Management Decision-Making for Logistics Systems Using a Fuzzy-Neural Simulation

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1 Introduction

It is necessary to have data on future transportation volumes in order for management decisions to be correctly developed during the planning phase. At which the forecast should have an error of not more than 5%. Information on grain transshipment volumes through the offshore terminal is key for organizing the transportation process based on research object essence.

An increase in cargo turnover of Ukrainian seaports is evidence of growth dynamics in the future period compared to previous years according to their operation results during 2019 [1]. At the same time, certain loads may arise on logistics chain main links, especially in hubs of interaction between different kinds of transport. Therefore, there is a need to ensure the continuity and efficiency of transport processes.

Agricultural goods share transferred through Ukrainian seaports amounted to about 37.4% of the total volume of transshipment (160 million tons in 2019). This information was obtained according to statistical information, during the last reporting year. These were primarily cereals exported to European Union countries and other world regions.

The trend towards an increase in cargo flows processed by Ukrainian seaports is observed based on recent statistical data. Therefore, this aspect indicates an increase in storage capacity and processing capacity by overloading mechanisms [2]. However, significant investments and long payback periods are required for

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Fig. 1 Overloading of grain cargoes from trucks to ship using mobile loading mechanism

increasing these indicators of transport hub operations. Therefore, the search for alternative ways of interacting between different kinds of transport is more pragmatic for logistics operators during agricultural cargo transshipments [3].

As a result, the direct option of uploading a ship from trucks is increasingly used in European ports (Fig. 1).

The financial and time costs of the company will be minimal, using a direct interaction option. Forwarders should plan the process of interaction between road and sea kinds of transport considering the exact forecast to avoid port malfunctions during grain transshipment. Error-free forecasting of transshipment volumes allows optimizing works of all participants in grain supply chains [4]. However, the random nature of transportation processes complicates the forecasting and often leads to unacceptable error.

It is recommended to use integrated solutions to organize and plan production processes based on the latest researches in Industry 4.0. Such a concept involves the significant use of smart technologies, which helped to simplify distribution processes while sharing production resources. Mentioned-above significantly increases the efficiency of management decision-making, especially in conditions of difficulty in predicting future volumes [5, 6].

The mathematical tool of self-learning and self-tuning neural networks has become more often used recently as an adequate solution to indicated problems [7]. This approach allows for obtaining an adequate forecast of cargo transshipment volumes through port terminals. Application of approaches based on evolutionary principles allows us to significantly save time when making the right management decisions in conditions of constant distribution of material flow [8, 9] or multi-criteria [10] based on conceptual solutions according to the Industry 4.0 principles. The presented variation of simulation of various parameters of material flow allows achieving optimal solutions when researchers have a small amount of information. It is also suggested that neural network-based modeling should be used to make correct management decisions in logistics systems, same as using managerial skills for innovation support [11].

The presented approach to modeling delivery processes is acceptable from the point of view of interests rationalizing of port operators responsible for logistics at transshipment terminals, as well as costs reducing of agricultural business for renting trucks for transporting grain to ports. Accurate forecasting allows the carrier to determine the required truck quantity for transporting grain to ports bypassing warehouses [12]. This will significantly reduce the cost of paying for grain transportation services by truck renters.

The issue of transport reliability has, at the same time, the highest priority in each delivery level of supply chains. It is because increasing transshipment volume through ports increases the probability of certain failures in multimodal transportation processes, especially in bulk goods delivery [13]. Products of agro-industrial manufacturing (AIM) are primarily mass shipments [14] for Ukraine, as an agrarian state.

Given that the ports of Ukraine export grain most than other agricultural products (according to data for 2018), we can talk about the relevance of the chosen research area. This makes it necessary to develop a forecast model considering modernity factors. A similar approach can be successfully applied when forecasting cargo flows during regular mass shipments.

Therefore, the research aim is to develop an approach that enables management decision-making to organize logistical issues at the port during interactions between two kinds of transport, considering forecasting results using evolutionary self-learning models.

2 Literature Review

Research study [15] describes the interaction problems of road and river transports in freight transportation. The example of cargo transshipment simulation from trucks to ships through the Boom Baru river pier (Indonesia, Palembang) proves the necessity for correct forecast models that predict volumes of cargo brought to the port by road immediately before of ship arriving.

