Development of a Methodology for Introducing Robotic Devices for Technical Inspection of Power Lines Based on Data Mining

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Keywords: Robotic devices, Power lines, Data mining, Methodology, Safety, Efficiency.

Abstract: This article describes the development of a methodology for introducing robotic devices for technical inspection of power lines based on data mining. The methodology includes the stages of requirements analysis, system identification, risk analysis, technical requirements generation, data mining, robot type selection, control system design, testing, personnel training and maintenance. Emphasis is placed on data mining, including generating statistical data, forecasting using predictive models, and conducting correlation, regression, and cluster analysis. The use of these methods ensures more efficient management of the technical condition of power lines, increasing their reliability and reducing the risk of failures. The article highlights the need for continuous monitoring, optimization and training to ensure successful implementation and long-term sustainability of the proposed methodology.

1 INTRODUCTION

Developing a methodology for introducing robotic devices for technical inspection of power lines based on data mining is a complex process that includes several stages. Below are the main steps that can be taken when developing such a methodology (Yuan, 2021; Blatnický, Dižo, Gerlici, Sága, Lack, Kuba, 2020):

1. Analysis of requirements and goals:

• Determination of basic requirements for technical inspection of power lines.

• Identifying the goals of introducing robotic devices: increasing efficiency, reducing risks, reducing costs.

2. System identification (Mammadov, Valiyeva, gizi Huseynova, gizi Hasanova, 2022):

• Defining system boundaries: what is included in the robotic system and what is not.

• Identifying key components and subsystems.

3. Analysis of Risks and Benefits:

• Assessment of possible risks associated with the introduction of robotic devices (Blaga, Pop, Hule, Indre, 2021; Heimig, Kerber, Stumm, Mann, Reisgen, Brell-Cokcan, 2020).

• Identification of potential advantages and benefits.

4. Formation of technical requirements:

• Drawing up technical requirements for robotic devices.

• Taking into account the characteristics of power lines and the environment.

5. Data mining

• Obtaining and processing statistical data on the demand for robotic devices for technical inspection of power lines.

• Estimation of the demand indicator for the mouth using predictive models.

• Study of factors influencing the demand for robotic devices using the multiple regression method

• Conducting cluster analysis to evaluate the results obtained

6. Selecting the type of robots:

• Selecting the type of robotic devices depending on the tasks (Krestovnikov, Cherskikh, Saveliev, 2020).

• Consideration of mobile robots, unmanned aerial vehicles (drones), robotic manipulators, etc.

7. Control system design (Sorrentino, 2019; Badarinath, Prabhu, 2021; Betancur-Vásquez, Mejia-Herrera, Botero-Valencia, 2021):

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• Development of a control system for coordinating the actions of robots.

• Integration with artificial intelligence technologies to automate processes.

8. Testing and optimization (Kaur, Kim, Kim, 2021):

• Testing robotic devices in real conditions.

• System optimization based on testing results.

9. Training and service:

• Development of training programs for personnel working with robots.

• Establishment of a maintenance and technical support system.

10. Implementation stage:

• Development of an implementation plan, taking into account step-by-step procedures and minimizing the impact on the current infrastructure.

• Providing feedback and adjustments to the implementation process.

11. Monitoring and evaluation of effectiveness:

• Implementation of a monitoring system to evaluate the performance of robotic devices.

• Conducting regular assessments of achieved results.

12. Optimization and development (Martirosyan, Martirosyan, Mir-Amal, Chernyshev, 2022; Kukharova, Utkin, Pershin, 2021; Ilyushin, 2022):

• Carrying out continuous optimization of the system based on received data and feedback.

• Development of technologies and methods in accordance with changes in requirements and standards.

13. Training and social aspects:

• Providing training to staff and the general public regarding the use of robotics in this area.

• Consideration of social and ethical issues associated with the introduction of robots.

2 MATERIALS AND METHODS

Data mining in the context of robotic devices for technical inspection of power lines includes several stages:

1. Receiving and processing data:

• Collection of statistical data on the demand for robotic devices for technical inspection of power lines. This data may include information on frequency of use, technical parameters, maintenance costs, etc.

