European Research Studies Journal
Volume XXVII, Special Issue 2, 2024

pp. 59-71

Analysis System for Logistics and Production Processes: A Methodological Approach to Signal Analysis for Forecasting

Submitted 18/02/24, 1st revision 16/03/24, 2nd revision 20/04/24, accepted 16/05/24

Krzysztof Król[1], Paweł Kaleta[2], Dariusz Kasperek[3], Sylwia Skrzypek-Ahmed[4], Emanuel Józefacki[5], Agnieszka Chmielowska-Marmucka[6]

Abstract:

Purpose: *The article aims to present elements for analysis systems in industrial and logistics processes.*
Design/Methodology/Approach: *The article presents the preparation of a module for the analysis of production processes and support for logistics processes. The use of time series, randomness test, and correlation test is presented—a comparison of measurement results from various sensors used in industry and transport.*
Findings: *The study's result was the analysis of waveforms from sensors for controlling the operating parameters of production and logistics systems. Preparing such a forecast solution allows you to check many possible measurement process results and support decisions in the system's operation, allowing for better decision-making in conditions of uncertainty.*
Practical Implications: *The presented method of signal analysis for forecasting the system's behavior and operation can support decision-makers in taking appropriate actions, and in the future, it will allow the system to manage itself automatically.*
Originality/Value: *A new feature uses time series, randomness, and correlation tests to review and monitor the performance of various types of sensors in logistics and production systems.*

Keywords: *Time series, randomization test, correlation test, detection of non-stationarity.*

JEL codes: *C53, C61, D24, L23, L91, M11.*

Paper type: *Research article.*

[1]*Corresponding Author: Netrix S.A./WSEI University , Lublin, Poland,*
e-mail: krzysztof.krol@netrix.com.pl;
[2]*WSEI University, Lublin, Poland, e-mail: Pawel.Kaleta@wsei.lublin.pl;*
[3]*WSEI University, Lublin, Poland, e-mail: Dariusz.Kasperek@wsei.lublin.pl;*
[4]*WSEI University, Lublin, Poland, e-mail: Sylwia.Skrzypek-Ahmed@wsei.lublin.pl;*
[5]*WSEI University, Lublin, Poland, e-mail: Emanuel.Jozefacki@wsei.lublin.pl;*
[6]*Wyższa Szkoła Biznesu - National Louis University, e-mail: amarmucka@wsb-nlu.edu.pl;*

1. Introduction

With globalization, rapid market changes, and growing customer expectations, the modern business environment requires continuous improvement and optimization of logistics and production processes. Effective management of these processes is crucial to achieving a competitive advantage and ensuring customer satisfaction.

Logistics and production process analysis systems are complex management tools that integrate supply chain management and production management to optimize the company's operations (Król, Niderla *et al.,* 2023; Tyagi *et al.,* 2023)

This article focuses on the analysis of logistics and production processes, bringing closer the issues related to the functioning of monitoring systems in such processes (Król, Rymarczyk *et al.,* 2023; Kadlubek *et al.,* 2022). In particular, the challenges related to the monitoring module, which plays a vital role in the analysis and control process, are discussed.

The monitoring module in the logistics and production process analysis system is the central element responsible for collecting, analyzing, and interpreting data on process progress. Its main goal is to enable managers to make informed decisions based on reliable information. However, with the increasing complexity of processes and the increase in data, the monitoring module faces several challenges.

One of the main problems is the efficient processing of vast amounts of data in real time and their interpretation to draw meaningful conclusions (Król, Marciniak, *et al.,* 2021). In addition, it is a significant challenge to ensure the accuracy and reliability of the data so that the decisions made on its basis are robust and accurate.

2. Concordance and Correlation Study

Wireless sensors are becoming increasingly popular to measure various physical quantities such as temperature, humidity, acceleration, or pressure. Their application covers multiple fields, such as medicine, aerospace, automotive, construction, etc. Accurate measurements are crucial for many temperature, humidity, acceleration, and pressure applications.

