This study considers those processes predicting the functional efficiency of robotic platforms that affect the optimization of their mission planning. Given the growing demand for autonomous mobile systems, a critical task is to ensure high efficiency of their dynamics under different loads, terrains, and speeds, which requires reliable tools for decision-making even before physical launch.

To solve the task, a method based on a customized Kernel Activation Network (KAN) was devised and programmatically implemented to predict the functional efficiency of the platform. The results demonstrate a significant increase in accuracy: KAN achieves an MSE of 0.00055727 on synthetic data and 0.00041720 on the experimental sample, while other architectures demonstrate 0.00105989 and higher.

The key innovation of KAN is the use of an asymmetric chi-square kernel in parallel with the Gaussian kernel, as well as the integration of input estimates that take into account the triple interaction of factors. This explains the network's ability to effectively capture complex nonlinear dependences between numerous platform parameters (rolling resistance, aerodynamic drag, climbing force, etc.) and environmental conditions. The use of an asymmetric kernel significantly simplifies the network architecture, allowing for high accuracy at lower computational complexity.

In practice, the results serve as an additional tool for optimizing mission planning of robotic platforms. This makes it possible to optimize equipment selection, construct strategic logistics routes, and increase the safety and reliability of autonomous systems under actual conditions. The achieved Technology Readiness Level is 4

Keywords: functional prediction, factor interaction, asymmetric kernel, neural network, robotic platform

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PREDICTING ROBOTIC PLATFORM MISSIONS USING A KERNEL ACTIVATION NETWORK WITH AN ASYMMETRIC KERNEL

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1. Introduction

Given the current growing demand for autonomous mobile systems, in particular ground robotic systems (GRSs), their use increasingly involves complex operational environments – from military and rescue operations to civil logistics and research missions. This trend leads to high requirements for reliability, adaptability and, most importantly, functional efficiency of such systems. Confirmation can be found in studies focused on increasing the resistance of robotic platforms to electronic warfare [1], conceptual design of new unmanned vehicles [2], and ensuring the fault tolerance of their computing systems [3]. The ability of GRSs to perform tasks in changing and unpredictable environments is key to their successful deployment. An important aspect of ensuring their reliability is effective control, diagnostics, and error correction, including at the level of computing systems [4].

Scientific research focusing on the design of models for predicting the functional efficiency of GRSs is becoming extremely important. Studies make it possible to unify and automate the decision-making process during mission planning, taking into account a number of critical variables: engine power, surface type, terrain, payload, energy consumption, and stability [5]. Early and accurate assessment of these factors is indispensable for minimizing risks and optimizing resources.

Practical demands for modern GRS use require the design of tools for intelligent analysis and forecasting [6, 7], which make it possible to assess the reliability and efficiency of technical means even before physical launch. In this context, hybrid approaches to data analysis are of particular interest. They combine conventional physical models with modern machine learning methods, in particular neural networks [8, 9]. Such approaches open up new opportunities for designing adaptive and accurate forecasting systems.

Thus, research aimed at devising methods for assessing and predicting the functional efficiency of robotic platforms is not only scientifically sound but also practically necessary. The results of such work will contribute to increasing the level of autonomy, adaptability, and safety of mobile systems under real operating conditions. This is a key factor for the effective application of GRSs in a wide range of areas, including military, search and rescue, agricultural, industrial, and transport tasks. Therefore, devising an advanced method for planning missions of robotic platforms, capable of accurately predicting their functional efficiency under dynamic conditions, is an extremely relevant scientific and applied task.

2. Literature review and problem statement

In [10, 11], data clustering methods for object categorization and identification are considered. In particular, in [10], a method for categorizing wheeled combat vehicles based on their static technical characteristics using fuzzy cluster analysis (FCM) is proposed. Similarly, in [11], an improvement in the accuracy of clustering of air alert hazard levels using a hybrid clustering algorithm is investigated. However, despite the importance of [10, 11] for static classification and clustering tasks, key issues in predicting the functional efficiency of robotic platforms under dynamic conditions remain unresolved. Both approaches focus on the categorization and identification of existing objects, rather than on modeling and predicting the behavior of the system under varying operational parameters. In addition, these papers do not provide an effective mechanism for taking into account complex nonlinear interactions between numerous operational variables and do not address the issues of mission planning optimization.

In [12], the application of machine learning to predict and optimize plant growth is investigated, demonstrating the effectiveness of neural networks for prediction in dynamic biological systems and the significant advantages of the ReLU activation function in terms of MSE, RMSE, and MAPE. This work is important because it highlights the potential of neural networks for prediction tasks. However, in [12], questions remain unresolved regarding direct application to the dynamics of robotic platform motion. The study focuses on plant growth prediction, which is significantly different from predicting the behavior of a mechanical system with variable loads and terrain. Moreover, the work does not investigate customized neural network architectures or specialized activation functions that can effectively capture extremely complex nonlinear interactions between numerous physical parameters of a robot. Paper [12] also does not consider the possibility of integrating physical models or engineering constraints into the prediction process, which is critical for realistic predictions in robotics.

In [13], a hybrid deep neural network (DNN) is used to predict natural disasters, and in [14], a method for assessing the quality of interaction between system elements is proposed, taking into account the triple interaction of indicators. These studies demonstrate the capabilities of neural networks in forecasting and the importance of considering complex interactions. However, [13] focuses on large-scale natural phenomena, without providing specific mechanisms for modeling the physical dynamics of robotic systems using nuclear activation functions. Paper [14] focuses on static evaluation of the interaction of production systems, rather than on dynamic prediction of the efficiency of mobile platforms under changing conditions. The reason for these limitations is the differences in the objects and goals of the studies.