Forwarding companies must have proven forecast transportation volumes obtained using self-learning systems in order to apply innovative technological solutions (direct grain overload). Forwarders can predict transshipment volumes with minimal error based on smart approaches. Different structures of neural and hybrid networks (based on a genetic algorithm) have shown their expediency as an excellent predictor [16] to find optional decisions of such problems.

The efficiency of ports functioning has been increased by using neuro-network mathematical tools in practice, considering the possibility of self-training and the ability to evolve [17–19]. Nevertheless, forecast models of this category have a drawback that does not allow them to be used with significant fluctuations in cargo flow with a small sample for the formation of the time series [20–22]. The volume increasing of grain transshipment through Ukrainian seaports is usually associated with an increase in the cost of this category of agricultural products in world markets. It explains big errors in classical predictors that are used for forecasting.

The design of initial databases (input signals) must be carried out, focusing on the principles of the fuzzy logic theory. It will ensure that a wide range of values, according to considered processes, are taken into account [23–25]. This nuance makes it possible to find many factors characterizing each value of the time series in order to reduce randomness in prediction.

The implementation of neural models makes it possible to abandon from the formation of a significant dataset when predicting cargo flows for medium terms. This nuance was established from the analysis of previous studies in this area [26, 27].

Article [28] describes patterns of possible oscillations for cargo flow arriving at transport hubs. Of particular importance in the development of cargo supply chains [29–31] is the interaction specificity of various categories of enterprises. The synchronization of logistics events [32] has a significant impact on the stability of supply chains, which guarantees the greatest synergy. This ensures the correct generation of management decisions based on the forecast values of cargo flows [33, 34].

It should be noted that there is a certain specificity that occurs when cereals are delivered to ports. It manifests itself primarily in the technological aspects of transportation. The railway is the main transport which delivery cargoes to Ukrainian seaports. However, a significant deficiency of specialized grain railway carriages has created a situation where road carriers carry out a long-distance delivery by trucks. The big transportation prime cost using trucks increases grain export prices, which negatively affects the competitiveness of domestic agricultural products in world markets.

On the other hand, using a large number of grain-trucks poses many technological problems, especially in terms of ensuring coordinated operation between two kinds of transport [35, 36]. It is firstly due to practical aspects of technical capabilities for grain transshipment according to the direct option of "automobile—ship."

3 Research Methodology

The reliability of supply chain functioning directly depends on the reliability of each element according to the studies carried out and also if the supply chain considers based on principles of systems theory. The negative impact can be reduced on the delivery process from possible failures of certain elements of the system during agricultural goods transportation. Following actions should be taken to achieve these improving:

1. Innovative models must be developed to predict future volumes of agricultural transportation. Process organization, in terms of technological aspects, will be improved using fuzzy-logic theory [37] and smart technology elements, such as a neural network. It will help to predict the volume of cargo transshipment through a port or using a blockchain system to design a flexible set of management decision-making in cargo transportation in Industry 4.0 [38] conditions, especially during an interaction between two kinds of transport in ports during transshipment according to the direct option.
2. The modern management decision support system is appropriate for flexible decision-making in the operational planning period and direct delivery of agricultural goods. This system can improve the quality of transportation management and must be designed according to the last tendencies in Industry 4.0. The best is using in this situation specialized software products, which can speed up processes of obtaining rational solution sets. Especially if the virtual complex is able not only to carry out certain calculations but also to carry out simulation of processes.

These two main actions will improve management issues in the transportation process of agricultural goods. Moreover, they also reduce the negative impact of possible delivery system failures, which will keep the reliability indicator in supply chains at required levels.

Mathematical tools of fuzzy-neural networks apparatus were chosen for prediction. Some elements of this specifical approach can be found in parallel researches [39–43].

The primary structure of the neural network was represented by seven inputs, which received signals about the corresponding values of transshipment volumes for each day of the week. A set of initial data is generated to identify the function $y(k)$ from statistical processing results. The original time series (1095 transshipment volume signals for the previous period) was divided in the next step into two identical halves (547 and 548 signals, respectively, in each part): the first 547 values used as input signals and the remaining 548 as output values. It is possible to approximately train the neural network in the first step using this research technology. Figure 2 shows changes in cargo transshipment volumes over time of network training.