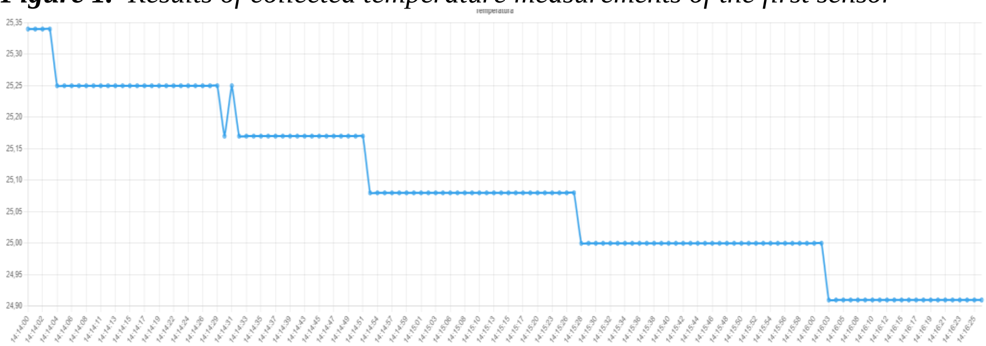
For example, precise pressure and acceleration measurements are essential in the aerospace and automotive industries to ensure systems' safety and optimal operation. In medicine, exact temperature and humidity measurements are essential in diagnosing and treating diseases. In transport, to provide products with the correct parameters for storage and transport.

Therefore, it is necessary to test the consistency and correlation of the measurement results obtained by the previously designed wireless sensors used to measure the aforementioned physical quantities. These studies will determine these sensors' accuracy and reliability, enabling them to be used more confidently and effectively in various fields and applications (Kozlowski, 2019).

To determine the correlation and degree of agreement between the measurements of the sensor responsible for measuring temperature and humidity, a test was carried out in which two sensors were placed under the same, strictly controlled conditions. The two sensors were then used to collect current temperature and humidity data. The data collected in this way allowed for the analysis and mutual comparison of the obtained measurements. The results of the analysis are presented below.

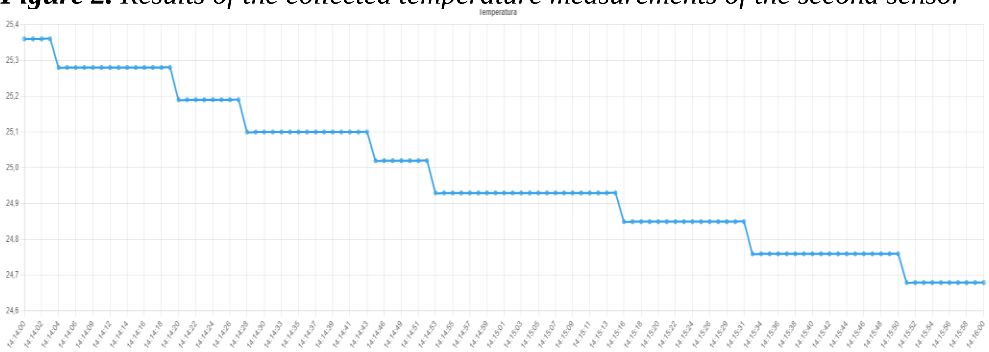
The tests were carried out in an environment with a fluctuating ambient temperature, which allowed us to test the correctness of the collected data under conditions other than static. Several hundred temperature and humidity measurements were collected over two minutes during the tests. Measurements were made simultaneously using two sensors placed very close to each other. During the tests, the temperature in the test environment changed from about 25.4°C to about 24.8°C at the end of the measurement. The results collected from both sensors are shown in the graphs below.

Figure 1. *Results of collected temperature measurements of the first sensor*



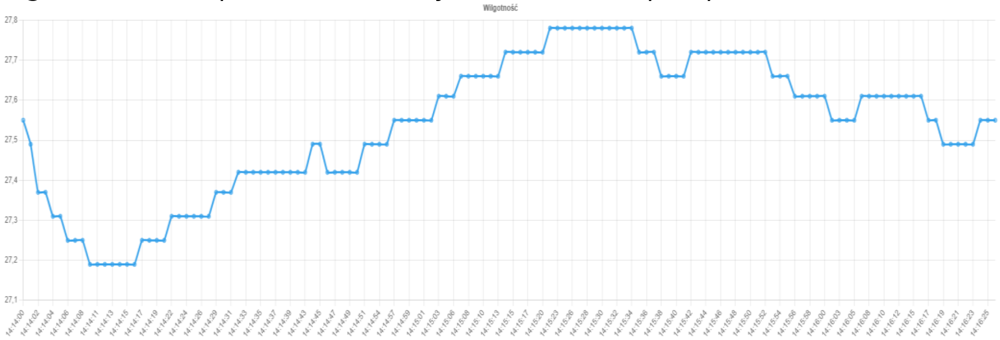
Source: *Own creation.*

Figure 2. *Results of the collected temperature measurements of the second sensor*