• Cleaning data from outliers, errors and incomplete records.

• Converting data into a format convenient for analysis.

2. Assessing demand using predictive models (Martirosyan, Ilyushin, 2022):

• Application of machine learning methods to build predictive models based on available data.

• Use of time series or other suitable methods to assess the dynamics of demand for robotic devices.

• Validation of models on separate test data sets.

3. Factor study using multiple regression method:

• Identification of potential factors influencing the demand for robotic devices.

• Construction of a multiple regression model to assess the degree of influence of each factor.

• Analysis of the significance of coefficients and interpretation of results.

4. Conducting cluster analysis (Pershin, Kukharova, Tsapleva, 2021; Asadulagi, Ioskov, 2018; Andreikovets , Vasil’tsov, 2013):

• Grouping data based on similar characteristics using cluster analysis methods.

• Assessment of cluster formation and interpretation of results.

• Using the results of cluster analysis to better understand the characteristics of the demand for robotic devices in various groups.

2.1 Receipt and processing of data

Any text or material outside the aforementioned margins will not be printed.

After cleaning the data from outliers, errors and incomplete records, as well as converting the data into a convenient format, we got at ffigure 1 like this:

Year	№	Month	y	x1	x2	x3	x4	x5
2022	1	January	5.1	0.21	0.23	0.01	0.21	0.01
	2	February	5.0	0.22	0.24	0.01	0.01	0.01
	3	March	5.4	0.22	0.24	0.01	0.01	0.02
	4	April	4.8	0.22	0.25	0.02	0.01	0.02
	5	May	5.0	0.24	0.26	0.03	0.02	0.02
	6	June	5.3	0.24	0.25	0.04	0.03	0.03
	7	July	5.7	0.24	0.25	0.09	0.05	0.03
	8	August	5.8	0.25	0.25	0.05	0.04	0.03
	9	September	6.0	0.25	0.26	0.05	0.04	0.05
	10	October	6.2	0.26	0.25	0.05	0.06	0.05
	11	November	6.8	0.26	0.26	0.07	0.06	0.05
	12	December	7.1	0.27	0.27	0.08	0.07	0.07
2023	13	January	7.0	0.27	0.27	0.03	0.07	0.07
	14	February	7.3	0.27	0.26	0.07	0.09	0.09
	15	March	7.5	0.28	0.27	0.08	0.09	0.09
	16	April	8.0	0.29	0.25	0.10	0.10	0.11
	17	May	8.3	0.30	0.26	0.10	0.11	0.11
	18	June	8.5	0.30	0.27	0.11	0.12	0.13

Figure 1: Initial data on the demand for robotic devices.

To analyse the demand for the use of robotic devices for technical inspection of power lines, the following factors were taken:

y – percentage of use of robotic devices for technical inspection of power lines, %;

x1 - productivity improvement, relative unit of measurement;

x2 - improvement of processing quality, relative unit of measurement;

x3 - reduction of the human factor, relative unit of measurement;

x4 – increasing the versatility of work, relative unit of measurement;

x5 - cost reduction, relative unit of measurement.

All statistical data were obtained as a result of a survey of employees of enterprises involved in technical inspection of power lines.

2.2 Assessing Demand Using Predictive Models

To solve the prognostic problem, a distribution graph was constructed for the percentage of use of robotic devices for technical inspection of power lines (Fig. 2) for the period January 2022 – June 2023, data taken from figure 1.

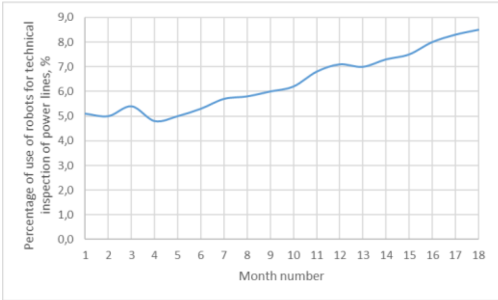

Figure 2: Initial data distribution graph.