Study [15] makes an important contribution to understanding the role of activation functions in deep neural networks by conducting a comparative analysis of standard ReLU functions and their derivatives. This analysis is valuable for choosing optimal activation functions. However, the authors of [15] do not consider the possibility of using customized activation functions based on kernels, which are a key element of research. The analysis is limited to standard ReLU variants, indicating an existing gap in research on the development of innovative activation functions specifically adapted for modeling complex interactions in physical systems.

The existing experience of using artificial intelligence tools to predict the functional efficiency of complex systems indicates a wide range of applications – from ranking the technical condition to optimizing energy consumption. Work [16] deals with ranking ships by technical condition and using this information for forecasting and decision-making. This makes it possible to use artificial intelligence methods to build appropriate models, in particular classifications, regressions to automate the process of monitoring the technical condition of aircraft. To speed up calculations and reduce resource consumption, there are works where the research tasks are focused on optimizing energy consumption [17]. This makes it possible to reduce the system's electricity consumption, but it is not clear how the proposed idea would work within the framework of the specified study.

In [18], a hybrid fault-tolerant tool for task planning is proposed. The planning process takes place in real time, and the proposed ideas, like in [19], reduce energy consumption. The research is indeed valuable but the problem of mission forecasting by a robotic platform has not yet been studied.

The task of selecting anti-aircraft missile weapons systems was addressed in [19]. An author's methodology is proposed to evaluate the optimal weapons system, which includes several algorithms. The advantage of the proposed solution is the use of fuzzy integral calculus.

In addition to fuzzy logic, risk-oriented [20] and human-centered [21] approaches are used in mission planning. These tools expand the possibilities for mission planning. Risk assessment significantly affects the decision-making process. Work [22] complements and expands the ideas of [20] and [21]: the influence of each component, unit, etc. on the efficiency of the entire enterprise is studied. It is proven that the resource costs for equipment repair are reduced when using an effective control model. In fact, in [22], the forecasting problem is studied, which includes many models. Some tools for working with a large number of models are proposed in [23]. A fundamentally new mechanism for improving the forecast is proposed, which is associated with correction.

Our review of the literature [10–23] convincingly demonstrates the limitations of existing approaches. Despite significant achievements in the areas of clustering, forecasting of biological processes, systems analysis, and the study of activation functions, a comprehensive and universal solution is still lacking. In particular, there is no accurate prediction of the functional efficiency of robotic platforms under dynamic and changing operating conditions.

Current research often focuses on static classification or object identification, while for robotics, detailed modeling and prediction of the dynamic behavior of mechanical systems is vital. In addition, existing methods are not effective enough to take into account the extremely complex, nonlinear interactions between numerous physical and operational parameters, such as rolling resistance, aerodynamic drag, climbing force, or the impact of component failure. The importance of these factors is also confirmed by studies on the impact of diagnostic errors on functional safety indicators [24]. This is due to the lack of customized neural network architectures equipped with specialized activation functions, in particular based on asymmetric kernels, which could more effectively capture these complex dependences. Most studies also ignore the need to integrate physical models and engineering constraints directly into predictive algorithms, which is critical to enable realistic and reliable predictions. Finally, there is a lack of research that directly focuses on the direct application of the results of such forecasting to optimize mission planning and the selection of optimal equipment under real-world conditions.

Existing studies operate with other objects of analysis, for example, biological systems or natural disasters. Or they use methodologies (clustering, standard activation functions) that do not make it possible to capture the unique complexity of the dynamics of robotic platforms and their multifactorial nature. The objective reason for these unresolved issues is the difficulty of modeling multifactorial nonlinear dependences in combination with the lack of universal tools that integrate deep machine learning with engineering knowledge for targeted forecasting and optimization in robotics. In addition to purely functional aspects, one should also remember the general relevance of cybersecurity and information protection in modern intelligent systems, as indicated, for example, by work [25] on strategic directions for ensuring economic cybersecurity of business.

All of the above justifies the feasibility of research into predicting the functional efficiency of robotic platforms to optimize mission planning under various loads and environmental conditions.

3. The aim and objectives of the study

The aim of our study is to devise a method for predicting the functional efficiency of robotic platforms based on KAN with an asymmetric core, which would allow for an accurate assessment of performance for mission planning optimization. This could make it possible to plan missions of a robotic platform depending on the terrain.

To achieve the goal, the following tasks were set:

– to determine the structure of the method for predicting the functional efficiency of a robotic platform for a given route based on the KAN architecture with an asymmetric core, which could serve as a tool for optimizing mission planning;

– to verify the method based on experimental studies and software implementation to confirm its operability and efficiency, ensuring the achievement of Technology Readiness Level 4 and substantiating the possibility of optimizing mission planning.

4. The study materials and methods

4. 1. The object and hypothesis of the study

The object of our study is the processes of predicting the functional efficiency of robotic platforms and their impact on the optimization of mission planning. This includes the analysis of motion dynamics, energy consumption, as well as stability, when moving along a given route.

The main hypothesis of the study assumes that high accuracy in predicting the functional efficiency of robotic platforms under complex, multifactorial conditions is achievable. This is possible using a customized Kernel Activation Network with a hybrid activation functionality, which includes an asymmetric chi-square kernel and integrates indicators of triple interaction of factors. This will make it possible to effectively optimize the planning of their missions.

