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Automated method based on a neural network model for searching energy-efficient complex movement trajectories of industrial robot in a differentiated technological process

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Purpose of the work: Researching possibility of creating a method for improving the energy efficiency of differentiated robotic technological process (RTP) in the food industry. The high rates of development of production processes robotization, including in the food industry, leading to increase the cost of electrical energy, determine the research tasks relevance in finding energy-efficient methods for controlling industrial robots.

Methodology: The proposed approach is based on principles of object-oriented design and possibility of classifying robotic technological process: Applying specific model sets and methods to improve energy efficiency to individual classes. The existing possibility of energy consumption synthesizing models of robots inside differentiated robotic technological process, such as stacking loads, in reduced form, made it possible to use neural network methods to identify non-linear dependencies. At the same time, training sample for intelligent modules was formed on the basis of classical experiment planning algorithms. The synthesis of methods, models and procedures was implemented on the basis of high-level programming languages C++, MATLAB.

Results: A mathematical model and automated algorithms for its synthesis are proposed, which make it possible to adjust robotic technological process simulation model taking into account its specifics and implement a method for finding the optimal parameters of its functioning. To confirm the effectiveness of proposed solution, the obtained neural network model and optimization method were tested on real robotic technological process, and the calculation of economic efficiency of proposed solution was also given.

Conclusion/recommendations: The application of this approach will significantly reduce energy costs for robotic operations in the food industry.

KEYWORDS

technological process, robotization, food industry, industrial robot, neural network model, energy efficiency, optimization

1 Introduction

In the conditions of an unstable world economy, increasing tensions at the geopolitical level and global climate change, the likelihood of emergency situations in the country is increasing. In order to reduce the impact of negative consequences, specialized services and structures are working to improve the national security systems of the country, including in the field of food security, which is one of the main goals of the agrarian and economic policy of the country. Thus, one of the important subsystems of ensuring food security is the warehousing and storage of products, essentials, devices, mechanisms, *etc.* At the same time, due to the constant correction of the nomenclature of stored objects towards its expansion, the issues of increasing the «productivity» of specialized warehouses are becoming more urgent. Qualitative indicators can be achieved by solving logistical problems inside a specialized room, as shown in (Ivanov et al., 2021), which can be achieved through the development of adequate mathematical models of processes and the use of modern automation tools, in particular, industrial robots (IR), sensor systems and intelligent control algorithms. Thus, the performance indicator of the removal, loading, reassembly subsystems, location changes, confirmation of the quality of objects and storage classes will be determined, among other things, at the stage of technological design processes at manufacturing enterprises, for example, the weight and size indicators of the combined cargo on a pallet, options for laying, packaging and fastening. Palletizing, packaging and fastening operations also make a significant contribution to the formation of the cost of storage of products. To date, the quality indicators of these operations are achieved through the use of automation tools—IR, which is confirmed by the results of work (Kaczmarek and Borys, 2016). Nevertheless, due to the specifics of their device, there is an increase in electric energy costs, which ultimately negatively affects the cost of product storage. Thus, the issues of searching for algorithms for optimizing the process of assembling cargo intended for the formation of a strategic reserve, in the direction of reducing the cost of storage by reducing the electric power costs of IR, are very relevant. The approach proposed in this paper is based on the results obtained earlier by the authors of the study of the processes of increasing the energy efficiency of robotic machining and welding (Efimov et al., 2021; Gorkavyy et al., 2021).

2 Materials and methods

A distinctive feature of robotic technological complex (RTC) from other technological complexes is their high versatility and the ability to quickly adapt to changing working environment conditions. In this regard, universal automated technological complexes in production can be used, among other things, for the execution of simple technological operations characterized by a limited set of complexes of movement trajectories. Examples of such processes are: palletizing/depalletization, loading/unloading of machines, contact welding (Kozhevnikov et al., 2016; Kozhevnikov et al., 2019), trimming of contours of parts (Kozhevnikov et al., 2020), various test operations. In such cases, the RTC functionality is redundant to perform the operation, and the complex itself can be described by a reduced model based on intelligent tools. The advantage of using a reduced model when describing the above simple technological operations is the ability to quickly adjust the model to the changed working conditions of the RTC.