To assess the quality of the selected model, the coefficient of determination is calculated using the following formula:

$$r^2 = 1 - \frac{S_y{}^2}{S_1{}^2}. \quad (1)$$

Standard error value:

$$S_y{}^2 = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n-m}. \quad (2)$$

Total variance:

$$S_1{}^2 = \frac{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2}{n-m}. \quad (3)$$

The coefficient of determination must be within $0 \leq r^2 \leq 1$. The closer the coefficient value is to one, the higher the quality of the selected model (Makhov, 2014; Cherepovitsyn, Evseeva, 2020).

For acceptable models, it is assumed that the coefficient of determination should be at least 0.5. Models with a coefficient of determination above 0.8 can be considered quite good. The value of the coefficient of determination $r^2 = 1$ means the functional relationship between the variables.

Table 1 presents the coefficients of determination for forecast models built using dynamic data for three years.

Table 1: Summary table of coefficients of determination.

Predictive model	**Determination coefficient**
Linear model	0.941
Exponential model	0.961
Hyperbolic model type 2	0.967

From Table 1 it follows that all models are acceptable for making a forecast, but the hyperbolic model of the second type (figure 3) has the largest (closest to unity) coefficient of determination. Consequently, the following forecasts will be based on it.

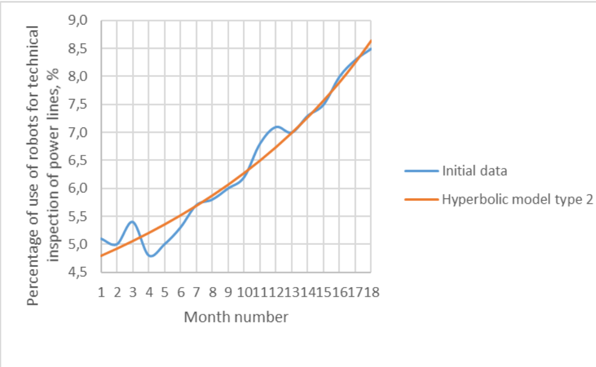

Figure 3: Hyperbolic model type 2.

2.3 Study of Factors Using Multiple Regression Method

First, we build a multiple linear regression equation of the following form (Gusev, Blishchenko, Sannikova, 2022; Karimshoushtari, Novara, 2020):

$$\tilde{y}_x = b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + b_4 x_4 + b_5 x_5. \quad (4)$$

To do this, it is necessary to conduct a regression analysis of these factors using the table editor MS Excel. The results of the regression analysis are presented in Figure 4.

Regression statistics	
Plural R	0,986079
R-square	0,972352
Normalized R-squared	0,960832
Standard e	0,240149
Observatic	18

Analysis of variance

	df	*SS*	*MS*	*F*	*Significance F*
Regressior	5	24,33905	4,867811	84,40598	6,32E-09
Remainder	12	0,692057	0,057671		
Total	17	25,03111			

	Odds	*Standard error*	*t-statistic*	*P-Value*	*Bottom 95%*	*Top 95%*	*Bottom 95.0%*	*Top 95.0%*
Y-intersect	1,107679	2,229004	0,496939	0,628211	-3,7489	5,964263	-3,7489	5,96426
x1	11,3147	8,970795	1,261282	0,231176	-8,23098	30,86039	-8,23098	30,8603
x2	4,182992	9,906505	0,422247	0,680311	-17,4014	25,76741	-17,4014	25,76741
x3	0,074053	3,865326	0,019158	0,98503	-8,34777	8,495874	-8,34777	8,49587
x4	2,806507	1,428733	1,964333	0,073078	-0,30643	5,919449	-0,30643	5,91944
x5	20,13051	5,422201	3,712608	0,002967	8,316546	31,94447	8,316546	31,9444

Figure 4: Result of using the "Regression" tool.

For this regression model, the multiple correlation coefficient is R = 0.986, which indicates a high close relationship between the selected factors and net income (Alcan, Unel, Aran, Yilmaz, Gurel, Koprubasi, 2019; Zhukov, Butsanets, Sherban, Igonin, 2018; Randall, 2011).

Let's create a multiple regression equation:

$$\tilde{y}_x = 1{,}1 + 11{,}31x_1 + 4{,}18x_2 + 0{,}07x_3 + 2{,}81x_4 + 20{,}13x_5.$$

Regression coefficients show the average change in the resulting characteristic with a change of 1 unit of its measurement of this factor, provided that all others are constant.