The assumptions adopted in the study:

– the customized Kernel Activation Network (KAN) architecture with an asymmetric kernel has a higher ability to model complex nonlinear dependences compared to conventional neural networks and machine learning models;

– the selected set of input parameters and their interaction is sufficient for an accurate and comprehensive description of the functional efficiency of the robotic platform in various conditions;

– the effect of ambient temperature and internal heating of engines on their efficiency is taken into account indirectly through thermal stability, without deep thermodynamic modeling;

– a composite assessment of functional efficiency, which takes into account the parameters of resistance, energy consumption, and reliability, is a valid integrated metric for comparative analysis of platform performance;

– changes in the internal components of the platform, which are not the object of direct modeling (for example, bearing wear, minor frame deformations), do not have a critical impact on the predicted functional efficiency in the short term.

The simplifications adopted in the study:

– the robotic platform is considered as a single object with aggregated weight and dimensions parameters to simplify the calculations of resistance forces;

– aerodynamic drag is considered in a simplified way based on coefficients, without detailed modeling of air flows;

– engine failure modeling is considered as a binary indicator (failure/no failure) without detailing intermediate states or failure causes;

– different types of surfaces are aggregated into discrete categories with corresponding drag coefficients.

4. 2. Formal statement of the research task

Determining the input data on the modeling day. There is a robotic platform with two motor wheels of the front axle and a shank on which a third motor wheel is fixed. All three motor wheels have a radius of 0.1651 m and a power of 500 W. To control the shank, a fourth RS775 24 Volt 6000 rpm DC motor with a ZENG 42GP-775 gearbox and a Nema 23 gearbox is used.

The robotic platform will be used on various terrain, including asphalt, gravel, grass, sand, clay, dispersed soil, swamp. The possibility of transporting cargo weighing in the range of [1, 40] kg, at speeds in the range of [1, 30] km/h or [0.28, 8.33] m/s on surfaces with a terrain slope in the range of [0, 55] percent is considered.

Given the variability of platform equipment (engines, cargo) and operating conditions (terrain, speed), the study focused on building a recommendation system for strategic planning of logistics routes. This requires a systematic approach to the analysis of numerous interdependences between the platform speed, surface inclination angle, cargo weight, engine power, and terrain type.

The processing of these issues will make it possible to construct a table or matrix $m \times n$ of all possible combinations of actions. To make decisions based on these combinations and in order to effectively select equipment for a robot for specific tasks, it is proposed to devise an indicator of the functional efficiency of the platform, the main idea of which is considered in [13].

Formal statement of the problem. There is a set of parameters for a robotic platform. The task is to find a certain combination of parameters of the robotic platform for mission planning.

4. 3. Research procedure

Our study of mission planning of the robotic platform included the following stages. At the first stage, the engine power is calculated in two ways [26, 27] to select the optimal one. The results of the calculations are given in Table 1.

Table 1

Input data on possible parameters of the robotic platform

No.	Variable 1	Variable 2	...	Variable n	Target variable Y
1	X_{11}	X_{12}	...	X_{1m}	Y_1
...	...	...	...	...	...
n	X_{n1}	X_{n2}	...	X_{nm}	Y_n

The formation of the estimates in Table 1 involved the use of a real robotic platform and additional equipment, in particular a set of disks with a total weight of 20 kg per set. The results are used to build neural networks with classical activation functions and with activation functions based on kernels. The sample size depends on the number of variables under consideration, which is justified in the results of the study. An important aspect of using the estimates from Table 1 is the normalization using the MinMaxScaler method [28] to the range of [0, 1] as StandardScaler [29] makes it possible to obtain positive and negative estimates.

At the second stage, to justify the choice of architecture for neural networks with activation functions based on kernels, a theoretical sample of estimates $N = 625$ estimates was built, where x_1, x_2, x_3, x_4 were considered in the range of [1, 5] with a step of 1, Table 2.

Table 2

Input data on possible parameters of a robotic platform for substantiating the architecture of neural networks with kernel-based activation functions

No.	x_1	x_2	x_3	x_4	Target variable Y, determined by technique 1	Target variable Y, determined by technique 2	Target variable Y, determined by technique 3
1	1	1	1	1	Y_1	Y_1	Y_1
...	...	...	...	...	...	...	...
625	5	5	5	5	Y_n	Y_n	Y_n

The use of a theoretical sample of 625 estimates was considered as a minimum condition for building a network, therefore four chi-square variables were used. Target variables were determined in various ways, in particular as the average of pairwise products.

At the third stage, networks with classical activation methods, in particular ReLU and kernel-based networks, are considered as architectural solutions for neural networks. Networks based on ReLU activation functions were given the estimates from Table 1 as input, and networks based on kernels were given the estimates from Table 2. This was used to configure the network and find ways to customize it.

To confirm the relevance of building a neural network on an experimental set of estimates, cross-validation was performed [30]. The generalization ability of Linear Regression, Gradient Boosting, SVR, K-Neighbors machine learning models was studied at cv = 5, scoring = 'r2', test_size = 0.35, shuffle = True.

To study the sensitivity of the proposed neural network, the StandardScaler normalization method was used, where the values of the coefficients of determination and MSE on the test sample were studied.

At the fourth stage, relief maps of the European Union countries were used to verify the proposed solutions [31].

A detailed consideration of the methodology begins with the formation of input data for prediction. For this purpose, the engine power was calculated using two techniques described in [26, 27]. The first technique for determining the engine power is approximate since it does not take into account a number of critical factors.

The first technique for determining the engine power includes the following steps [26]:

Step 1. Collection and specification of input parameters for the robotic platform.

Step 2. Calculation of the traction wheel rotation speed, rpm

$$N = \frac{60 \cdot v_n}{3.14 \cdot D}, \tag{1}$$

where v_n is the rated rotation speed of the robot, m/s;

D is the diameter of the traction wheel, m.