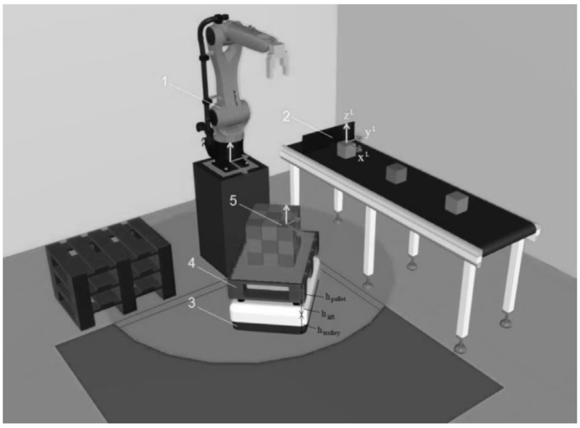

FIGURE 1
Robotized technological complex virtual model: 1—Industrial robot-manipulator, 2—Conveyor belt, 3—Robotic cart (RC), 4—Pallet, 5—Base unit in the loading zone. Source Compiled by the authors.

Thus, a typical RTC of laying blocks can be described by a reduced model reflecting only the indicators of energy and time spent on performing a robotic operation. The developed models can be aggregated in the future to build models of more complex processes with the aim of further optimization due to modularity and the possibility of quick readjustment of models to the changed requirements of the technological task.

A typical technological process of robotic loading of pallets with loads passing through a conveyor belt is shown in the figure (see Figure 1).

The main elements of RTP are: An industrial robot-manipulator, the working area of which is described by the set R_b, global coordinate system G is fixed in the center of the robot base according to the figure. $O(0,0,0)$– center of the global coordinate system. Another element of the presented scheme is the loading block (hereinafter referred to as the block) in its original position on the conveyor belt. Local coordinate system L is attached to the block. Its center is the position of the robot working body - the robot end effector (REE) at the moment of capturing the block. In the work, L was obtained by shifting the origin of coordinates without rotating the axes, therefore, the plane $ZOX \| Z^L O^L X^L$, axis OX^L runs along the axis of symmetry of the block and the conveyor belt. The block has dimensions $l \times w \times h$ axial length OX^L, width—along OY^L and height—along the axis OZ^L. In the case of obtaining L by shifting the origin and rotating the axes, the direction cosines $cos\, R^{x'}{}_L$, $cos\, R^{y'}{}_L$ and $cos\, R^{z'}{}_L$ should be determined.

Robotic cart 3 height $h_{trolley}$ performs positioning the pallet 4 height h_{pallet} within the loading area defined by the 2D set S, robotic cart has the ability to lift the pallet to a height h_{lift}. Then the 3D loading zone, i.e., the set of points at which, there may be a groupage cargo on a pallet, is described by a set $W = R_b \cap S_{cyl}$, where S_{cyl}—Cylindrical body bounded from below by a plane $\lambda \| XOY$, passing from her at a distance $h_{trolley} + h_{pallet} + h_{lift}$; above the ceiling of the technological area; along the

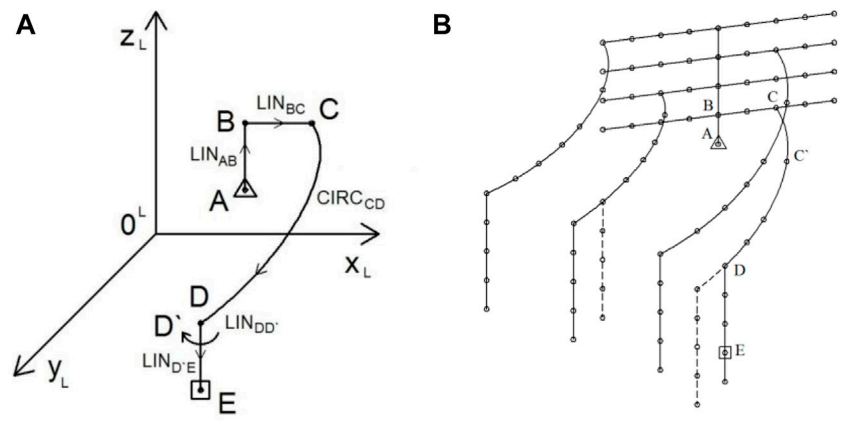

FIGURE 2
The REE trajectories. **(A)** Typical block movement trajectory, **(B)** Complex of trajectories for measurements. Source Compiled by the authors.