2.3.1 Comparative assessment of the Strength of the Relationship Between Factors and the Result Using Average (General) Elasticity Coefficients

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Average elasticity coefficients $\bar{Э}_{yx_i}$ show by what percentage of the value of its average $\bar{y}$ the result changes when a factor changes x_i by 1% from its average $\bar{x}_i$ and with a fixed effect on y of all other factors included in the regression equation. For linear dependence (Gabriel, Alin, Nicolae, 2006; Tusov, Bezyukov, Afanaseva, 2012):

$$\bar{Э}_{yx_i} = b_i \frac{\bar{x}_i}{\bar{y}}, \quad (5)$$

where b_i is the regression coefficient at x_i in the multiple regression equation.

The results of calculating the corresponding indicators for each characteristic, obtained using the "Descriptive Statistics" data analysis tool, are presented in Figure 5.

y		*x1*		*x2*		*x3*		*x4*		*x5*	
Average	6,377778	Average	0,255556	Average	0,255556	Average	0,055556	Average	0,066667	Average	0,055556
Standard e	0,286009	Standard e	0,006828	Standard e	0,002511	Standard e	0,007399	Standard e	0,011639	Standard e	0,009151
Median	6,1	Median	0,257229	Median	0,253819	Median	0,054348	Median	0,058282	Median	0,046358
Fashion	5	Fashion	0,218072	Fashion	0,269444	Fashion	0,01087	Fashion	0,01227	Fashion	0,019868
Standard d	1,213432	Standard d	0,028968	Standard d	0,010652	Standard d	0,03139	Standard d	0,049382	Standard d	0,038825
Sample vai	1,472418	Sample vai	0,000839	Sample vai	0,000113	Sample vai	0,000985	Sample vai	0,002439	Sample vai	0,001507
Excess	-1,20366	Excess	-0,79725	Excess	-0,83798	Excess	-1,06121	Excess	2,435163	Excess	-0,84303
Asymmetr	0,363904	Asymmetr	-0,03587	Asymmetr	-0,20627	Asymmetr	0,040435	Asymmetr	1,297449	Asymmetr	0,629373
Interval	3,7	Interval	0,096386	Interval	0,034722	Interval	0,097826	Interval	0,193865	Interval	0,125828
Minimum	4,8	Minimum	0,206024	Minimum	0,234722	Minimum	0,01087	Minimum	0,01227	Minimum	0,006623
Maximum	8,5	Maximum	0,30241	Maximum	0,269444	Maximum	0,108696	Maximum	0,206135	Maximum	0,13245
Sum	114,8	Sum	4,6	Sum	4,6	Sum	1	Sum	1,2	Sum	1
Check	18	Check	18	Check	18	Check	18	Check	18	Check	18

Figure 5: Result of using the "Descriptive Statistics" tool.

Let us calculate the average elasticity coefficients using formula (5). The calculation results are presented in Figure 6.

	bi	xi	Эу
x1	11,3147	0,255556	0,453377
x2	4,182992	0,255556	0,167611
x3	0,074053	0,055556	0,000645
x4	2,806507	0,066667	0,029336
x5	20,13051	0,055556	0,175353

Figure 6: Values of average elasticity coefficients.

Based on the values of the average elasticity coefficients, we can conclude that the characteristics of factors x1, x2, x5 have a stronger influence on the result y than the characteristics of factors x3 and x4.

2.3.2 Sub Subsection Titles

The values of the linear pairwise correlation coefficients determine the closeness of the pairwise related variables used in a given multiple regression equation (Hruntovich, Moroz, Panfilov, Zhuk, Mikhailova, 2020; Gabriel , Mihaela , Dumitru , 2006; Chi, Di Maio, Lieven, 2020).

Pairwise correlation coefficients are calculated using the Correlation function in MS Excel presented in Figure 7.

From the matrix you can see that the factors $x_1$and x_2 are multicollinear x_3 , x_1 because correlation coefficients exceed 0.7. Thus, we can say that they duplicate each other.