Step 3. Determining the value of a traction force, N

$$F = 9.8 \cdot k \cdot (m_L + m_R), \tag{2}$$

k – coefficient of maximum inclination of the robotic platform;

m_L – weight of the load on the robotic platform, kg;

m_R – weight of the robotic platform, kg.

Step 4. Calculation of mechanical power for the movement of the entire robot at rated speed, W

$$P = F \cdot v_n. \tag{3}$$

If the robot has three motors, then the mechanical power is $P/3$.

Step 5. Calculation of torque, N·m

$$T = \frac{D}{2} \cdot F. \tag{4}$$

The second technique for calculating engine power, which takes into account rolling resistance, aerodynamic drag, acceleration force, and the force required to overcome hills, includes the following steps [27]:

Step 1. Determining the value of rolling resistance from the following formula

$$F_{rr} = \mu \cdot m \cdot 9.81, \tag{5}$$

μ – coefficient of rolling resistance;

m – the weight of the platform and the load, kg.

The rolling resistance coefficient μ is a critical parameter that depends on the type of surface and the characteristics of the tire. For an electric vehicle tire on hard surfaces, it can be about 0.005. However, its value varies significantly depending on the road surface: for asphalt, it is 0.01; for concrete – 0.011. On less hard and homogeneous surfaces, this coefficient increases significantly: for gravel/crushed stone – 0.0; grass – 0.05; clay – 0.1; sand – 0.15; and mud – 0.2 [27].

Step 2. Calculation of aerodynamic drag using the following formula

$$F_{ad} = 1/2 \cdot \rho \cdot A \cdot C_d \cdot v^2, \quad (6)$$

where ρ is the air density of 1.25 kg·m^{-3};

A is the front area, 0.7 m^2;

C_d is a constant termed the drag coefficient, which is 0.7;

v is the wheel speed, m/s.

Step 3. Determining the value of the hill climbing force from the following formula

$$F_{hc} = m \cdot g \cdot \sin \psi, \quad (7)$$

g is the acceleration coefficient; on Earth, this value is approximately equal to 9.80665 m/s^2;

ψ is the angle of inclination of the slope from 0° to 60°.

Step 4. Calculation of the acceleration force from the following formula

$$F_{la} = m \cdot a, \quad (8)$$

a – linear acceleration, m/s^2.

Step 5. Determining the total tractive effort from the following formula

$$F_{te} = F_{rr} + F_{ad} + F_{hc} + F_{la}. \quad (9)$$

Step 6. Calculation of engine power according to the following formula

$$P_e = \frac{\left(F_{rr} + F_{ad} + F_{hc} + F_{la}\right) \cdot v}{\eta \cdot 1000}, \quad (10)$$

η – engine efficiency.

The results of calculations using formulas (1) to (10) make it possible to combine physical models of platform motion dynamics to build an input dataset containing an array of power values, maximum tilt angles, and cargo weight. These data are necessary for training a predictive model based on neural networks.

To automate the prediction of the platform's functional efficiency for a specific route, neural networks with various customizations and a classical appearance were used. To ensure uniform conditions for comparative analysis, the distribution of scores into training and learning subsamples was carried out with the following parameters: test_size = 0.35, shuffle = True, random_state = 42. Model training was carried out by the Adam optimizer at lr = 0.01, where 500, 1000 epochs were used. The criteria for comparing the quality of the constructed networks were r2_score, mean_squared_error for the learning/training samples.

The implementation of the studied tools was carried out in the python programming language with a number of libraries, in particular torch [32], for building a Kernel Activation Network. For the graphical representation of neural networks, the tool [33] was used, into which the saved model in the .pkl format was loaded. The developed software was implemented on the Google Colab platform.

5. Results of investigating intelligent software for predicting the functional efficiency of robotic platforms

5. 1. Structure of the method for predicting the functional efficiency of robotic platforms

The determined structure of the method for predicting the functional efficiency of a robotic platform is based on a systems approach that integrates physical calculations and modern machine learning methods to obtain accurate predictions. It consists of seven key stages, each of which is necessary for building and validating the model:

Stage 1. Data collection and pre-processing. At this stage, estimates describing the parameters of robotic platforms are collected. The data are examined for gaps, and if they are detected, the corresponding records are deleted.

Stage 2. Calculation of functional efficiency. This stage includes the calculation of the power of the motors of the robotic platform according to the methodology from [27]. The resulting data set is used to determine the functional efficiency of the platform on a given route. The functional efficiency of the platform (f) for the desired route is determined as a dependence on the key physical parameters: rolling resistance, aerodynamic drag, hill climbing force, acceleration force. Based on the calculated traction force, the required power of the motors (P_e) is determined, which is a key indicator of functional efficiency. This power, together with the indicators of engine failure, thermal stability, range, braking efficiency, and lateral stability, forms the input dataset for further modeling. This comprehensive approach makes it possible to obtain realistic data, which is critically important for accurate prediction. The proposed model is the main tool for determining the functional efficiency of the robotic platform.

Stage 3. Construction of a neural network. At this stage, a neural network is built to predict the functional efficiency of the platform. The architecture of the proposed neural network is as follows: input – parallel processing Gaussian Kernel Layer (16 cores), Chi2 Kernel (16 cores) – Concatenation – Dense(64) + ReLU – Dense(1) – output. The mathematical representation of the neural network architecture is described by the following formula

$$f(x) = U_2 \,\mathrm{ReLU}\,(U_1 \,\phi\,(x) + b_1) + b_2, \quad (11)$$

where U_1 is the weight matrix of the first layer (dimensionality: hidden_dim × n_kernels);

U_2 is the weight matrix of the output layer (dimensionality: 1 × hidden_dim);

b_1, b_2 are the offsets.