The database used in the experiment consists of values set for training ($k = 1, \ldots, 274$) and a subset of the signals used for network testing ($k = 275, \ldots, 548$). It is possible to generate the number of inputs for future predictors using the ARX model due to such a previous separation of the source database. The best model structure can be found by retrieving the entire possible set of combinations $[m, n, d]$. The signals values $[m, n, d]$ varied randomly in the interval [1–110] during the ranking (Fig. 3).

A variant of the optimal predictive model based on ARX was found, which corresponds to the following quantitative structure: $[m, n, d] = [4, 4, 11]$. The proposed predictor ensures obtaining the value 8.3 of a square root of a mean square error (RMSE) on the training sample and on the test RMSE = 7.9.

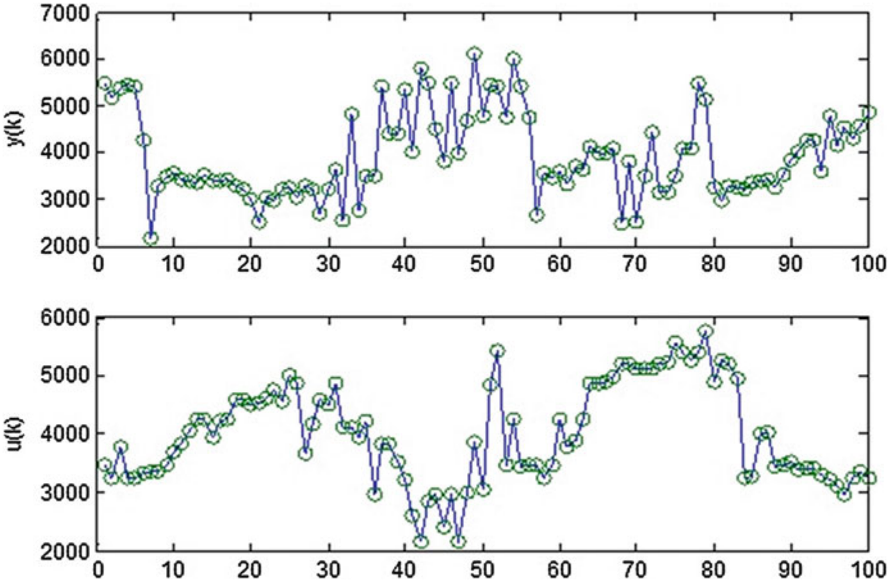


Fig. 2 Graphical interpretation of input signals (y) (grain transshipment volumes in the port) from output signals (u) of the same parameter