edges—Generators of a cylindrical body, passing through the boundaries of the set S and perpendicular to λ. Pallet dimensions: Length L_{pallet}, width W_{pallet} and h_{load}—The technological height of the cargo on the pallet makes it possible to determine the number of blocks placed on the pallet and their number in each row N_l, N_h, N_w. Coordinate system attached to base unit $L_{i,j,k}$ with center coordinates $R_{ijk}\,(x_i, y_j, z_k)$, all other blocks are considered relative to it, the mathematical description of the set of points of the block U_{ijk} is presented as:

- $REE_{i,j,k}\,(x_i, y_i, z_k)$—Center of the local coordinate system, as well as the position of the working body of the robot at the moment the grip is released;
- For $\forall A\,(x^{L_{ijk}}, y^{L_{ijk}}, z^{L_{ijk}}) \in W$ the system of inequalities is fulfilled

$$\begin{cases} -h \le z^{L_{ijk}} \le 0 \\ -\dfrac{l}{2} \le x^{L_{ijk}} \le \dfrac{l}{2} \\ -\dfrac{w}{2} \le y^{L_{ijk}} \le \dfrac{w}{2} \end{cases}$$

- direction cosines $cos\,R^{x'}{}_{L_{ijk}}$, $cos\,R^{y'}{}_{L_{ijk}}$, $cos\,R^{z'}{}_{L_{ijk}}$.
- $f_{cylinder}$: $\{x_i, y_j, z_k\} \rightarrow \{r_i, \varphi_i, z_i\}$;

f_{sphere}: $\{x_i, y_j, z_k\} \rightarrow \{r_i, \theta_i, \varphi_i\}$

The last two functions are necessary if the RC does not position the pallet parallel to one of the planes of the global system XOZ, YOZ. The paper further considers the situation when L_{ijk} is obtained by only transferring the origin of the coordinate system without rotating its axes.

The set of all blocks on the pallet together with the set P_t must be included in the loading area: $(P_{t_{ijk}} \cup (U^1_{ijk} \cup U^2_{ijk} \cup \ldots \cup U^m_{ijk}))\complement W = \Rightarrow true$, m- number of blocks on pallet, where $m = N_l \times N_h \times N_w$.

Technological operations of placing loads (blocks) on pallets, as well as other operations of a similar class, such as conveyor assembly operations (for example, in the automotive industry, aircraft manufacturing), painting, radiography, *etc.*, are characterized by a narrow range of changes and can be, in most restrictions, a small number of typical movements (Parisi et al., 2020), in contrast to the processes of machining and welding (Frolov, 2021a; Efimov et al., 2021; Gorkavyy et al., 2021). In such technological processes, the movements of the robot are carried out in a very limited segment of its working area. So for the considered RTP (see Figure 1), one of the typical complexes of REE movement trajectories for loading one block can be a complex of ten trajectories, shown in Figure 2A.

The set of trajectories consists of five trajectories AB, BC, CD, DD', and $D'E$, realizing the movement of the captured block to the point of unloading, and five trajectories $ED', D'D, DC, CB,$ *and* BA, ensuring the return of the REE to its original position in the loading area. On the IR KUKA there are two types of commands that generally used to implement such motion paths: LIN - moving REE in a straight line and CIRC - moving REE by a circle (KUKA Roboter GmbH, 2014; KUKA Roboter GmbH, 2016a; Anistrantsev and Bespalova, 2021). Figure 2A shows the commands of the programming language Kuka Robot Language (KRL) (KUKA Roboter GmbH, 2016b), that implement REE movements. Each REE movement is characterized by energy costs $E_{AB}, E_{BC}, E_{CP}, E_{PP'}$ *and* $E_{P'E}$, at the same time, the studies reflected in (Anistrantsev and Bespalova, 2021) show that the values of energy consumption by the robot when implementing the same movements in different areas of the working area are not the same. This fact is physically and mathematically described in (Cao et al., 2020), in the form of models that require significant computing resources for their processing. Without a mathematical model, relying only on empirical experience, it is extremely difficult to establish the most energy efficient zone for performing operations. On the other hand, it is not economically feasible to use complex identification mechanisms and build a detailed high-dimensional mathematical model based on the physical laws underlying the processes occurring in the robot mechanisms for RTP, which is characterized by relative simplicity and limited REE movement (see Figure 1). Thus, the paper sets the task of developing a reduced model of IR energy consumption in RTP, characterized by a limited number of types of motion trajectories (differentiated