Source: *Own creation.*

Figure 3 *Results of collected humidity measurements of the first sensor*

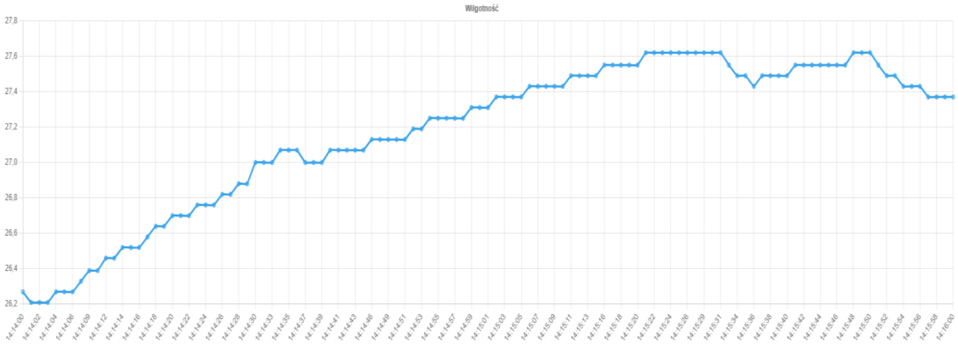


Source: *Own creation.*

A high correlation and mutual agreement of the obtained values can be observed from the obtained temperature change curves measured by both sensors. In both cases, you can see a gradual drop in temperature from the initial level of about 25.4°C to about 24.8°C at the end of the measurement. The differences in the measured temperature value between the sensors are a maximum of 0.1-0.2°C at any given time. This proves the high accuracy of the measurements performed, the presence of correlations, and a high degree of agreement between the sensors.

At the same time, humidity data was collected during the temperature measurements. As in the previous case, the two sensors were placed very close to each other and exposed to similar environmental conditions. Humidity measurements were collected over two minutes, and the results were expressed as a percentage. The results are shown in the graphs below.

Figure 4. *Results of collected humidity measurements of the second sensor*



Source: *Own creation.*

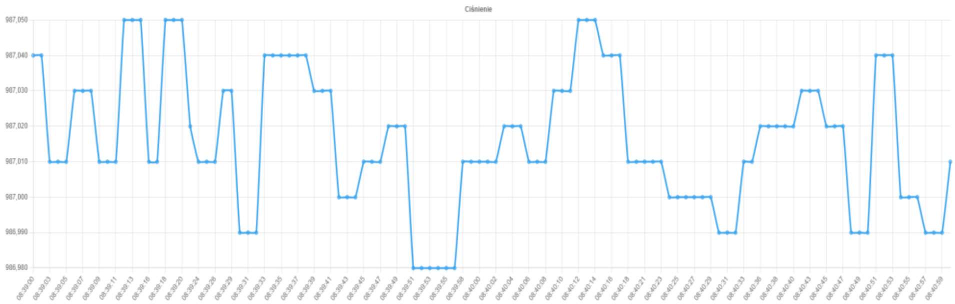
As in the case of temperature measurement, there is also a high correlation and agreement between the data received from both sensors in the case of humidity. In both cases, the measured humidity value shows a clear upward trend. The humidity varies from around 26.5% to 27.5% at the end of the measurement. The obtained results prove the correlation of the obtained results and the high consistency of the measurements made.

3. Testing the Correlation and Degree of Compatibility of Pressure Sensor Measurements

Similar tests have been carried out for the temperature sensor and pressure sensor. The sensor allows you to measure atmospheric pressure from 26 kPa to 126 kPa. The study involved placing two sensors in very close proximity under controlled environmental conditions.

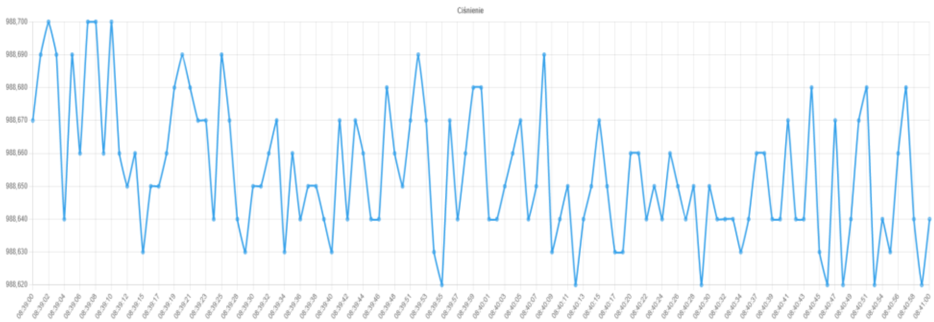
Then, the measurement was run simultaneously on two sensors, and two measurement series were collected, containing several hundred individual pressure measurements. The examination lasted about two minutes. The obtained measurement results are presented in the graphs below.

