DOI: 10.21062/mft.2024.073 http://www.journalmt.com

Optimizing the Position of a Robotic Arm Using Statistical Methods

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Robotics plays a key role in industry, and its use continues to grow. Robots are used in many sectors to increase the efficiency, productivity, and safety of work processes. This manuscript focuses on the spatial calibration of collaborative robot arms using appropriate statistical tools. Nowadays, there are many dedicated programming languages, simulations or virtual reality (VR), which in most cases perform calibration using matrix relations. The mathematical-statistical solution is not often addressed, and the use of linear relationships is valid only in certain parts of the workspace of the collaborative robot. The purpose of this article is to demonstrate how to find a suitable statistical method that would respect the wear of the arm mechanism in predefined positions based on the requirements of ISO 230-2:2015. Based on these measurements, it is possible to assume that optimal solutions can be obtained using a polynomial regression function. This optimization method will be explored using the Newton and Markwartel methods.

Keywords: Industrial Robots, Kinematic Models, Polynomial Regression, Error Measurement, Collaborative Robot

1 Introduction

Since the beginning, humankind has been dealing with the question "How to simplify and facilitate work". The first mention of the robot's theme can be found in Greek mythology. However, the term robot was first coined by Karel Čapek thanks to his brother Josef in 1920 in the R.U.R. (Rossum's Universal Robots) [1]. It was not until the second half of the 20th century that robotics took off. The father of robotics is often called J. Engelberger. The first robots were basically only able to move an object from point A to point B. Today, this movement would be insufficient and robotics had to adapt to new requirements such as assembly, welding, and spraying paint. Robots have become a multidisciplinary engineering devices. Mechanical engineering is a branch of engineering that deals with the design of individual mechanical components, arms, end effectors, kinematics, dynamics, and control analyses of robots. Robotics plays a key role in industry, and its use is increasing. Robots are used in many industries to improve efficiency, productivity, and safety of work processes. In industry, robotics has the potential to fundamentally change the way we work and how products are manufactured and delivered. With the development of technologies such as artificial intelligence, machine learning and advances in sensors, robotics is expected to play an even more important role in industry in the future.

Industrial robots are specialized robotic systems designed for use in industrial environments. They are developed to perform specific tasks to improve the efficiency, productivity, and safety of industrial operations. The status of robotic arm calibration solutions can vary depending on specific technologies and systems. In general, calibration of robotic arms is an important process to ensure correct and accurate movements of robots and their end effectors.

Publications [2 - 6] deal with the improvement of robotic arm calibration using corrections based on local linear neurofuzzy models. After standard calibration of geometric parameters in the robot kinematic model, residual errors persist between the measured positions and the positions predicted by the model.

Studies [7 - 10] focus on the inertial measurement unit (IMU), which is the core of inertial positioning and navigation systems. Each IMU consists of at least three accelerometers and three gyroscopes (angular velocity sensors).

Another possible solution for the robot kinematic parameters is addressed in studies [11 - 13] using nonlinear least squares optimization. Nonlinear Least Squares (NLS) optimization is a mathematical method for solving problems where we seek values of the model parameters that minimize the squared error between the observed data and the values predicted by the model.

The principle of nonlinear least squares optimization is to find the values of the model parameters that minimize the sum of the squares of the residuals (the differences between the observed data and the model values). The basic goal is to find a set of parameters that achieves the best fit between the model and the real data. There are several algorithms for solving nonlinear least squares optimization, including the Gauss-Newton method, Levenberg-Marquardt method, and the conjugate gradient method. These algorithms iteratively update the parameter values to minimize the error function. Nonlinear least squares optimization is useful in situations where the data cannot be modeled with a linear model and allows efficient parameter estimation for more complex nonlinear models.

Other publications [14 - 17] describe LIDAR (Light Detection and Ranging), which is a ranging technology that uses laser beams to map and sense the surrounding environment. The working principle of LIDAR is based on sending a laser beam into the environment and then detecting the reflected light from the surfaces of objects. In this way, distances from the device to surrounding objects can be measured, creating a detailed three-dimensional map of the environment. The resulting map is called a LIDAR image or point cloud, which is a collection of three-dimensional points that represent individual objects in the scene.