TABLE 1 **Presentation format of measurement results.**

Rise index	Shift index	Turn index	Descent index	z_{up}	x_{side}	φ_0	z_{down}	E (W·h)	T (ms)
1	1	1	1	400	400	−86.8699	200	1,059668	8881
1	1	1	2	400	400	−86.8699	250	1,070366	8725
1	1	1	3	400	400	−86.8699	300	1,023373	8533
. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
4	9	5	2	250	800	−30.556	100	0,98745	8100
4	9	5	3	250	800	−30.556	150	0,973699	7909
4	9	5	4	250	800	−30.556	200	0,937983	7693

Source Compiled by the authors.

RTP), as well as a method for synthesizing a control program that ensures minimization of RTC energy consumption by searching for the optimal set of robot and RC motion trajectories (positioning option, pallet height adjustment).

In order to be able to estimate the energy consumption of the robot associated with the trajectory of movement, it is necessary to have the function $E = f(arguments)$. It is proposed to restore (identify) a non-linear dependence using well-established tools of neural networks (Martínez and Velásquez, 2011; Gordin et al., 2020; Ivanov et al., 2021), fuzzy logic (Voskoglou, 2022) or hybrid (neuro-fuzzy systems) (Marakhimov et al., 2018) in the automatic synthesis mode based on the training sample. To obtain a training sample, it was decided to perform a limited but sufficient number of movement trajectories, representing the set W and the loading zone (Figure 2B), having carried out all the necessary measurements. In each trajectory, the movement DD' was combined with the movement CD.

In the KRL language, the REE movement commands would be: $LIN\{X\,x_A, Y\,y_A, Z\,z_A, A\,\alpha_1, B\,\alpha_2, C\,\alpha_3\}$ C_DIS – command to move to the starting point; $LIN\{X\,x_B, Y\,y_B, Z\,z_B, A\,\alpha_1, B\,\alpha_2, C\,\alpha_3\}$ C_DIS; $LIN\{X\,x_C, Y\,y_C, Z\,z_c, A\,\alpha_1, B\,\alpha_2, C\,\alpha_3\}$ C_DIS; $CIRC\ \{X\ x_{C'},\ Y\ y_{C'},\ Z\ z_{C'}\ \ldots\}\ \{X\ x_D,\ Y\ y_D,\ Z\ z_D\ \ldots\}$ C_DIS; $LIN\{X x_E,\ Y y_E, Z z_E \ldots\}$ C_DIS.

The number of trajectories required to form a training sample is determined empirically by setting the discreteness of changing parts of the trajectory. For example, Figure 2B defines the possibility of existence of 4·9·5·4 = 720 movement paths. The arguments $f(arg)$ were taken as z_{up}—The implicant of point B in the linear coordinate system of global L, x_{side}—The abscissa of point C in global coordinate system L, φ—The angle of rotation of the robot arm relative to the center of the global coordinate system in the XOY plane and z_{down} in the global coordinate system pallets. Measurements are performed when the robot passes all the given trajectories by the electrical energy consumption recorder according to Table 1.

The KRL program for performing the necessary set of movements is formed automatically using specially developed software in C++ (Frolov, 2021b; Tretyak et al., 2021). Taking into account the specifics of the training sample, it is proposed to identify a non-linear dependence by a neural network of the feed-forward backprop type, as discussed in (Glorot and Bengio, 2010; Sozykin, 2017). An analysis of the effectiveness of using neural networks of different types in the framework of complex tasks is presented in (Martínez and Velásquez, 2011). After the dependence $E = f(z_{up}, x_{side}, \varphi, z_{down})$, has been established, it seems possible to obtain the optimal set of motion trajectories within the working area, ensuring the loading of the entire volume of blocks on a pallet. The search for the optimal set of REE movement trajectories, as well as the option of positioning the pallet with a robotic cart is presented below. In this case, it is assumed that the axes of the local coordinate system of the pallet are aligned with the axes of the global coordinate system. To simplify the search algorithm, it is proposed to enclose the set W in a parallelepiped bounded by planes $x = x_{min}, y = y_{min}, z = z_{min}$, where x_{min}, y_{min} and z_{min}—The smallest values of all coordinates of all points belonging to W and $x = x_{max}, y = y_{max}$ and $z = z_{max}$—The largest value of the coordinates, respectively. The next step is to set $\Delta x, \Delta y\, and \Delta z$—Which determine the search step along three axes: OX, OY and OZ respectively. Then for each point $\{x_i, y_j, z_k\}$, determined by the step $\Delta x, \Delta y, \Delta z$ on each integration, a four-dimensional array $F_{i,j,k,l}$ is built, where $F_{i,j,k} = \{z_{up\_opt}, x_{side\_opt}, \varphi_{opt}, z_{down\_opt}, E_{min}, flag, E_{sum}\}$, z_{up_opt}, $x_{side\_opt}, \varphi_{opt}, z_{down\_opt}$—Function argument $f(z_{up}, x_{side}, \varphi, z_{down}$, under which it takes the minimum value E_{min} under the constraints caused by the need to move the block to the point $\{x_i, y_j, z_k\}$, that is, for this point $\varphi = const$, $x_{side} = const$, $z_{down} = const$, while z_{up} bound by limitation

