careful energy consumption. Moreover, this algorithm's implementation on the FPGA will significantly accelerate control operations and facilitate quick decision-making regarding the technical condition of the electronic component.

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Reference

1. Precioso, G. Tuna-AI: tuna biomass estimation with Machine Learning models trained on oceanography and echosounder FAD data / G. Precioso, D. Navarro, K. Barran, D. Gallego // Cold Spring Harbor Laboratory. – 2021. – V.1. - P.1-16.
2. Skrobova N. Statistical data analysis in the DANSS experiment / N. Skrobova // Journal of Physics. – 2019. – V.1. - P.1-6.
3. Skorlupkin, D. Selection of sensors of normally distributed random variables for statistical modeling in assessing the effectiveness of system / D. Skorlupkin, V. Sladkov // Applied electromechanics and devices. – 2017. – V.1. – P.63-69.
4. Eadie, W. Statistical Methods in Experimental Physics / W. Eadie, D. Drijard, F. James, B. Sadoulet // Journal of the American Statistical Association. – 2013. – V.1. – P.123-134.
5. Gustavo, M. Fractional Laplace transform and fractional calculus / M. Gustavo, O. Nelson, P. Jose, L. Romero // International Mathematical Forum. – 2017. – V. 12(20). – P. 991-1000.
6. Pyatakovich, V. Criteria for comparing artificial intelligence systems / V. Pyatakovich, V. Rychkova, N. Levchenko // Marine intellectual technologies. – 2021. – V. 3(4). - P. 21-26.
7. Gzyl, H. Fractional Moments and Maximum Entropy: Geometric Meaning / H. Gzyl, P. Inverandi, A. Tagliani // Communication in Statistics- Theory and Methods. – 2014. – V. 43(17). –P. 1-7.
8. Clavier, L. Impulsive noise modeling and robust receiver design / Clavier, L., Peters, G.W., Septier, F. et al. // J Wireless Com Network - 2021, 13 (2021), https://doi.org/10.1186/s13638-020-01868-1
9. von Hallern, C. A derivative-free Milstein type approximation method for SPDEs covering the non-commutative noise case / von Hallern C., Rößler A. // Stoch PDE: Anal Comp (2022). https://doi.org/10.1007/s40072-022-00274-6
10. Sun, Manman. Comparison of processing results of median filter and mean filter on Gaussian noise /M.Sun // Applied and Computational Engineering. - 2023. - P. 779-785, DOI:10.54254/2755-2721/5/20230702.
11. Songqing, Ma. A comparative study of multiple music signal noise reduction algorithms in music processing / Ma Songqing // Noise & Vibration Worldwide. - 2023. - 54. – P. 291-296. DOI:10.1177/09574565231179732.
12. Lan, Tianwei & Han. An Attention-Based Residual Neural Network for Efficient Noise Suppression in Signal Processing / Lan, Tianwei & Han, Liguo & Zeng, Zhaofa & Zeng, Jingwen // Applied Sciences. - 2023. - 13. - 5262. DOI: 10.3390/app13095262.
13. Shi, Lin & Palmer. Low Intensity Noise Exposure Enhanced Auditory Loudness and Temporal Processing by Increasing Excitability of DCN / Shi, Lin & Palmer, Katie & Wang, Haolin & Xu-Friedman, Matthew & Sun, Wei // Neural Plasticity. - 2022. - P. 1-11. 10.1155/2022/6463355.
14. Asghari, Mohsen & Zareinejad. Robust Matched Field Processing Using an Empirical Characteristic Function Approach Under Impulsive Noise Environments / Asghari, Mohsen & Zareinejad, Mohammad & Rezaei, Seyed & Amindavar, Hamidreza // Acoustics Australia. - 2023. DOI:10.1007/s40857-023-00287-8.
15. Chien, Y.-R. Signal Processing and Machine Learning for Smart Sensing Applications / Y.-R. Chien, M. Zhou, A. Peng, N. Zhu, J. Torres-Sospedra // Sensors. – 2023. – 23. - 1445. https://doi.org/10.3390/s23031445
16. Manjunatha G, Chittappa H.C. and Dilip Kumar K. Fault Detection of Bearing using Signal Processing Technique and Machine Learning Approach / G. Manjunatha, H.C. Chittappa and K. Dilip Kumar //Journal of Mines, Metals and Fuels. - 70, 10A. – 2023. - P. 380–388. DOI: https://doi.org/10.18311/jmmf/2022/32937.
17. P, Rini. Application of Signal Processing Techniques and Intelligent Classifiers for High Impedance Fault Detection in Ensuring Reliable Operation of Power Distribution Systems. /