This paper proposes statistical methods for calibration. This provides a way to substantially improve the positioning of robotic arms and refine the calibration model. At the same time, it was found that the wear of the arms is different, which has to be taken into account in practice. It will have to be found separately for each arm using the regression function, which will be eventually implemented at defined points in the robot.

2 Materials and Methods

Robot calibration is performed to improve the positioning accuracy of robots by making changes to the robot software instead of changes to the kinematic structure. The factors that affect robot accuracy are similar to those affecting the precision of other mechanical devices, such as manufacturing tolerances of the components used, component wear, and assembly accuracy. Some of these influences can be eliminated to varying degrees by calibration. Calibration does not affect repeatability. Accuracy is defined as the degree of agreement between the desired position and the achieved position. Factors influencing robot accuracy include, in particular, component accuracy, assembly accuracy and gravitational deformation. [18] Repeatability is defined as a measure of the system's ability to return to the same position. It does not depend on the accuracy of the desired position. Highly repeatable systems exhibit low variance in repeated movements to a given position, regardless of the direction from which the position was reached. We can further define unidirectional repeatability as the ability of a system to return to the same position from a given direction.

The factors affecting repeatability are mainly clearances in the positioning system, thermal deformations and other random errors. The relationship between accuracy and repeatability significantly affects the application and programming capabilities of robots. If the robot is programmed by guiding it to individual working positions, the problem of absolute accuracy is eliminated. In fact, the operator essentially calibrates the robot in each working position during programming. Conversely, if the robot is programmed in advance of being placed on the workstation (so-called offline), absolute positioning accuracy is essential. Absolute positioning accuracy is therefore essential for virtual actuation options or for the implementation of production technology directly by the robot (applications where the robot carries the spindle).

2.1 Standart ISO 230-2:2015

The ISO 230-2:2015 Test code for machine tools Part 1: Geometric accuracy of machines operating under no-load or quasi-static conditions provides a comprehensive framework for testing the geometric accuracy and performance of machine tools [19]. Furthermore, it can also be used to refine the positioning of a robotic arm. The following steps could have been taken with respect to this standard:

- Analysis of positioning requirements,
- Identification of geometric parameters,
- Measurement planning,
- Analysis of results,
- Refinement of positioning,
- Documentation and maintenance.

2.2 Reflectors

In this way, ISO 230-2:2015 was used to refine the positioning of the robotic arm and ensure optimal performance. When evaluating the repeatability and reproducibility of robotic arm positioning using the laser interferometric method, a fundamental problem arises in the fitting, the appropriate mounting of the interferometric reflectors and laser beam splitters. For this reason, it was necessary to design and subsequently manufacture single-purpose mounts. The basic task of the designed clamps is to ensure correct guidance of the reflectors in two planes, namely the horizontal and vertical planes and their positioning in the Cartesian system [20]. The practical realization of the individual clamps was realized in the form of 3D printing of CF15/ASA material, which provides sufficient shielding of the reflectors against vibrations that arise during the operation of the motors that ensure the movement of the arms (figure 1).

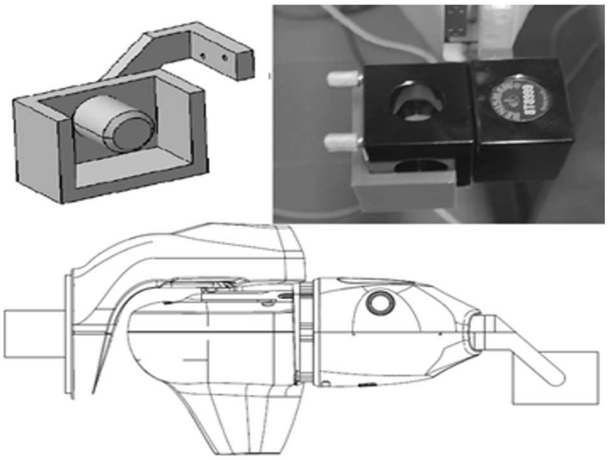

Fig. 1 *Grip prototype attachment*

The functional component of the clamps was implemented by designing bolted connections, attached to the individual arms, through damping washers. The design of the clamp is adapted to ensure the possibility of quick exchange of the reflectors and dividers.