When selecting factors for the model, preference is given to the factor that, while quite closely related to the result, has the least close connection with other factors. In our example, we find that the informative factors are: $x_1$and x_5.

	y	x1	x2	x3	x4	x5
y	1					
x1	0,950523	1				
x2	0,741093	0,809428	1			
x3	0,833348	0,870698	0,644032	1		
x4	0,489432	0,323294	0,110529	0,326104	1	
x5	0,979503	0,950316	0,732619	0,831166	0,4397	1

Figure 7: Matrix of pair correlation coefficients.

2.3.3 Building a Model in a Natural Form with only Informative Factors and Estimating its Parameters

Let's construct a multiple linear regression equation of the following form:

$$\tilde{y}_x = a + b_1 x_1 + b_5 x_5. \qquad (6)$$

Let's calculate the parameters of this model (Figure 8).

Regression statistics	
Plural R	0,981542
R-square	0,963425
Normalized R-squared	0,958549
Standard error	0,24705
Observations	18

Analysis of variance

	df	SS	MS	F	ignificance F
Regression	2	24,1156	12,0578	197,5592	1,67E-11
Remainder	15	0,915508	0,061034		
Total	17	25,03111			

	Odds	andard err	t-statistic	P-Value	Bottom 95%	Top 95%	ottom 95.0	Top 95.0%
Y-intersection	2,837479	1,440074	1,970371	0,067542	-0,23197	5,906924	-0,23197	5,906924
x1	8,509999	6,6447	1,28072	0,219741	-5,65284	22,67284	-5,65284	22,67284
x5	24,57938	4,957836	4,957682	0,000172	14,012	35,14675	14,012	35,14675

Figure 8: Result of using the Regression tool.

We get the following equation:

$$\tilde{y}_x = 2{,}84 + 8{,}51 x_3 + 24{,}58 x_5.$$

According to the matrix of pairwise correlation coefficients, informative factors were selected: increasing productivity and reducing costs. The multiple correlation coefficient for this information model is R = 0.981, which is 0.005 less than that of the original model. This value indicates a high close relationship between the selected factors and net income (Goyal, Pabla, 2016). The equation as a whole, as well as its parameters, are statistically significant.

2.4 Conducting Cluster Analysis

Next, cluster analysis was carried out using the Statgraphics application package to confirm the data. Ward's method was chosen for analysis (Gavrilov, Zhukov, 2022; Moiseev, 2002; Saucedo-Dorantes, Delgado-Prieto, Ortega-Redondo, Osornio-Rios, de Jesus Romero-Troncoso, 2016).

Cluster analysis is necessary for a more detailed study of data on the effectiveness of robot implementation. It was decided to start by dividing into 4 clusters.

To carry out the analysis, the Cluster function was applied to the source data presented in Figure 9.

	y	x1	x2	x3	x4	x5
	Numeric	Numeric	Numeric	Numeric	Numeric	Numer
1	5,1	0,21	0,23	0,01	0,21	0,01
2	5,0	0,22	0,24	0,01	0,01	0,01
3	5,4	0,22	0,24	0,01	0,01	0,02
4	4,8	0,22	0,25	0,02	0,01	0,02
5	5,0	0,24	0,26	0,03	0,02	0,02
6	5,3	0,24	0,25	0,04	0,03	0,03
7	5,7	0,24	0,25	0,09	0,05	0,03
8	5,8	0,25	0,25	0,05	0,04	0,03
9	6,0	0,25	0,26	0,05	0,04	0,05
10	6,2	0,26	0,25	0,05	0,06	0,05
11	6,8	0,26	0,26	0,07	0,06	0,05
12	7,1	0,27	0,27	0,08	0,07	0,07
13	7,0	0,27	0,27	0,03	0,07	0,07
14	7,3	0,27	0,26	0,07	0,09	0,09
15	7,5	0,28	0,27	0,08	0,09	0,09
16	8,0	0,29	0,25	0,10	0,10	0,11
17	8,3	0,30	0,26	0,10	0,11	0,11
18	8,5	0,30	0,27	0,11	0,12	0,13

Figure 9: Input data for cluster analysis.

Thus, a division into clusters was obtained (Figure 10).