Figure 5. *Results of collected pressure measurements of the second sensor*



Source: *Own creation.*

Figure 6. *Results of collected pressure measurements of the second sensor*



Source: *Own creation.*

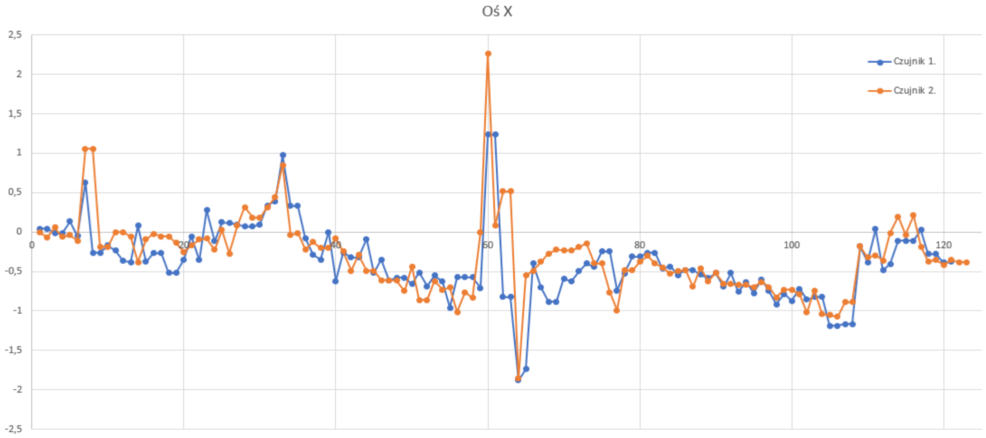
The results indicated a very high stability of the measurements. With stable environmental conditions and constant atmospheric pressure, the measurements fluctuate within a few hundredths of a hPa. There is also a very high agreement and correlation between the measurement results of both sensors. In both cases, the pressure is approximately 987-988 hPa and does not change significantly throughout the test period.

4. Testing the Correlation and Degree of Consistency of Acceleration Sensor Measurements

A test bench was set up using an industrial robotic arm to investigate the correlation and consistency of acceleration sensor measurements. Two identical acceleration sensors are placed near each other at the robotic arm's end. A test sequence was created in which the arm rapidly moved in all directions. This allowed for significant changes in acceleration in all axes, which is a perfect test environment for the sensors to be tested.

The study collected acceleration data in the X, Y, and Z axes for both acceleration sensors over time when the robotic arm performs a pre-programmed sequence of movements. The measured acceleration values were expressed in units of acceleration due to gravity. During the study of the test sequence, about 125 acceleration measurements were collected on each axis. The data collected is presented in the graphs below.

Figure 7. *Comparison of X-axis acceleration measurements for both sensors*

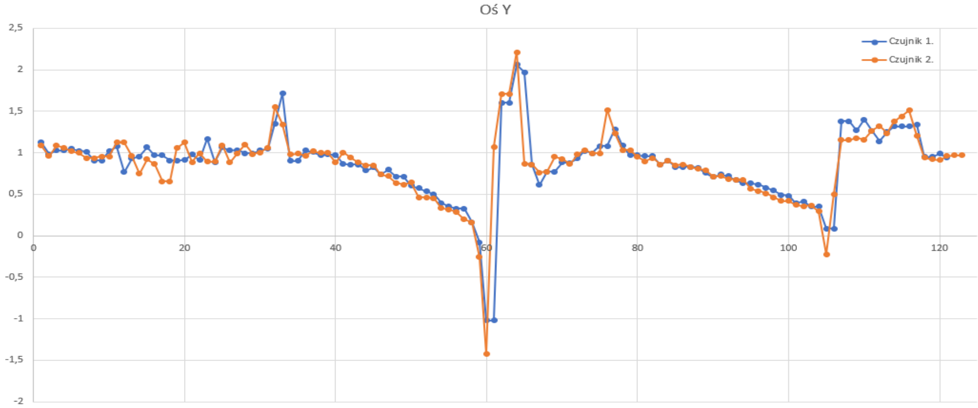


Source: *Own creation.*

The obtained results indicate a very high agreement between the measurements from both sensors and the existence of mutual correlation. Both measuring series reproduces the programmed sequence of movements very accurately.