$$\begin{cases} z_{up} = z_{up_1}, z_{up_2} + \Delta z_{up}, \ldots z_{up_i} + \Delta z_{up}, \ldots z_{max} \\ z_{up} > z_{down} \end{cases}$$

if $\{x_i, y_j, z_k\} \notin W$ the value of *flag* is set to 0. After for each $\{x_i, y_j, z_k\}$, all elements except E_{sum} are calculated, the optimal trajectory and the energy consumption associated with it are found, the search for the optimal set of movement trajectories and the energy consumption associated with it $E_{sum_{i,j,k,7}}$ by the formulas:

$$\begin{cases} E_{sum_{i,j,k,7}} = \sum_{l=i}^{i+N_l} \sum_{h=j}^{j+N_h} \sum_{w=k}^{k+N_k} (F_{l,k,w,5}); \text{if } \forall\ l, h, w;\ F_{l,h,w,6} = 1; \\ E_{sum_{i,j,k,7}} = 0;\ \text{if } \exists\ l, h, w;\ F_{l,h,w,6} = 0. \end{cases}$$

After the array is completely calculated, it is necessary to search $F_{l,h,w,7} \to min$ and restore the base point $D_{opt}\{x_i, y_j, z_k\}$, determine from it the set of installation points for all blocks and, accordingly, the optimal trajectories for moving blocks. Also, it seems appropriate to rank the options for movement complexes, taking

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TABLE 2 Geometric and physical parameters of experimental objects.

No	Name	Main characteristics
1	Coordinates of key points, coordinates of systems and offsets	- x_start = 600; y_start = 300; z_start = 200.
		- L { 600, 300, 200 }, cos $R^{x`}{}_L = 1$, cos $R^{y`}{}_L = 1$, cos $R^{z`}{}_L = 1$
		- $\Delta x = 0.01$; $\Delta y = 0.01$; $\Delta z = 0.01$.
		- dimensions of RC (l × w × h) = 0.58 × 0.376 × 0.14 (m)
		- dimensions of pallet (l × w × h) = 0.6 × 0.4 × 0.145 (m)
		- dimensions of loading block (l × w × h) = 0.05 × 0.05 × 0.05 (m)
		- dimensions of cargo (l × w × h) = 0.15 × 0.15 × 0.15 (m)
2	Loading area restrictions	$y < y_0$_zone
		$z \geq$ z start − 4·Δz
		$z \leq$ z start + 4·Δz
		$x^2 + y^2 \leq r^2_{max} \rightarrow$ (r_{max} – radius of outermost arc)
		$x^2 + y^2 \geq r^2_{min} \rightarrow$ (r_{min} – radius of closest arc)
3	Robot movement parameters	Speed V = 2 m/s; acceleration a = 2 m/s^2; smoothing type - along the arc; operating mode – AUT (automatic); time spent on executing the code for the formation of the training sample - 3.5 h; energy spent on the execution of the code for the formation of the training sample is 1.36 kW·h

Source Compiled by the authors. As a result of the optimization method, the base point D_{opt} {530; −300; 200}—The center of the local coordinate system of loading blocks, which determines the set of trajectories of movements, characterized by the lowest consumption of electrical energy equal to: 22.35 W·h per movement in one direction.

TABLE 3 Used hardware and software.