$\phi(x)$ is the vector of kernel features of Gaussians and chi-squares (χ^2), calculated on the input x from the following formula

$$\phi(x) = \begin{bmatrix} K_g\left(x, c_1^g\right), \ldots, K_g\left(x, c_m^g\right), \\ K_{\chi^2}\left(x, c_1^{\chi^2}\right), \ldots, K_{\chi^2}\left(x, c_m^{\chi^2}\right) \end{bmatrix}^T, \quad (12)$$

K_g – Gaussian core;

K_{χ^2} – chi-square kernel;

c_m^g – center of the m-th Gaussian kernel;

$c_m^{\chi^2}$ – center of the m-th chi-square kernel;

m – number of kernels of a certain type;

T – vector transpose.

The innovation is that the network uses an asymmetric chi-square kernel together with Gaussian, which makes it possible to better capture the nonlinear dependences. In addition, integrated estimates are fed to the input, which take into account the triple interaction of key factors. This is a key difference from existing solutions and explains the high accuracy of prediction.

Stage 4. Model training and testing. The model is trained on the prepared dataset according to the information described in the research procedure. The distribution of estimates into the training and test subsamples is carried out with the parameters test_size = 0.35, shuffle = True, random_state = 42. The Adam optimizer with lr = 0.01 is used to train the models over 500–1000 epochs.

Stage 5. Evaluation of the quality of the results. At this stage, the quality of the model is assessed using the Mean Squared Error (MSE) metrics and the coefficients of determination for the training and test samples.

Stage 6. Iterative optimization. If the obtained model quality results do not meet the requirements, a return to Stage 4 is made to re-tune and train the network.

Stage 7. Decision making. After achieving the required accuracy, the model is used as a tool for making decisions regarding the planning of robotic platform missions.

The defined structure of the method is a sequential algorithm that integrates the stages of data preparation, modeling, and evaluation for further use in planning robotic platform missions.

5. 2. Results of software implementation and experimental studies of the prediction method

A comparative analysis of determining the power of the robotic platform engines by technique 1 and technique 2 was carried out. The calculation of the engine power was carried out by technique 1. The input data used were a speed of 10 km/h or 2.78 m/s, a wheel diameter (13 inches = 330.2 mm) of 0.3302 m, an inclination angle of 0.12°, and a robot/cargo weight of 25/15 kg, respectively. We obtained: $N = 160.8753$ rpm, $F = 47.0880$ N, $P = 130.9046$ W, $T = 7.7742$ N·m. In other words, to transport a 15 kg load at a speed of 2.78 m/s, an engine power of 130.9 W must be provided.

If the input values of the studied data are specified, then it is possible to determine all possible combinations of data and model the behavior of the dependence of the engine power of the robotic platform on the maximum angles of inclination, weight of cargo and speed.

The coefficients of the maximum angles of inclination of the robotic platform in the range of [0.1, 0.5], the weight of cargo in the range of [1, 36] at a constant or specified in a certain range of speed in the range of [1, 30] km/h or [0.28, 8.33] m/s are considered. The results from investigating the dependence of engine power on all possible values of the weight of cargo, angle of inclination, and speed, are shown in Fig. 1.

Fig. 1 shows the power values at a maximum speed of 18 km/h or 5 m/s. As can be seen, at most, the robotic platform at $k = 0.5$ is able to transport a load weighing 36 kg at a speed of 5 m/s. The power and torque vary linearly. Having all possible power options at different values of the surface inclination angle, load weight, and speed, it is possible to simulate the movement of the platform.

An analysis of the second technique for determining engine power was carried out. If, for a given weight of the loads in the range of [1, 50] kg, at speeds in the range of [1, 15] km/h or [0.28, 4.17] m/s, with acceleration in the range of [0, 1.5] m/s^2 and 10 possible coverage options, 120,000 combinations of estimates were obtained. Our data represent the input dataset: Table 3.

Table 3

Input data on possible parameters of the robotic platform

No.	Load (kg)	Robot weight (kg)	...	Available power (30° slope)
1	2	25	...	Yes
...	...	...	...	...
120000	50	25	...	No

The obtained estimates in Table 3, as noted, are used as input estimates for building neural networks. A graphical interpretation of our results is shown in Fig. 2.