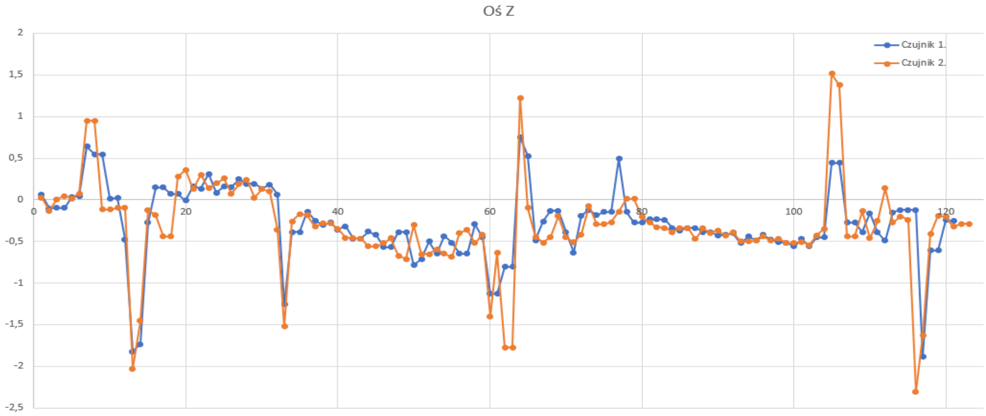
The difference between the measured acceleration values in individual moments is minimal. It occurs mainly in the case of significant changes in acceleration, i.e., when performing very rapid movements.

Figure 8. *Comparison of Y-axis acceleration measurements for both sensors*



Source: *Own creation.*

Figure 9. *Comparison of Z-axis acceleration measurements for both sensors*



Source: *Own creation.*

5. Randomness Test

We are analysing the implementation of a number of $\{x_j^i\}_{\max(0,t-m)\leq j\leq t}$. To verify that the elements of a series are evaluating randomly around a level $\bar{x} = \sum_{j=\max(0,t-m)}^{t} x_j^i$ we use the Wald-Wolfowitz test, e.g. (Wooldridge 2015; Wald 1940). First, we define a number of differences $\{\varepsilon_j\}_{\max(0,t-m)\leq j\leq t}$, where $\varepsilon_j = x_j - \bar{x}$.

At the significance level, we construct a working hypothesis α

H_0: String Elements $\{\varepsilon_j\}_{\max(0,t-m)\le j\le t}$ evolve randomly around level zero and the alternative hypothesis

H_1: Elements $\{\varepsilon_j\}_{\max(0,t-m)\le j\le t}$ contain a non-random component.

For the fulfillment string $\{\varepsilon_j\}_{\max(0,t-m)\le j\le t}$ we determine the number of series S. A series is any subsequence composed of only positive or negative elements. Next, we determine the number of positive residuals n_1 and number of negative residuals n_2 (zero elements are omitted!).

Random variable tends asymptotically to normal distribution $SN(\mu,\sigma^2)$, where the mean value and variance estimators

$$\hat{\mu} = \frac{2n_1n_2}{m+1}+1, \qquad (2.1)$$

$$\hat{\sigma}^2 = \frac{2n_1n_2(2n_1n_2-m-1)}{(m+1)^2m}. \qquad (1)$$

Statistics

$$U = \frac{S-\hat{\mu}}{\hat{\sigma}} \qquad (2)$$

has a normal distribution $N(0,1)$. The test probability is equal to $p.val = 2\big(1-F(|U|)\big)$, where is the distribution of the normal distribution $FN(0,1)$.

If $p.val > \alpha$,, then at the level of materiality alfa, there are no grounds for rejecting the working hypothesis H₀. Otherwise, reject the workingypothesis H_0 against the alternative hypothesis H_1 (non-random components or correlations between elements).

6. Correlation Test

For a series of $\{\varepsilon_j\}_{t-m\le j\le t}$ (number of elements in a series $m+1$) we analyze the

existence of relationships between the elements (Kozłowski 2015). At the severity

level α for offsets $\tau = 1,2,\dots,k \le \left[\frac{m+1}{4}\right]$, where [ ] means the integer part, we create working hypotheses

$H_0: r_1 = r_2 = \cdots = r_k = 0$ (no correlation between the elements of the series) against alternative hypotheses

$H_1: \exists\tau \quad r_\tau \neq 0$ (correlation between elements at offset τ is important).