P, Rini & Subathra, M. & George, et al. // Frontiers in Energy Research. - 2023. - 11. - 1114230. DOI:10.3389/fenrg.2023.1114230

18. Ma, Chunchi. Parallel Processing Method for Microseismic Signal Based on Deep Neural Network. / Ma, Chunchi & Yan, Wenjin & Xu, Weihao et al. // Remote Sensing/ - 2023. -15. 1215. DOI: 10.3390/rs15051215.
19. Buccino, D. Precision of Spacecraft Doppler Tracking at Low Signal-To-Noise Ratios / Buccino, D. & Oudrhiri, K. & Parisi, Marzia et al. // Radio Science. - 2023. – 58, DOI: 10.1029/2023RS007703.
20. Al-Attabi, Ali. Spectral Graph Filtering for Noisy Signals Using the Kalman filter. / Al-Attabi, Ali & Al, Ali. // ECTI Transactions on Electrical Engineering, Electronics, and Communications. -2023. - 21. 249818, DOI:10.37936/ecti-eec.2023212.249818.
21. Dorzhigulov, Anuar. Vishal Spiking CMOS-NVM mixed-signal neuromorphic ConvNet with circuit- and training-optimized temporal subsampling / Dorzhigulov, Anuar & Saxena // Frontiers in Neuroscience, 2023. – 17, DOI:10.3389/fnins.2023.1177592.
22. Shukla, Piyush. Cryptography-Based Medical Signal Securing Using Improved Variation Mode Decomposition with Machine Learning Techniques/ Shukla, Piyush & Akanbi, Oluwatobi & Asakipaam, Simon et al. // Computational Intelligence and Neuroscience, 2022. 1-13. DOI: 10.1155/2022/7307552.
23. Chen, Dong-Dong. A Survey on Analog-to-Digital Converter Integrated Circuits for Miniaturized High Resolution Ultrasonic Imaging System / Chen, Dong-Dong & Cui, Xinhui & Zhang, Qidong & Di // Micromachines. - 2022. - 13. - 114. DOI: 10.3390/mi13010114.
24. Fei, Jianbo. Interactive Multimedia Data Coscattering Point Imaging for Low Signal-to-Noise Ratio 3D Seismic Data Processing / Fei, Jianbo & Wang, Yanchun // Wireless Communications and Mobile Computing. - 2022. 1-12. DOI:10.1155/2022/6904653.
25. Wei, Zhiqing. Iterative Signal Processing for Integrated Sensing and Communication Systems /Wei, Zhiqing & Qu, Hanyang & Jiang, Wangjun et al. // IEEE Transactions on Green Communications and Networking. - 2023. PP. 1-1. DOI:10.1109/TGCN.2023.3234825.
26. Kremer, Thomas. Review of Acquisition and Signal Processing Methods for Electromagnetic Noise Reduction and Retrieval of Surface Nuclear Magnetic Resonance Parameters / Kremer, Thomas & Irons, Trevor & Müller-Petke, Mike et al. //Surveys in Geophysics. - 2022. – 43. - 1-55. DOI:10.1007/s10712-022-09695-3.
27. Lu, Tao. Underwater Noise Signal Processing Method Based on LMD Envelope Spectrum / Lu, Tao & Zheng, Yi & Mudugamuwa, Amith // IEEE 18th International Conference on Communication Technology (ICCT), 2018, https://doi.org/10.1109/icct.2018.8600264.
28. Anbiyaei, Mohammad. White Noise Reduction for Wideband Linear Array Signal Processing/ M. Anbiyaei, W.Liu, D McLernon // IET Signal Processing - 2017. – 12, DOI: 10.1049/iet-spr.2016.0730.
29. Zhao, Ping. Low-Noise Phase-sensitive Parametric Amplifiers Based on Integrated Silicon-Nitride-Waveguides for Optical Signal Processing / P. Zhao, Zh. Ye, M. Karlsson, et al.// Journal of Lightwave Technology. - 2022. - 40. 1847-1854. DOI: 10.1109/JLT.2021.3119425.
30. Teschner M. Effects of Signal-to-Noise Ratio on Auditory Cortical Frequency Processing / M. Teschner, B. Seybold, B. Malone et al. // The Journal of Neuroscience: The Official Journal of the Society for Neuroscience. - 2016. - 36. - 2743-2756, DOI:10.1523/JNEUROSCI.2079-15.2016.
31. Sozanski, Krzysztof. Overview of Signal Processing Problems in Power Electronic Control Circuits. Energies. - 2023. - 16. - 4774. DOI: 10.3390/en16124774.
32. Raoul R. Nigmatullin. Application of the Complex Moments for Selection of an Optimal Sensor / Raoul R. Nigmatullin and Vadim S. Alexandrov // MDPI, Sensors. – 2021. - 21(24), 8242; https://doi.org/10.3390/s21248242.