2.3 Linear cycle

The linear approach is a classical solution using the ISO 230-2:2015 standard. The linear cycle of the robotic arm interacting with the reflector can be described as a carefully coordinated sequence of movements, designed to optimise the interaction between the two components. At the beginning of the cycle, the robotic arm initiates the cycle by moving towards the reflector, moving in a straight and stable trajectory that minimizes unnecessary vibrations and increases the accuracy of the trajectory. [20] The movement from the starting position to the ending position is designated by +, and movement back or from the ending position to the starting position is designated by -. Figure 2 shows the variance of position errors in micrometers (µm) versus position in millimeters (mm) for two variables: X+ and X-. This data can be interpreted as a measurement of the positional accuracy of a device that moves along an axis, looking at how accurately it can hold a specified position in both directions (to plus and minus values).

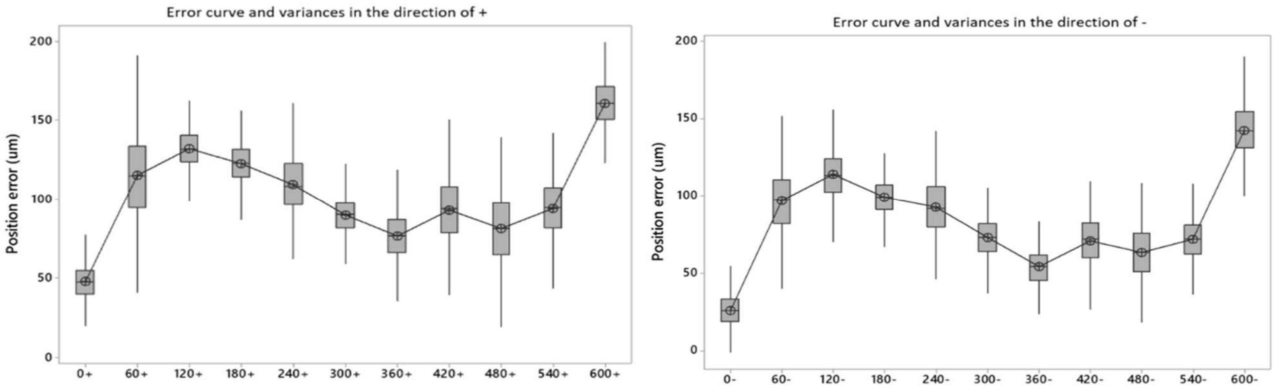

Fig. 2 *Variance of positional errors*

The 95% Bonferroni confidence intervals for the standard deviations in the different groups are presented below. The horizontal axis represents the standard deviations, and the vertical axis indicates the different groups, which are indicated by a number, such as 0+, 60+, 120+. The confidence intervals provides a range within which we can assume with 95% confidence that the true standard deviation is located. The Bonferroni correction is used to account for multiple comparisons, which makes the intervals wider than they would be without this correction, thus controlling the number of Type I errors.