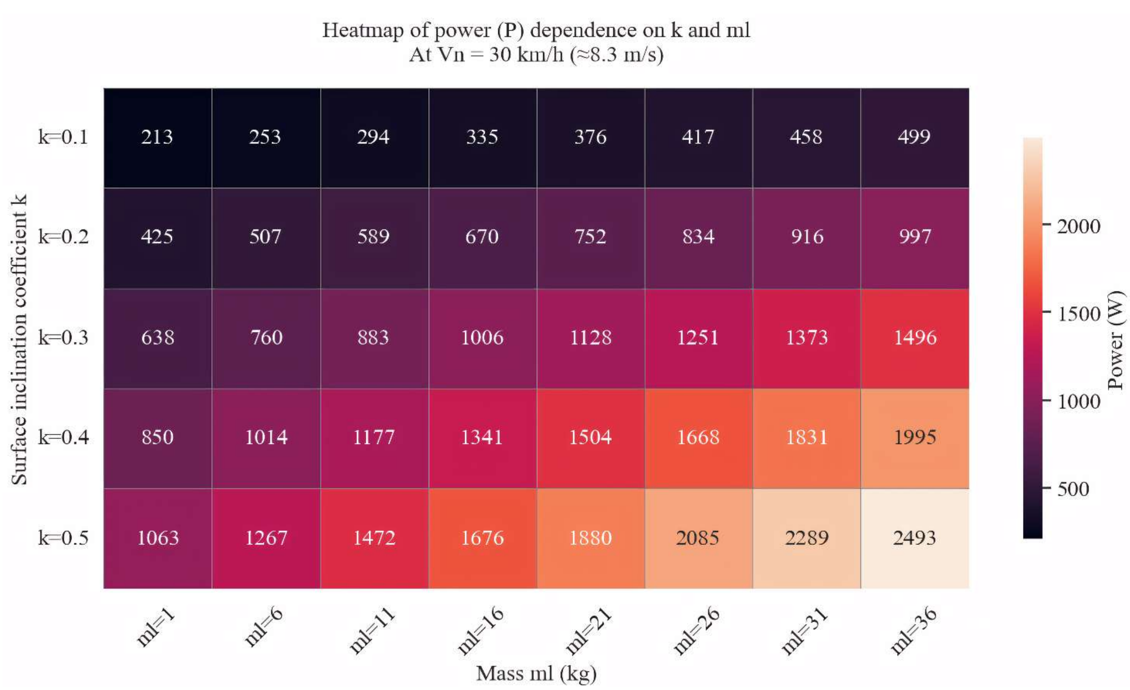

Fig. 1. Results of the study (as an example) of the dependence of engine power on all possible values of cargo weight, angle of inclination, and speed; engine power determined by technique 1

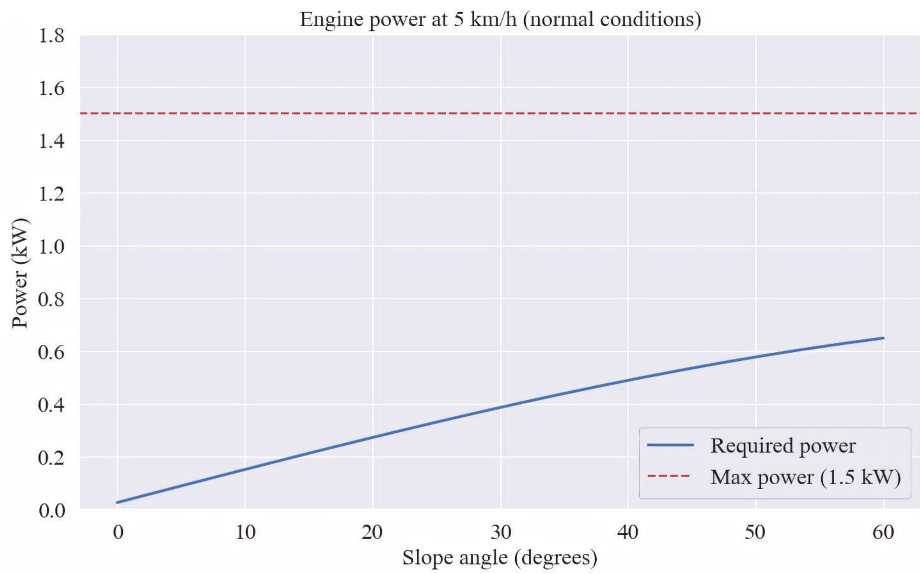

Fig. 2. Results of the study (as an example) of the dependence of engine power on all possible values of cargo weight, angle of inclination, and speed; engine power determined by technique 2

Fig. 2 demonstrates the results of the study; the recommended engine power is shown as an example to move at a speed of 5 km/h or 1.39 m/s. The software also makes it possible to simulate the thermal stability of motor wheels (13 inches, aluminum, 36 Volt 500 W), range (10S 6P 36 Volt battery), cross-country ability, lateral stability for the studied modes.

A study was conducted to investigate the feasibility of using the proposed neural network architecture. Analyzing the input estimates from Table 3, it was established that the following variables have the greatest contribution to the influence of engine power: load (kg), total mass (weight of cargo and robotic platform) (kg), speed (m/s), acceleration (m/s^2), rolling resistance coefficient (μ). To confirm the effectiveness of using neural networks, rather than machine learning methods, cross-validation was carried out. Generalization ability of machine learning models Linear Regression, Gradient Boosting, SVR, K-Neighbors, where we obtained the Mean Squared Error of 0.180220, 0.006813, 0.002164, 0.000604, respectively. To study the possibility of obtaining the optimal Mean Squared Error, the following neural network architectures were considered: Table 4.

Input estimates for neural networks with classical activation functions were obtained in the research process described above. And input estimates for neural networks with kernel-based activation functions involved the use of a theoretically created set of estimates x_1, x_2, x_3, x_4 in the range of [1, 5].

The first kernel-based network was given input estimates of x_i, and y_i was determined as the arithmetic mean. The second kernel-based network was given initial estimates of x_i, and y_i was determined as the sum of products $y_i \times y_j$ for all pairs $i \times j$, where $i < j$. Snorm = 1 + (S–Smin)/(Smax–Smin) × 4. The third and fourth kernel-based networks were given initial estimates of x_i, and y_i was determined as y = the average value of normalized triple products.

The architecture of the first Sequential neural network was analyzed, which receives the original values of the platform parameters as input and determines the pairwise products of the platform variables. This is the first way to improve the network. Next, two hidden layers of 64 and 32 neurons with ReLU activations are used. The output layer has 1 neuron without activation. The Mean Squared Error and the Adam optimizer are used as the loss function. The quality of the results of the constructed network is measured by MSE and the coefficient of determination.