No.	Title	Main characteristics
1	Industrial robot-manipulator	KUKA KR10 R1100 sixx
2	Robotic cart	KUKA YouBot Platform
3	Conveyor belt	Imitator, steel table with PVC substrate, substrate dimensions (l ч w ч h) = 0.8 ч 0.3 ч 0.005 (m)
4	Measuring device	- Components: Arduino UNO platform, AC voltage sensor ZMPT101B, current sensor TA12-200.
		- Measured quantities
		1) I (A), U (V) – current, input voltage (instantaneous values); 2) t(s) – time (processor readings).
		- Programming language: Arduino IDE.
5	Programming language IIP/automated synthesis of KRL commands/neural network generation	KUKA Robot Language (KRL)/C++/MATLAB

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into account the increase E_{sum}. Such a rank can be useful in case of additional restrictions or optimization criteria, for example, minimizing the execution time of a set of motion trajectories. In this case, it is necessary to expand the element $F_{i,j,k}$, with two variables t_{min} and t_{sum}, determined by analogy with E_{min} *and* E_{sum}, and perform optimization according to the required criteria, for example, minimizing the implementation time of a set of movement trajectories with minimal energy costs.

It should be noted that as a result of the optimization, a set of trajectories of movement will be obtained only in the forward direction, while the trajectories of movement in the opposite direction are taken as "mirror" or return to point A using the PTP command. Energy consumption work when moving back is not taken into account in optimization algorithms, since the results of studies (Paesa et al., 2014; Qiu et al., 2021) showed a slight deviation in energy consumption in the forward and reverse directions.

In addition, it is possible, in case of energy expediency, to lay blocks by a robot in one layer, while the depth of laying is regulated by layer-by-layer lowering of RT pallets with cargo. At the same time, it is also necessary to take into account the difference between the saved energy for moving the REE to a depth and the energy

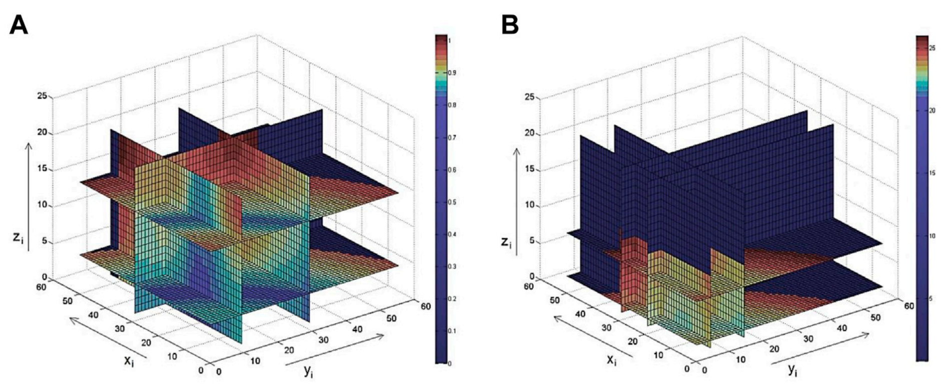

FIGURE 3
Graph of functions $E(x, y, z)$. **(A)** IR energy consumption map when laying one block, **(B)** IR energy consumption map when stacking a groupage cargo. Source Calculated and built by the authors.

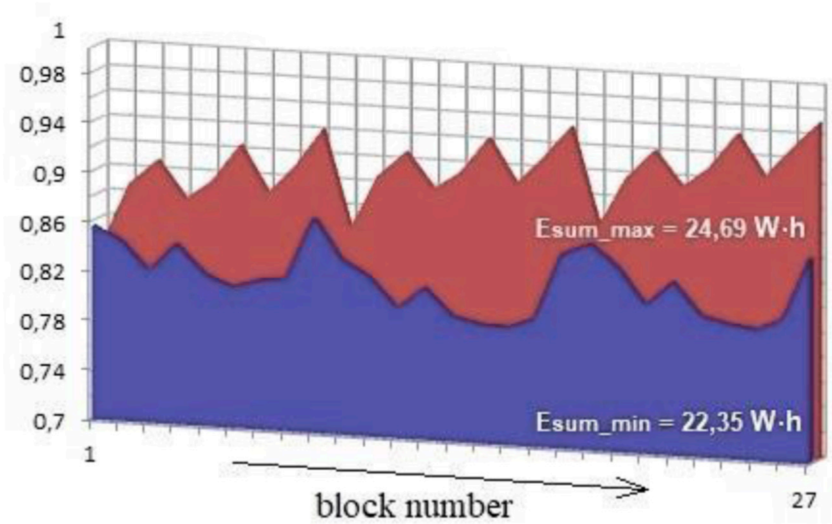

FIGURE 4
Energy values for the assembly of a complex of blocks relative to the base point. Source Calculated and built by the authors.

required for the initial lifting of the pallet and its subsequent lowering.