As an estimator of the correlation coefficient r_τ, $\tau = 1,2,3,\dots,k$ we determine using the formula

$$\hat{r}_\tau = \frac{(m+1)\sum_{j=t-m}^{t-\tau} \varepsilon_j\, \varepsilon_{t+\tau}}{(m+1-\tau)\sum_{j=t-m}^{t} \varepsilon_j^2}. \quad (3)$$

Statistics

$$T_\tau = \frac{\hat{r}_\tau}{\sqrt{1-\hat{r}_\tau^2}}\sqrt{m-1-\tau} \qquad (4)$$

has a Student's t-distribution of $(m-1-\tau)$ degrees of freedom. Test Probability for Offset τ is equal $p.val_\tau = 2\left(1 - F_t(|T_\tau|)\right)$, where F_t Student's t-distribution distributer of $(m-1-\tau)$ degrees of freedom.

If $p.val_\tau > \alpha$ for each $\tau = 1,2,\dots,k$,at the level of materiality α there are no grounds for rejecting the working hypothesis $.Thus H_0$, thus, we assume that the elements are uncorrelated. Otherwise, if there is one for which we reject the working hypothesis τH_0 Against the Alternative Hypothesis H_1 and we assume that the elements of the series are not independent.

Another way to verify the existence of correlations between the elements of a series $\{\varepsilon_j\}_{t-m\le j\le t}$ is to use the Ljung-Box or Box–Pierce test (Wooldridge, 2015;

Woodward, 2017).

Test Ljunga-Boxa

In 1978, G.M. Ljung (Ljung 1978) proposed a test of independence. Test Statistics

$$L = (m+1)(m+3)\sum_{j=1}^{k}\frac{\hat{r}_\tau^2}{m-k} \qquad (5)$$

has a distribution χ^2 degrees of freedom. The test probability for the offset is equal to$k$ $p.val = \left(1 - F_{\chi_k^2}(L)\right)$, where $F_{\chi_k^2}$ decomposition distributor χ^2 degrees of freedom.k

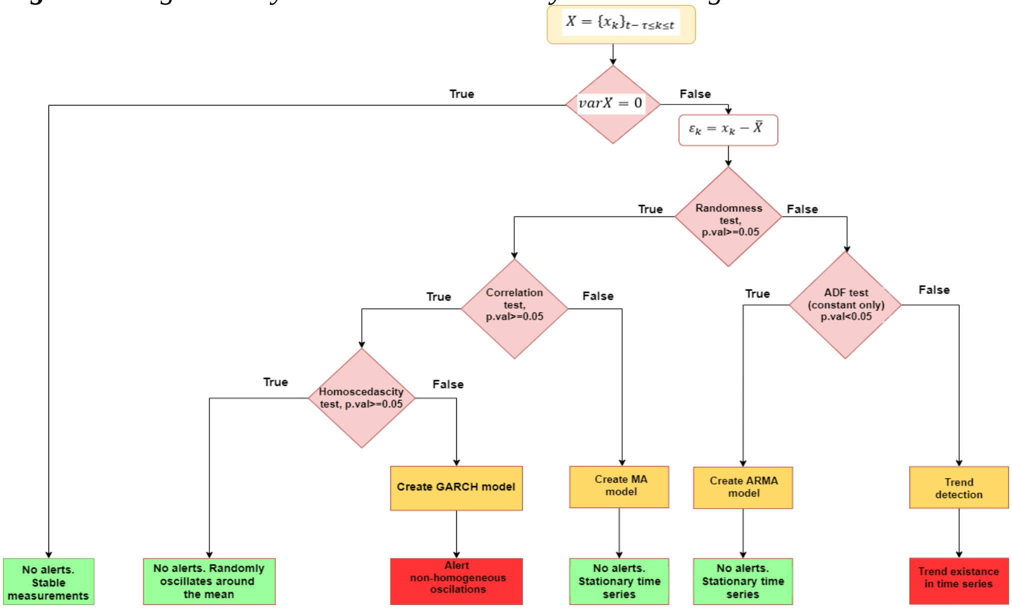
Test Boxa-Pierce'a

A few years earlier (in 1970) they proposed a different test of independence. Test Statistics

$$Q = (m+1)\sum_{j=1}^{k} \hat{r}_\tau^2 \qquad (6)$$

has a distribution χ^2 degrees of freedom. The test probability for the offset is equal to $kp.val = \left(1 - F_{\chi_k^2}(L)\right)$, where $F_{\chi_k^2}$ decomposition distributor χ^2 Degrees of freedom$k$.