Table 4

Neural network architectures under investigation, with different activation functions

1	Neural network architectures with classical activation functions
1.1.	Architecture of the proposed neural network 1 with ReLU activation functions
	Pre-processing of estimates (determining the products of features based on the original estimates) – input (original features + their products) – 2 hidden layers with ReLU – output
1.2.	Architecture of the proposed neural network 2 with ReLU activation functions
	Input (original features) – nonlinear variable accounting layer (original variables are combined with nonlinear ones) – hidden layer 1 with ReLU – hidden layer 2 with ReLU – output
1.3.	Architecture of a well-known neural network with ReLU activation functions (neural network 3)
	Input layer – hidden layer 1 with ReLU – hidden layer 2 with ReLU – output
2	Neural network architectures with kernel-based activation functions
Kernel Activation Network	
2.1.	Input – Gaussian Kernel Layer (16 kernels) – Dense Layers (16–32 ReLU) – Dense (32–1) – output
2.2.	Input – Gaussian Kernel Layer (32 kernels) – Dense Layers (32–64 ReLU) – Dense (64–1) – output
2.3.	Input – Gaussian Kernel Layer (32 kernels) – Dense Layers (32–64 ReLU) – Dense (64–1) – output

The network was trained with the following parameters: epochs = 20, batch_size = 32, validation_split = 0.2, verbose = 1. That is, the architecture of network 1 involves the use of more accurate input estimates, which is implemented by pairwise products of variables.

The first neural network demonstrated high coefficient of determination on the training/test samples, which is 1.0/1.0 and an MSE of 0.0016/0.0016. High coefficient of determination values on the training and test samples (1.0/1.0) and low MSE (0.0016/0.0016) for the first neural network indicate its overtraining [34].

The results of the training of the second neural network were analyzed. The architecture of the second neural network Sequential receives 6 variable platform parameters as input. Next, it has a layer of generation of pairwise interactions between variables, which are combined with the original variables for use in the ReLU activation function. After that, two layers Dense(64, activation = 'relu') and Dense(32, activation = 'relu') are used. That is, the architecture of network 2 has a layer after the input that takes into account nonlinear variables. The second neural network has similar training parameters and performance determination as the first.

The architecture of the second neural network demonstrated determination coefficients of 0.99/0.99 at an MSE of 0.0098/0.0098 on the training/test samples, indicating the absence of overtraining. The architecture of the third, well-known, neural network demonstrates on the training/test samples the coefficients of determination of 0.99/0.99 with an MSE of 0.0035/0.0035.

Despite the customization of the architectures of the first two networks, they demonstrated inefficient results compared to the third architecture. In percentage terms, the third neural network is 180% superior to the second and 54.3% inferior to the first. But the first neural network is overtrained, so its results are not adequate.

The results of the Kernel Activation Network networks were initially unsatisfactory, but all networks demonstrated high values for the dependences between variables at 0.99. Thus, the first Kernel Activation Network showed excellent values for the coefficient of determination on both samples at 0.99 and the MSE of the test sample at 0.001995. The second Kernel Activation Network on the test set showed MSE = 0.00168. This improvement was achieved by using the sum of the products of pairs of estimates fed to the network input. The third network on the test set showed MSE = 0.00105989, which is less than the previous ones.

Our results showed that the accuracy of the network improves when using more accurate input estimates. These observations formed the basis for the design of customized architecture. An attempt to use a double sum of products of the activation function complicated the network architecture and did not yield a positive effect. In this regard, the use of an asymmetric kernel, in particular the chi-square, was proposed. Fig. 3 shows a graphical representation of the proposed Kernel Activation Network.

The results demonstrated by the proposed neural network Kernel Activation Network based on theoretical input estimates, defined as a triple product, were analyzed. The customized network showed no overtraining; the coefficients of determination are 0.99 for the training and test samples. The MSE is 0.00055727, which is less than all previously studied networks.

Experimental verification of the use of the proposed network based on estimates of load (kg), total mass (kg), speed (m/s), acceleration (m/s^2), rolling resistance coefficient (μ) confirmed our theoretical result. The resulting MSE for the test sample is 0.00041720 at the coefficients of determination of 0.99/0.99. The obtained value is explained by the use of StandardScaler during normalization and the use of original estimates.

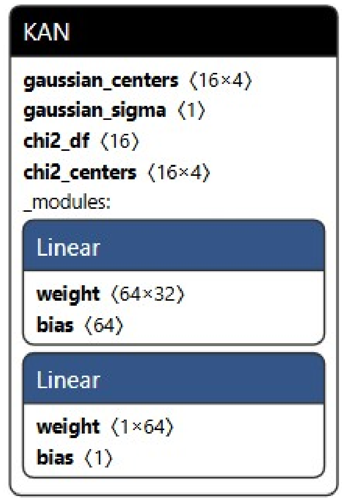

Fig. 3. Graphical representation of the proposed Kernel Activation Network based on an asymmetric kernel, built with the Netron tool

When comparing the obtained MSE value demonstrated by the network visualized in Fig. 3 with the indicators of other networks studied in our work, its superiority is recorded.

The practical use of the proposed model is illustrated in Fig. 4.

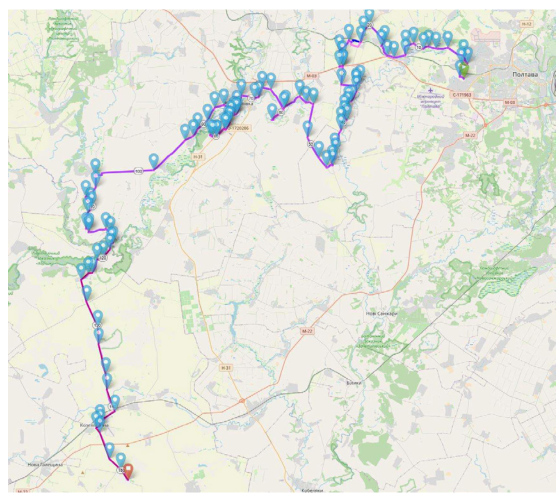

Fig. 4. Map of the area with a marked possible section of platform movement

Using the specified route as an example, terrain features are determined. Then, information about hills, etc. is used as input to predict the functional efficiency of the platform.