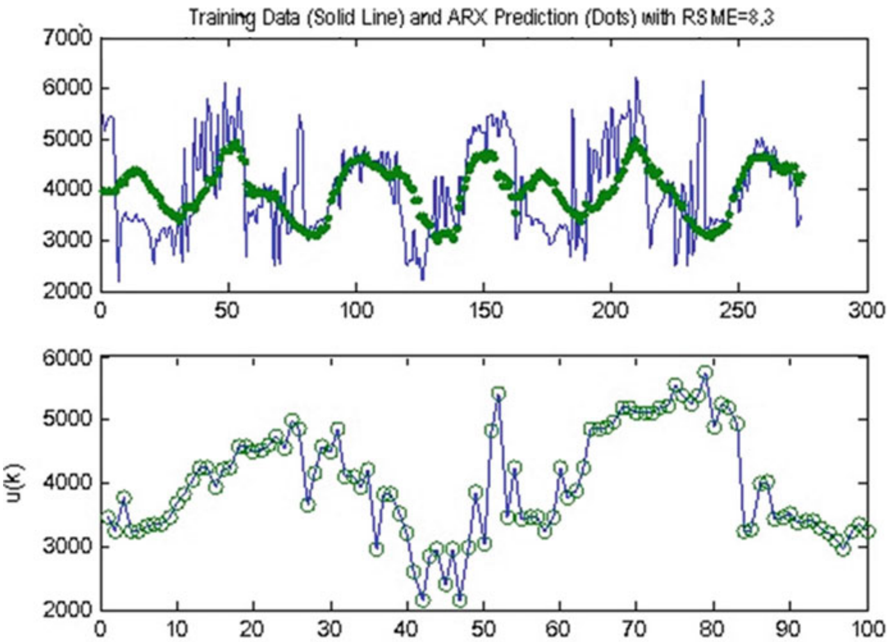


Fig. 3 Finding a rational structure for an ARX model

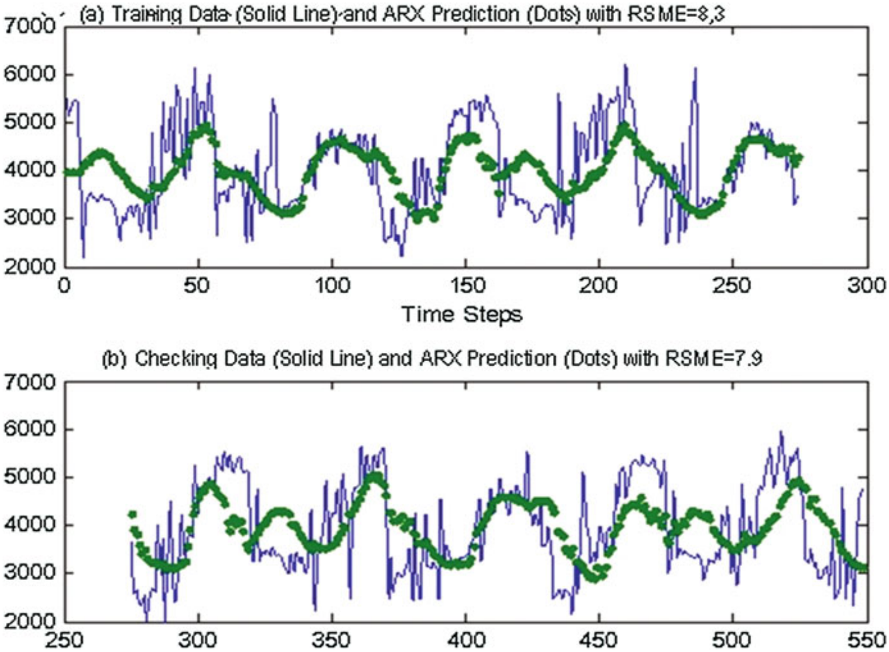


Fig. 4 Comparisons of simulation results between training samples (top graph) and checking (bottom graph) by ARX model

Graph (Fig. 4) shows the forecast trend obtained by the ARX model for predicting grain transshipment volumes at the port. Here, the blue curve denotes experimental data, and simulation results are represented by green dots.

A more accurate prediction can be obtained using a quasi-neural simulation. The best accuracy of identification is created using elements of fuzzy logic (fuzzy logical conclusion).

It includes elements of probability theory using a sequential forward search (SFS) approach. This simulation technology allows researchers to refine the input parameters of a future predictor. The model received an additional one variable at each experiment stage. This minimizes a mean square error of forecasting when applying SFS.

Figure 5 displays simulation results. Mean deviation values (forecast error) are highlighted in red circles when using a training sample. Deviation values are indicated by markers with green asterisks for a checking sample.

Table 1 presents the comparison results of different predictor identification methods. The ARX model is identified fastest but shows less accurate than others. At the same time, ANFIS using the SFS method for determining input signals has the best prediction accuracy, but a significant identification time. This is why the ARX model is useful for solving problems where the minimum time factor is important