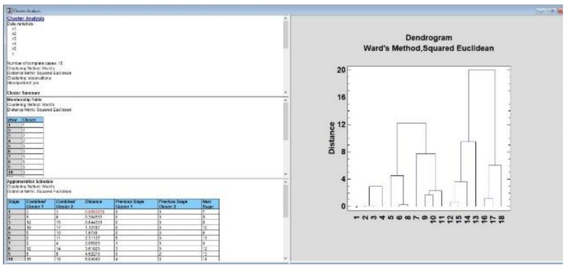

Figure 9: Result of Cluster operation Analysis.

In the table " Agglomeration" Schedule » shows the numbers of clusters that are combined at each stage. Let us consider it in more detail to evaluate the procedure for dividing into clusters (Figure 11).

Agglomeration Schedule
Clustering Method: Ward's
Distance Metric: Squared Euclidean

Stage	Combined Cluster 1	Combined Cluster 2	Distance	Previous Stage Cluster 1	Previous Stage Cluster 2	Next Stage
1	2	3	0,0893839	0	0	7
2	6	8	0,304553	0	0	9
3	12	15	0,644361	0	0	8
4	16	17	1,13787	0	0	10
5	9	10	1,6745	0	0	6
6	9	11	2,31127	5	0	11
7	2	4	2,95925	1	0	0
8	12	14	3,61825	3	0	12
9	5	6	4,52278	0	2	13
10	16	18	6,04048	4	0	14
11	7	9	7,73345	0	6	13
12	12	13	9,47347	8	0	14
13	5	7	12,1761	9	11	0
14	12	16	19,9786	12	10	0

Cluster Number	Smallest Row
1	1
2	2
3	5
4	12

Figure 11: Agglomeration table Schedule.

Distance column shows the distance between cluster cells. Based on the Distance data, it is clear that there is no sharp increase in the distances between steps.

Figure 12 provides general information about the clusters.

Cluster Summary

Cluster	Members	Percent
1	1	5,56
2	3	16,67
3	7	38,89
4	7	38,89

Centroids

Cluster	x1	x2	x3	x4	x5	y
1	0,21	0,23	0,01	0,21	0,01	5,1
2	0,22	0,243333	0,0133333	0,01	0,0166667	5,06667
3	0,248571	0,254286	0,0542857	0,0428571	0,0371429	5,82857
4	0,282857	0,264286	0,0814286	0,0928571	0,0957143	7,67143

Figure 12: Cluster statistics.

Based on this figure, it can be seen that clusters 3 and 4 are regions. Based on the data in Figure 11 and Figure 12, we can conclude that cluster 3 is optimal for this case.

Thus, the dendrogram of the clusters is presented in Figure 13.

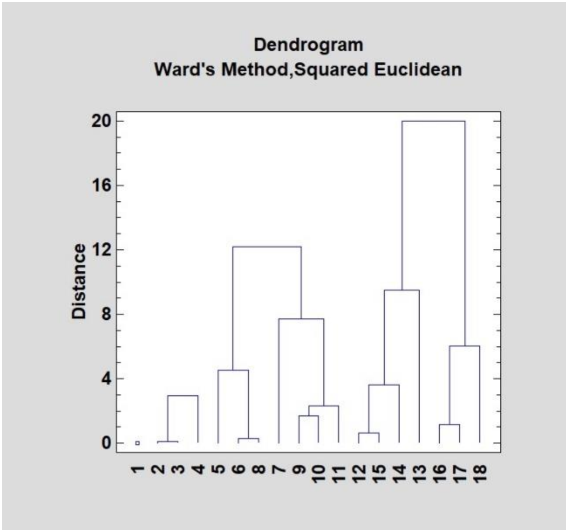

Figure 13: Dendrogram of clusters

Based on this dendrogram, the distribution by clusters can be seen, which is also presented in Figure 14:

Membership Table
Clustering Method: Ward's
Distance Metric: Squared Euclidean

Row	Cluster
1	1
2	2
3	2
4	2
5	3
6	3
7	3
8	3
9	3
10	3
11	3
12	4
13	4
14	4
15	4
16	4
17	4
18	4

Figure 14: Distribution by clusters.