3 Results

To confirm the effectiveness of the proposed solutions, an experiment was conducted under conditions close to industrial production using KUKA equipment (Table 2). Table 3 presents the initial data of experimental researches.

Figure 3 (a) shows a sweep of the graph of the function $E(x, y, z)$ for the loading area when laying one block at the base point; Figure 3 (b) - when laying a complex of blocks relative to this base point. This dependence is non-linear, the nature determines the difficulty of finding the optimal point empirically. So, for example, the intuitively set point $D_{operator}$ {540; −390; 290} is characterized by total energy costs equal to: 23,91 W·h, and the point $D_{\max}$ {760; −300; 290} is characterized by maximum energy costs equal to: 24.69 W·h.

Thus, as a result of the optimal choice of a set of movement trajectories, an effect is achieved, expressed in saving 1.56 W·h of electrical energy for laying one complete set of blocks.

Figure 4 shows in the form of a graph the energy values for assembling a complex of blocks relative to the base point with minimum and maximum costs.

The energy value for the point selected by the operator is within the interval E_{sum_max} - E_{sum_min}, so the energy savings can reach

$$\Delta E = (24.69–22.35)/24.69 \cdot 100\% = 9.48\%.$$

The total costs for the implementation of optimization measures can be found using the formula:

$$E_{alg} = E_{exp} + E_{program}$$

where E_{alg} is the total energy costs for the implementation of the algorithm; E_{exp} is the energy spent on conducting an experiment to measure the energy and time costs for each movement within a certain complex of movements; $E_{program}$ is the energy spent on the operation of the software of an external device (user PC) that implements the developed optimization algorithms and forms the RTC control program optimized according to the selected criterion (minimum time or energy).

The cost of electrical energy for each movement (Table 1) in total with the cost of return movements to the home position amounted to

$$E_{exp} = 680.8 \cdot 2 = 1361.6 W \cdot h$$

Since the time spent on the implementation of the optimization algorithm on a PC is 1 h, the cost of electrical energy for computing operations is equal to $E_{program}$ = 250 W·h (the average value is assumed).

Then the total cost of optimization measures is equal to

$$E_{alg} = E_{exp} + E_{program} = 1361.6 + 250 = 1611.6 (W \cdot h)$$

Since the obtained value of the cost of electrical energy for a single implementation of the proposed algorithm is comparable to the cost of conducting a robotic operation, the use of the algorithm seems to be the most profitable in conditions of continuous in-line production.

Because E_{sum_max} = 24.69 W·h, and E_{sum_min} = 22.35 W·h, the one-time energy costs for the implementation of the algorithm (E_{alg}) will pay off in

$$N = \frac{E_{alg}}{E_{sum\_max} - E_{sum\_min}} = \frac{1611.6}{24.69 - 22.35} = 688.71.$$

Thus, the implementation of the proposed algorithm will pay off after 689 technological cycles and then will bring net profit.

4 Conclusion

Thus, the presented research results demonstrate the possibility of a significant reduction in the energy intensity of the process of robotic stacking of blocks on a pallet, which ultimately reduces the cost of storing cargo in specialized premises within the strategic reserve, including through the use of the proposed solutions not only at the stage of primary assembly at the manufacturer, but also on robotic cargo sorting sites inside specialized storage locations. Thus, the potential for saving electrical energy with a typical variant of assembling cargo on a pallet can be up to 10%.

The proposed mathematical model and automated algorithms for its synthesis allow, with minimal time, information and intellectual costs, to set up a simulation model of RTP taking into account its specifics and implement a method for finding optimal parameters of its functioning: An optimal set of motion trajectories, energy consumption, execution time, RC positioning point.

As promising tasks for the development of the proposed topic, it seems appropriate to consider the influence of the rotation angle of the local coordinate system of the loading unit in the loading zone. In addition, it would be appropriate to ensure synchronization of RC consumption models and the robot in the case of laying a single layer by the robot with subsequent positioning of the RC of the local cargo base.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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