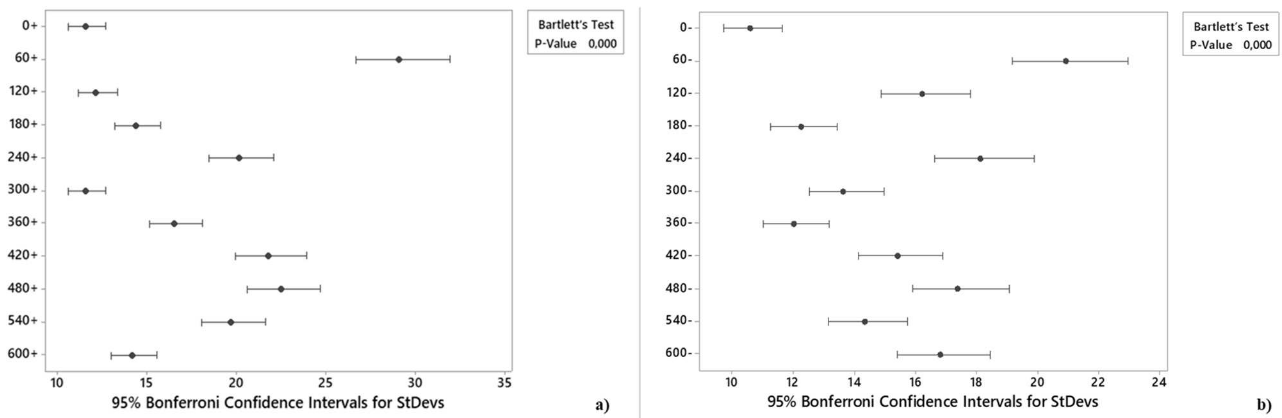

Fig. 3 *Bonferroni variance test a) direction +; b) direction -*

The results of Bartlett's test (figure 3) show that the test statistic is 957.86 and the p-value is 0.000. Bartlett's test is used to test the hypothesis that multiple samples have equal variances. In this graph, a p-value of 0.000 (meaning $p < 0.001$) strongly rejects the null hypothesis that the variances between groups are equal. This suggests significant heterogeneity in variances between groups. Thus, the graph shows that there is significant variability in the standard deviations between the groups, as indicated by Bartlett's test ($p < 0.001$). Bonferroni confidence intervals indicate the range within which the true standard deviations of the groups are likely to lie with 95% confidence.

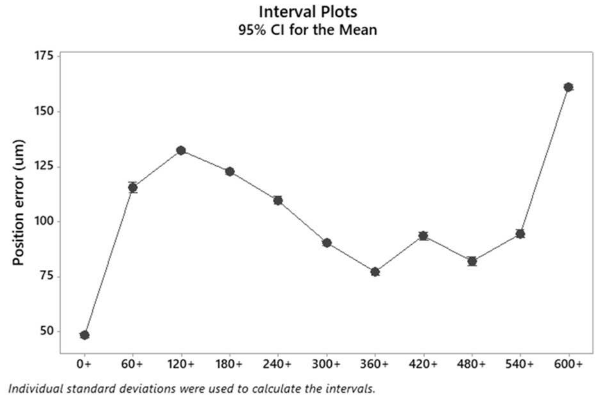

Fig. 4 *Confidence intervals for the mean error values in the + position*

Figure 4 shows the 95% confidence intervals for the mean values of position + errors (in micrometers) for the different factor levels. On the horizontal axis are displayed the factor levels (0+, 60+, 120+) and on the vertical axis represent the position error. The hypothesis of the test is as follows: The null hypothesis assumes that all means are the same, while the alternative hypothesis asserts that at least one mean is different. The significance level is set at $\alpha = 0.05$.

The Welch test was used to test for differences between means, which does not require the assumption of identical variances. The results of this test show an F-value of 2598.16 and a p-value of 0.000. A p-value of 0.000 ($p < 0.001$) strongly rejects the null hypothesis that the means are equal, indicating there is a significant difference between the means for different levels of the factor. The R-squared (R-sq), which shows how well the model explains the variability in the data, is 71.45%. The adjusted R-squared (R-sq(adj)) is 71.40% and the predicted R-squared (R-sq (pred)) is 71.34%. Thus, the graph and Welch's test show that there is a significant difference between the means of the position errors for the different factor levels ($p < 0.001$). The model explains approximately 71.45% of the variability in the data.

The graph (figure 5) shows the confidence intervals (95% CI) for the mean position error values (in micrometers) for various factors from 0 to 600 in steps of 60. The results show that the lowest position error is at factor 0 (approximately 26 μm) and highest at factor 600 (approximately 143 μm). The cutoffs vary, with a significant increase in error at factors 60 and 120 and a subsequent decrease that increases again after factor 360. The Welch test, which does not require equal variances, showed that there is a statistically significant difference between the means of each factor (p-value is less than 0.05). The model explains about 78.88% of the variability in the position errors, which means that it is quite accurate.