It should be noted that the best ratio is in cluster 3, which confirms the hypothesis of a high impact of increased productivity when introducing robotic devices.

3 RESULTS

A methodology for introducing robotic devices has been proposed, consisting of the following steps:

1. Analysis of requirements and goals:
2. System identification:
3. Analysis of risks and benefits:
4. Formation of technical requirements:
5. Data mining
6. Selection of robot type:
7. Design of the control system:
8. Testing and optimization:
9. Training and service:
10. Implementation stage:
11. Monitoring and performance evaluation:
12. Optimization and development:
13. Training and social aspects

Particular attention is paid to methods of system analysis (data mining), with the help of which the introduction of robotic devices on power lines will help optimize processes and increase efficiency. Systems analysis, especially in the context of data mining, plays a key role in the successful implementation of robotic devices on power lines.

4 DISCUSSION

When introducing robots, it is necessary to take into account technological and ethical aspects, as well as ensure that personnel are trained to effectively interact with robots.

Productivity increase. The study results indicate a significant increase in productivity when using robotic devices in the inspection of power lines. Automated systems can perform tasks more efficiently and quickly, reducing the time required to inspect and maintain lines.

Improved processing quality. The introduction of robots also leads to improved data processing and detection of potential problems on power lines. Robotic devices are equipped with sensors and artificial intelligence systems, which allows them to more accurately and reliably analyse the state of the infrastructure.

Reducing human factor. One of the significant results is the reduction of the human factor in the process of technical inspection. Robots can operate in environments that might otherwise be dangerous or difficult for humans to reach, reducing the risk of human error and improving operational safety.

Increasing the versatility of work. Robotic devices provide greater versatility in performing a variety of tasks when inspecting power lines. This is especially important in situations where a variety of tasks require adaptation to different conditions and requirements.

Reducing costs. The study shows that the introduction of robotic devices is associated with a significant reduction in the cost of inspection of power lines in the long term. Although the initial investment may be significant, the savings in operating costs and accident prevention outweigh the costs.

Technological and ethical aspects. It should be noted that, despite the positive aspects of the introduction of robots, technological and ethical issues should be taken into account. It is important to design and implement robotics solutions with transparency, accountability and safety in mind to avoid unwanted consequences.

Training. For successful symbiosis of man and robot, personnel training is required. It is important that workers are familiar with new technologies that can effectively interact with robots and use the data provided by automated systems.

In general, the discussion of the results emphasizes that the introduction of robotic devices for the technical inspection of power lines is a promising direction. However, attention must be paid not only to technical aspects, but also to social and ethical issues to ensure the sustainable and effective introduction of new technologies into the industry.

5 CONCLUSIONS

When introducing robots, it is necessary to take into account technological and ethical aspects, as well as ensure that personnel are trained to effectively interact with robots.

Productivity increase. The study results indicate a significant increase in productivity when using robotic devices in the inspection of power lines. Automated systems can perform tasks more efficiently and quickly, reducing the time required to inspect and maintain lines.

The development of a methodology for introducing robotic devices for technical inspection of power lines, based on the principles of data mining, is a multidimensional process covering various aspects from data collection to forecasting and decision making. The use of statistical methods such as correlation and regression analysis, as well as forecasting models, plays a key role in the effective implementation of this methodology.

Analysis of statistical data provides a comprehensive understanding of the current state of the infrastructure, and also identifies trends and patterns that can be used to predict future events. Predictive models created based on this data make it possible not only to anticipate possible system failures and degradation, but also to effectively plan maintenance.

Correlation and regression analysis help identify relationships between different variables, which in turn provides more accurate and informative models. These analytical methods play an important role in identifying factors affecting the technical condition of power lines and determining optimal strategies for controlling robotic devices.

An important element of the implementation of robotic devices is also the constant adjustment and improvement of the methodology based on accumulated experience and new data. This feedback loop enables adaptation to changing conditions and environmental dynamics, which is necessary for the long-term sustainability of the system.

Thus, intelligent analysis, which includes statistical methods and forecasting, not only ensures the successful implementation of robotic solutions for technical inspection of power lines, but also creates the basis for intelligent and efficient management of electrical power infrastructure

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