Figure 10. *Signal analysis and non-stationarity detection algorithm*



Source: *Own creation.*

For small samples, the distribution of the Ljung-Box statistic is closer to the distribution of $f\ chi\ do\ quadratus$ degrees of freedom than the Box-Pierce statistics. Therefore, the Ljung-Box test was used itoconstruct the monitoring module k

If $p.val > \alpha$, then at the level of materiality α there are no grounds for rejecting the working hypothes. Thrustsare uncorrelated, otherwise, the working hypothesis H_0 against the alternative hypothesis H_1 and we assume that the elements of the series are not independent.

For every moment $t \in \mathbb{N}$ we analyze the behavior of the elements of the $\{x_j\}_{\max(0,t-m) \le j \le t}$.

if $x_{\max(0,t-m)} = x_{\max(0,t-m)+1} = \cdots = x_t$ the readings from the sensor are

identical, so we don't have any alarming indications, we don't raise an alert;

In many cases, the elements of a series evolve randomly around a certain level. To verify randomness, we use the Wald-Wolfowitz test. If the elements of the series are uncorrelated and the condition of homogeneity of variance is met, then we assume that the series $\{x_j\}_{\max(0,t-m) \le j \le t}$ is the realization of a sequence of independent

random variables with the same distribution, and therefore we do not take any alert;

Where the postulate of homogeneity of variance on the basis of the realization of the $\{x_j\}_{\max(0,t-m) \le j \le t}$ is not met, then due to the heterogeneity of fluctuations around a

certain level, the alert should be raised. In this case, the series will be represented using GARCH models;

if the elements evolve randomly around a certain level and are correlated, then the series is presented using MA class models and no alert is raised;

If, on the basis of a sample, $\{x_j\}_{\max(0,t-m) \le j \le t}$ the randomness postulate is not met,

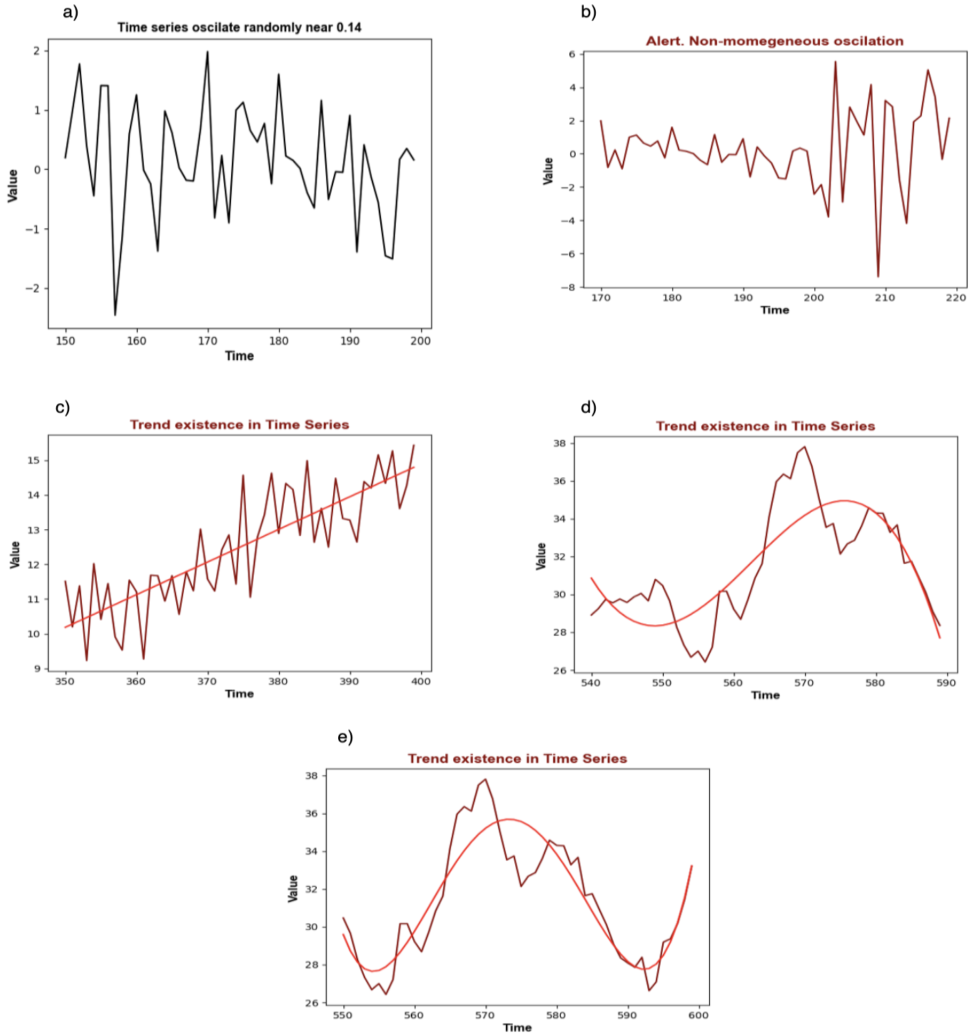
then we first check the property of stationarity, which we verify using the ADF test. Fulfilling the postulate of stationarity allows to represent a series using ARMA-class models. In this case, there are no alarming indications (we are not raising an alert).