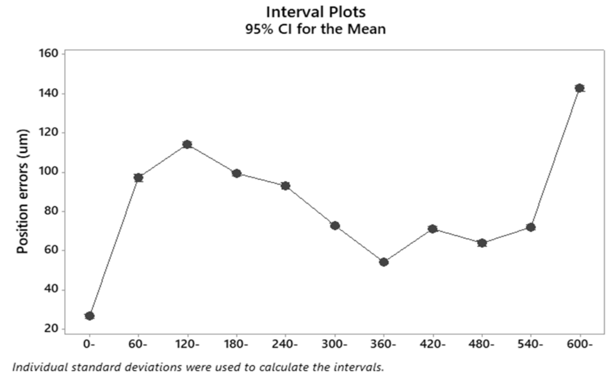

Fig. 5 *Confidence intervals for the mean error values in the – position*

2.4 Polynomial regression

Polynomial regression, as a statistical method, provides an effective means to model complex relationships between independent and dependent variables. In the context of refining robotic arm positioning, this method becomes a valuable tool for identifying and quantifying the factors influencing arm positioning and then constructing a mathematical model that describes this relationship. The use of polynomial regression allows for more complex modelling than simple linear methods and allows for the capture of indirect, non-linear and interaction effects between different variables. This produces a more robust and accurate mathematical description of the robotic arm positioning, which is key to achieving the desired level of accuracy and reliability in robotic system control. The integration of polynomial regression into the robotic arm positioning refinement process provides a systematic and statistically based approach to identify and quantify the factors that influence arm positioning and optimize the control of the robotic system to achieve the desired results.

Once the variables were identified, polynomial regression was performed to model the complex relationships between the independent and dependent variables. The polynomial model that best fitted the relationship between these variables was selected and evaluated. Statistical tests such as coefficients of determination, F-tests and t-tests of coefficients were used to assess the accuracy and relevance of the model.

For the methodology of using polynomial regression to refine the positioning of the robotic arm, several steps were included to systematically identify the relationships between the different variables affecting the arm position and the position itself. The following procedures describe this process in detail:

- Data collection: the first step was to collect data describing the position of the robotic arm and the variables that affect it. These variables included joint angles, movement speeds, force or moments at the end of the arm, the surrounding environment, and other relevant factors.
- Variable identification: identification of variables that have the potential to affect the position of the robotic arm.
- Model selection: Based on the identified variables, decide on the appropriate type of polynomial model. This may include a decision on the degree of polynomial, which determines how complex the formulas will be used to approximate the relationship between the variables.
- Data preparation: the data are prepared for analysis, which involves cleaning and possibly normalising the data. This step is important to ensure that the data are appropriately processed for polynomial regression.
- Application of polynomial regression: We perform the analysis using polynomial regression, using the identified variables as input variables and the position of the robotic arm as the output variable. The objective is to find a polynomial function that most accurately represents the relationship between these variables.
- Evaluation of the model: We examine the accuracy and precision of the model using statistical methods such as coefficient of determination R2, residual analysis and others. This provides us with information on how well the model fits the actual data.
- Optimisation and validation: if necessary, we can optimise the model and vali-date it on independent data. This ensures that the model is able to generalize well to new data and provide reliable predictions of the position of the robotic arm.
- Implementation: finally, if the model is successfully verified, it can be implemented in the control software of the robotic system. This allows the model to be used for real-time control of arm positioning to achieve desired accuracy and stability goals.