33. Raoul, R. Nigmatullin. Trendless Sequence as a New Source of Information: A Possibility to present it in the Form of the Compact 3D-surface / Raoul. R. Nigmatullin, Vadim S. Alexandrov, R.K. Sagdiev //Acta Scientific Computer Sciences 5.4 (2023): 23-38.
34. Bar, N. Constrained Fourier estimation of short-term time-series gene expression data reduces noise and improves clustering and gene regulatory network predictions / Bar, N., Nikparvar, B., Jayavelu, N. D. et al. // BMC Bioinformatics. – 23. - 330 (2022). https://doi.org/10.1186/s12859-022-04839-z.
35. R.R. Nigmatullin, A.V. Sidelnikov, E. I. Maksyutova, H. C. Budnikov, and E. V. Govorov., Differentiation of Different Sorts of Sugars by the CAPoNeF Method. / R.R. Nigmatullin, A.V. Sidelnikov, E. I. Maksyutova, et al. // Electroanalysis (2021), 33, 2508 – 2515, doi.org/10.1002/elan.202100291.
36. Alexandrov V. S. Processing of trend sequences using three-exponent method. VIII Youth International Scientific and Technical Conference of Young Scientists, Postgraduates and Students, "APPLIED ELECTRODYNAMICS, PHOTONICS AND LIVING SYSTEMS – 2021" April 8-10, 2021, Kazan, Russia, p. 70-73.

НОВЫЙ МЕТОД ИССЛЕДОВАНИЯ ШУМОВ ДАТЧИКА ТЕМПЕРАТУРЫ: КАК ВЫБРАТЬ ОПТИМАЛЬНОЕ УСТРОЙСТВО ПО КОРРЕЛЯЦИИ ВАЖНЫХ ПАРАМЕТРОВ?

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Аннотация. Сравнивая десять важных параметров, авторы данной работы представляют новый метод определения того, какой тестовый измерительный прибор наиболее близок к имеющемуся эталонному образцу – метод сравнительного анализа положительных и отрицательных флуктуаций (CAPoNeF). При отсутствии потенциальных внешних воздействий за исходные данные для сравнения использовались выходные сигналы, записанные с имеющегося набора датчиков температуры. Выбор оптимального датчика невозможен при существующих подходах к их обработке. Однако, вопрос можно решить, используя подход CAPoNeF, который позволяет выбрать оптимальный датчик по особенностям их флуктуаций и шумов.
Ранжирование датчиков и выбор лучшего из предложенных стали возможны, благодаря анализу приведенных матриц N (количество локальных минимумов) ⩾ M (количество значимых параметров). Анализ шумов датчиков температуры в заданном производителем температурном диапазоне по сравнению с эталонным образцом, представляющим собой среднее значение всех зафиксированных значений по температурной шкале, выявил высокую точность обработки данных. По мере дальнейшего развития этого метода появится возможность автоматически анализировать электронные компоненты и использовать их ранжирование по системе светофора.

Ключевые слова: температура, шум измерений, оптимальный выбор типа датчика, корреляция важных параметров, сравнительный анализ положительных и отрицательных флуктуаций.

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