If the demand for stationarity is not met, then on the basis of the implementation of the $\{x_j\}_{\max(0,t-m) \le j \le t}$ Identify the trend that occurs in the series. We model the

trend using a polynomial of a certain degree (if the degree is equal to one, then there is a regular linear trend).

The degree of the polynomial is determined using the difference method or by analyzing the linearity of the model, where we select successive powers of the variable (describing the effect) of time as predictors. Of course, the existence of a trend in the time series means that the oscillation level of the series (the expected value of the elements of the series) changes over time. In this case, you should raise an alert.

Figure 11. *Trend detection with a selected time window in a simulated time series*



Source: *Own creation.*

Trend detection with a selected time window in a simulated time series; m = 50; (a) the first two episodes without warning; (b,c) middle segments for the analyzed trend signal; (D,e) The last two segments of the time series with the trend detected. In the case of non-stationarity, the task is to identify the trend marked with a red line on the charts.

7. Conclusions, Proposals, Recommendations

Time series play a crucial role in analyzing logistics and production processes. They allow you to model and forecast behaviors and trends over time, enabling you to understand the dynamics of your processes better and identify potential areas for optimization. Statistical tests, such as randomness, correlation, stationarity, homogeneity, and linearity, are essential tools in data analysis.

They allow one to assess the significance of the relationships between variables and verify the assumptions made in the analysis models. Therefore, the monitoring module in the logistics and production process analysis system is a crucial element supporting effective management.

However, it requires a comprehensive approach and advanced data analysis methods, such as time series and statistical tests. This article aims to present the significance of these issues and discuss the associated challenges in improving logistics and production processes.

References:

Kadłubek, M., Thalassinos, E.I., Noja, G.G., Cristea, M. 2022. Logistics customer service and sustainability-focused freight transport practices of enterprises: Joint influence of organizational competencies and competitiveness. J. Green Econ. Low-Carbon Dev, 1(1), 2-15.

Kozłowski, E. 2015. Analiza i identyfikacja szeregów czasowych. Politechnika Lubelska.

Kozłowski, E., Mazurkiewicz, D., Żabiński, T., Prucnal, S., Sęp, J. 2019. Assessment model of cutting tool condition for real-time supervision system. Eksploatacja i Niezawodność – Maintenance and Reliability, 21(4), 679-685.

Król, K., Marciniak, A., Gudowski, J., Bojanowska, A. 2021. Intelligent Sensor Platform with Open Architecture for Monitoring and Control of Industry 4.0 Systems. European Research Studies Journal, vol. 24, Special Issue 2, 597-606.

Król, K., Niderla, K., Kozłowski, E. 2023. Multisensor platform using industrial tomography for monitoring and control of technological processes. Przegląd. Elektrotechniczny, 99, 165-168.

Król, K., Rymarczyk, T., Niderla, K., Kozłowski, E. 2023. Sensor platform of industrial tomography for diagnostics and control of technological processes. Inform. Autom. Pomiary Gospod. Ochr. Sr, 13, 33-37 doi: 10.35784/iapgos.3371.

Ljung, G.M., Box, G.E.P. 1978. On a measure of lack of fit in time series models, Biometrika. 65 297–303. https://doi.org/10.1093/biomet/65.2.297.

Tyagi, P., Grima, S., Sood, K., Balamurugan, B., Özen, E., Thalassinos, E.I. (Eds.). 2023. Smart analytics, artificial intelligence and sustainable performance management in a global digitalised economy. Emerald Publishing Limited.

Wald, A., Wolfowitz, J. 1940. On a test whether two samples are from the same population. The Annals of Mathematical Statistics, 11, 147-162.

Woodward, W.A., Gray, H.L., Elliott, A.C. 2017. Applied time series analysis with r. CRC Press. https://doi.org/10.1201/9781315161143.

Wooldridge, J. 2019 Introductory Econometrics. Cengage Learning, Inc., Boston, MA, USA.