6. Discussion of results based on investigating the prediction of the functional efficiency of robotic platforms

Our results, in particular the high accuracy of prediction, are attributed to the architectural features of the devised method. This method is a systematic approach that integrates physical calculations and modern machine learning methods to obtain accurate predictions. Below is a detailed analysis built in accordance with the tasks set.

The results of the network study, given in Table 4, namely the low values of the Mean Squared Error (MSE) (0.00055727 on synthetic data and 0.00041720 on the experimental sample) in comparison with the indicators of 0.00105989 and higher for other architectures, are explained by the unique architecture of the neural network. This is made possible by the ability of the hybrid kernel (combining symmetric Gaussian and asymmetric chi-square) to effectively analyze various data distributions, including those containing complex dependences (triple products of variables), as demonstrated by formula (12). The proposed method makes it possible to capture various data distributions and solve problems with nonlinear dependences. Its key difference from existing ones is the architecture of the neural network, which uses a hybrid asymmetric kernel (Gaussian and chi-square), which makes it possible to achieve high accuracy at lower computational complexity.

The resulting architecture, shown in Fig. 3, uses a hybrid kernel, which allows it to effectively model complex nonlinear dependences between numerous input parameters such as rolling resistance, aerodynamic drag, and climbing force. Since these parameters are calculated taking into account multifactorial relationships (e.g., the dependence of the drag force on speed, mass, and angle of inclination), as described in Step 2 of the Method, the model is able to capture these relationships, which is reflected in low MSE values.

The key advantage of our study is the Kernel Activation Network (KAN) architecture with a hybrid asymmetric kernel. Unlike conventional neural networks with ReLU activation functions (such as the architecture of the well-known neural network 3 from Table 4), which require a significant number of layers to model complex nonlinearities, our model achieves high accuracy with significantly lower computational complexity.

Compared to well-known machine learning approaches (such as Linear Regression, Gradient Boosting, SVR, K-Neighbors), which showed significantly higher MSE indicators (e.g., 0.180220 and 0.006813, respectively), the proposed method demonstrates a significant increase in generalization ability. This is made possible by the ability of the hybrid kernel (combining symmetric Gaussian and asymmetric chi-square) to effectively analyze various data distributions, including those containing complex dependences (triple products of variables).

Our solutions effectively solve the task identified in chapter 2, namely the lack of accurate and universal tools for predicting the functional efficiency of GRSs under dynamic conditions. The devised method makes it possible to do the following:

1. Predict the behavior of the system under variable operational parameters, in contrast to existing approaches that focus on static classification [10, 11].

2. Effectively account for complex nonlinear interactions between numerous physical parameters, which has been an unsolved problem in most works [12, 13, 15].

3. Integrate physical models (Stage 2) directly into the predictive algorithm, ensuring realistic predictions.

The limitations of the study include significant time costs for model training. This requires optimization of algorithms or the use of specialized hardware for real-time applications. In addition, the integration of terrain features from existing geographic maps into the proposed software is not fully implemented at present. The current model works with slope parameters but its full integration with geographic information systems requires further development. Additionally, our study focused exclusively on predicting the functional capabilities of the robotic platform, not covering other aspects of its performance such as autonomous navigation or route optimization in terms of time or energy consumption, which limits current applications.

The disadvantages of the study are the need for more fine-tuning of the network architecture and conducting additional A/B analysis for a comprehensive comparative analysis with other modern neural networks or hybrid models. In addition, the lack of a single aggregate formula for determining functional efficiency imposes certain limitations on direct comparative analysis with some theoretical models.

Further development of this study will consist in expanding the range of platform functionalities taken into account and adapting the proposed tools to different types of robotic equipment. It is also planned to derive a universal formula for aggregated assessment of the functional efficiency of the platform, which would make it possible to integrate and evaluate various aspects of its performance. This could contribute to designing more comprehensive and flexible mission planning tools and further increasing the level of autonomy and efficiency of robotic systems.

7. Conclusions

1. The structure of the method for predicting the functional efficiency of robotic platforms for a given route, which is based on a customized neural network Kernel Activation Network, has been defined and substantiated. A special feature of the proposed structure is the use of a hybrid activation functional, which includes an asymmetric chi-square kernel in parallel with a Gaussian kernel. This allowed for the effective integration of input estimates that take into account the complex triple interaction of key factors of platform motion dynamics (in particular, load variability, surface type, terrain relief, and engine power). The difference of this structure from known solutions is the increased ability to model complex data nonlinearities with an optimized architecture, which is critically important for accurate forecasting under conditions of changing operational parameters.

2. The devised method has been verified based on its software implementation and experimental studies, which confirmed its operability and efficiency, ensuring the achievement of Technology Readiness Level 4. The reliability of the results is confirmed by comparative analysis with other neural networks and machine learning models. The customized Kernel Activation Network demonstrated significantly higher accuracy, as evidenced by the low MSE of 0.00055727 on the synthetic test sample, while the other studied architectures showed an MSE of 0.00105989 and higher. These results were additionally confirmed on the experimental sample, in which the obtained MSE value for the test sample was 0.00041720, which emphasizes the high generalization ability and practical value of the method devised for optimizing the mission planning of robotic platforms.

Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study, as well as the results reported in this paper.

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Data availability

The manuscript has associated data in the data warehouse.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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