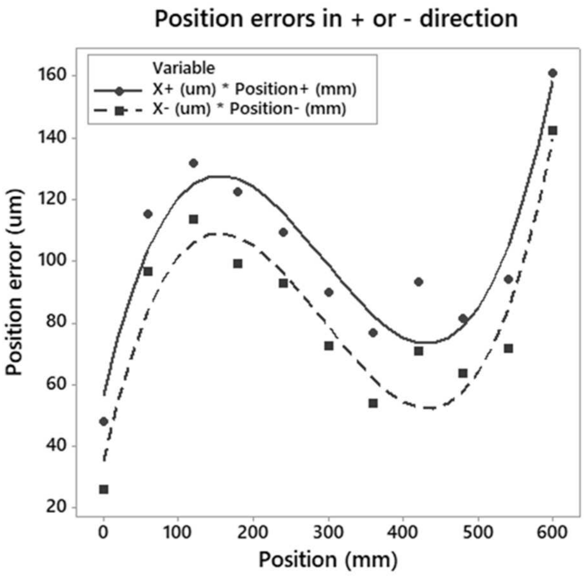

Fig. 6 *Polynomial regression*

This graph (figure 6) presents the results of a third-degree polynomial regression analysis for position errors in the + and - directions.

For the + direction, the model equation was as follows:

$$\text{Position error} = 56.66 + 1.04 \cdot \text{Position} - 0.0046 \cdot \text{Position}^2 + 5.18 \times 10^{-6} \cdot \text{Position}^3 \quad (1)$$

Key statistical indicators for this model include the multiple correlation coefficient $R_{ve}R_2$ was 0.90, indicating that 90% of the variability in position error is ex-plained by the model. The predicted correlation coefficient Rp was 310.89. Akaike's in-formation criterion was 56.84.

For the - direction, the model equation was as follows:

$$\text{Position error} = 35.32 + 1.08 \cdot \text{Position} - 0.0047 \cdot \text{Position}^2 + 5.34 \times 10^{-6} \cdot \text{Position}^3 \quad (2)$$

Both models were subjected to several statistical tests to verify their accuracy and significance. The Fisher-Snedecor test confirmed the significance of both models with high probability (p-value < 0.001). The Scott's multicollinearity criterion showed that the models were accurate and did not show multicollinearity. The Cook-Weisberg test for heteroskedasticity confirmed that the residuals exhibited homoskedasticity, indicating constant error variance. The Jarque-Berr normality test showed that the residuals have a normal distribution. Furthermore, the Wald autocorrelation test confirmed non-significant autocorrelation of the residuals, and the Durbin-Watson test showed neither positive nor negative autocorrelation of the residuals. The sign test of the residuals showed that there was no trend in the residuals.

Thus, it can be concluded that the third-order polynomial models provide significant and accurate descriptions of position errors as a function of position in both the + and - directions. All tests confirm that the models are statistically significant and correctly specified.

3 Results and Discussion

Polynomial regression is a powerful tool for modelling complex relationships be-tween independent and dependent variables when linear models are not sufficient. In our case, polynomial regression was performed on the variable "Position" and its parameter estimates were statistically tested. The results show that all included parameters are significant:

The constant (Abs) was estimated to be 45.993 with a relatively low standard deviation of 10.452. The linear coefficient for "Position" was 1.061 with a standard deviation of 0.159. The quadratic coefficient was negative, at -0.0046, with a very small standard deviation of 0.000634. Finally, the cubic term had a coefficient of $5.262 \cdot 10^{-6}$ and a standard deviation of $6.926 \cdot 10^{-7}$.

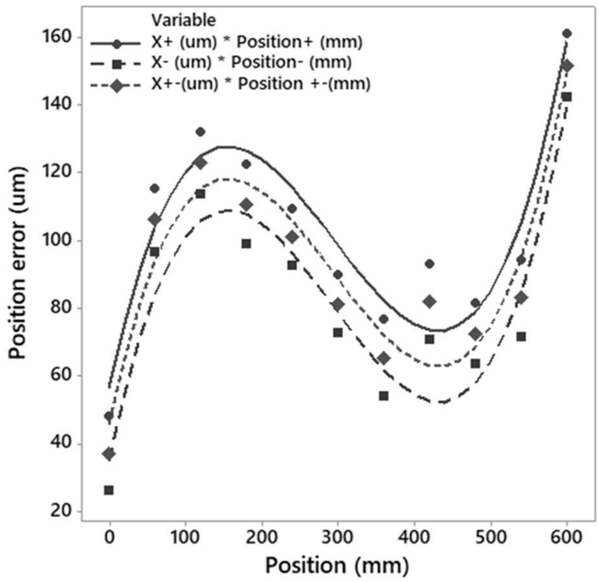

Fig. 7 *Graphical result of polynomial regression in the +/- position*

Various statistical characteristics were used in the model evaluation. The multiple correlation coefficient R was 0. 94806, indicating a strong linear relationship between predicted and actual values. The coefficient of determination R_2 was 0. 8988, indicating that the model explained approximately 89.88% of the variability in the data. The predicted correlation coefficient R was lower, 0.3876, indicating some margin in the predictive ability of the model (figure 7).

The mean square error of prediction (MEP) was 328.158 and the Akaike information criterion (AIC) was 57.247, which are important indicators of the quality and accuracy of the model.

To test the significance of the model, the Fisher-Snedecor test was used, where the F value was 20.727, which clearly confirms the significance of the model with an F quantile of 4.347 and a probability of 0.000736. Furthermore, it was tested for multi-collinearity using Scott's criterion, where the value -0.358 shows that the model is correct without the presence of multicollinearity. The Cook-Weisberg heteroskedasticity test showed a value of 0.437 at a critical quantile of 3.842, with a probability of 0.509, which means that the residuals are homoscedastic. The Jarque-Berr normality test showed a value of 1.0537 with a critical quantile of 5.992 and a probability of 0.591, thereby confirming a normal distribution of residuals.

Furthermore, the Wald test for autocorrelation was performed, which with a value of 0.032 and a probability of 0.858 showed that the autocorrelation is insignificant. Similarly, the Durbin-Watson test with a value of -1 and critical values of 0 and 2 showed no negative autocorrelation of the residuals. A sign test of the residuals then showed that there is no trend in the residuals, with a value of 0.029 and a probability of 0.977.

In conclusion, the polynomial regression is statistically significant, does not show multicollinearity, the residuals are homoscedastic and have a normal distribution, and there is no autocorrelation or trend in the residuals. These findings confirm the appropriateness of using polynomial regression for the given dataset and its ability to accurately model the relationship between the investigated variables.

4 Conclusions

The research presented in this paper demonstrates the effectiveness of using statistical methods, particularly polynomial regression, to refine the positioning of robotic arms. Using exponential-type nonlinear regression functions, it was possible to minimize positioning errors. The Newton and Levenberg-Marquardt methods played an important role in the search for optimal solutions.

The implementation of statistical methods in accordance with the ISO 230-2:2015 standard led to a significant improvement in positioning accuracy. The use of polynomial regression enabled the modeling of complex relationships between different variables, resulting in a robust and accurate mathematical model. The Newton and Levenberg-Marquardt methods have proven to be effective tools for optimizing regression models, thereby minimizing positioning errors.

Since there was a certain degree of error in the positioning of the robotic arm in different positions, it was necessary to perform an optimization using the error square. The data collected on the positions of the robotic arm at different points showed that there is some inaccuracy or fluctuation in the positioning, which can be caused by various factors such as mechanical deviations, unevenness in the surface or the influence of external conditions. To increase positioning accuracy, the method of optimizing the square of errors was selected, which allows minimizing the sum of squares of deviations between the actual position of the arm and the predicted position based on the selected model. Polynomial regression was used to create a mathematical model that describes the relationship between the various factors affecting arm position and the arm position itself. This model was optimized to align most closely with the real data and minimize the squared error.

The error squared optimization provided a systematic and efficient way to improve the positioning accuracy of the robotic arm and achieve the desired level of accuracy in our application. This resulted in the improvement of the control of the robotic system and the optimization of its performance in a real operating environment. The implementation of these statistical methods in industrial practice can significantly improve the positioning accuracy and efficiency of robotic systems. Future research should focus on further improving the models and adapting them to different types of robotic mechanisms. Moreover, it is recommended to carry out further tests in real operating conditions to verify the robustness and reliability of the proposed methods.

Acknowledgement

This work and the project were realized with financial support from the internal grant of TBU in Zlin No. IGA/FT/2024/002, funded by the resources of specific university research.

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