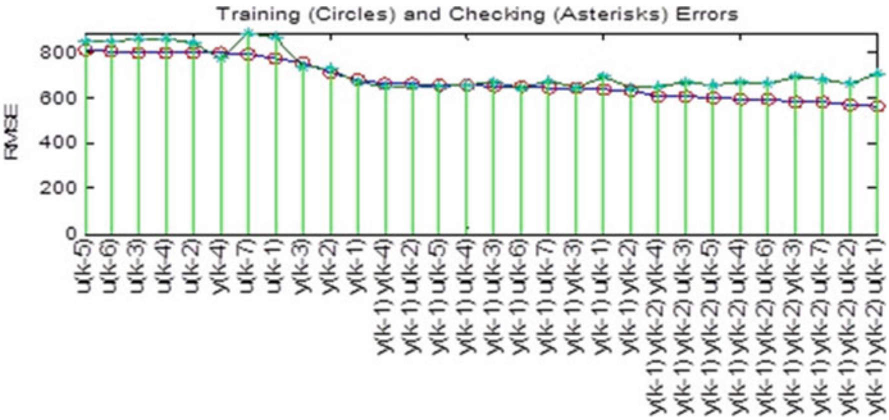


Fig. 5 Choosing input values of signals for a model using SFS method

Table 1 Results of comparison for various model identifications

Method of definition	ARX	ANFIS by using SFS method
Quantity of nodes for input signals	7	4
Value of RMSE for training sample	8.3	6.7
Value of RMSE for checking sample	7.9	5.3

for obtaining results. The ANFIS hybrid system is more suitable for predicting grain transshipment volumes since the error will be less than using heuristic models.

The number of input nodes for the ANFIS hybrid system has become less by three units (from 7 to 4) according to simulation results. That is why the first node receives a signal about volumes of grain transshipment on Monday and Tuesday; the second indicator inputs information about the values on Wednesday; third – data about volumes of cargo incoming on Thursday and Friday; information on values of cargo flows on weekends is supplied to the fourth node of the network.

Predictor error is 5.62% of empirical values after network training. The training period of the hybrid system does not exceed 15 eras, which in terms of machine time is 3.56 s. Figure 6 displays the visualization of ANFIS control using a training sample.

The designed ANFIS hybrid network makes it possible to generate 81 rules according to the previously described type of membership functions and the calculated number of nodes for supplying input signals. The optimal set of rules is determined using a genetic algorithm in this case.

In this case, the models become more adaptive to the appearance of sharp fluctuations in time series. After all, the hybrid network will be based not only on the local extremum but also considering a wider range of critical values of grain transshipment volumes in the port, which do not describe the general trend of time series.

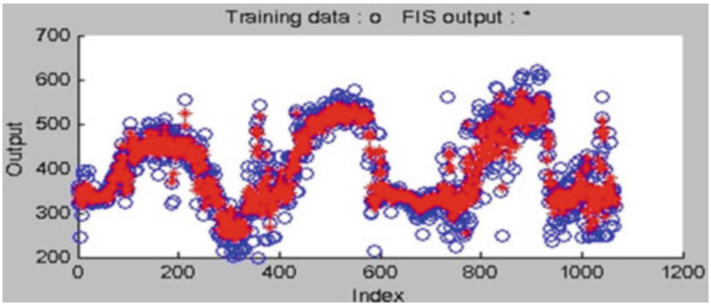
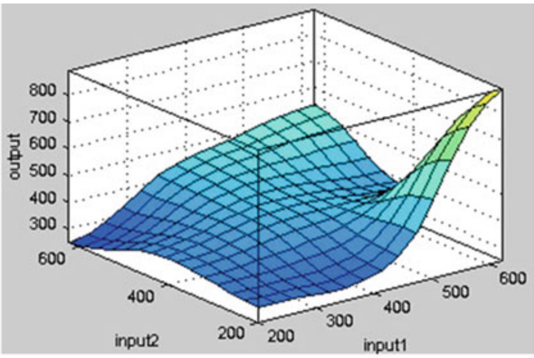


Fig. 6 Management of hybrid system ANFIS using a training sample



Notes: Input 1 – values of grain cargoes volume for training sample, ton*10; Input 2 – values of grain cargoes volume for training sample, ton*10; Output – results of forecasting, ton*10

Fig. 7 Dependence surface of forecasted results from incoming signals. Notes: Input 1—values of grain cargoes volume for training sample, ton*10; Input 2—values of grain cargoes volume for training sample, ton*10; Output—results of forecasting, ton*10

The hybrid network is trained based on a test sample to reduce prediction error. The trained ANFIS network showed an error of 4.49% as a result of checking it on the control sample.

The graphical dependence of input signals of volumes of grain transshipment in the port from the forecast results is shown in Fig. 7.

4 Results

The ANFIS hybrid system made it possible to predict seven values for potentially possible volumes of grain transshipment in the port zone. The forecast results made it possible to determine the error size in actual units (Fig. 8).

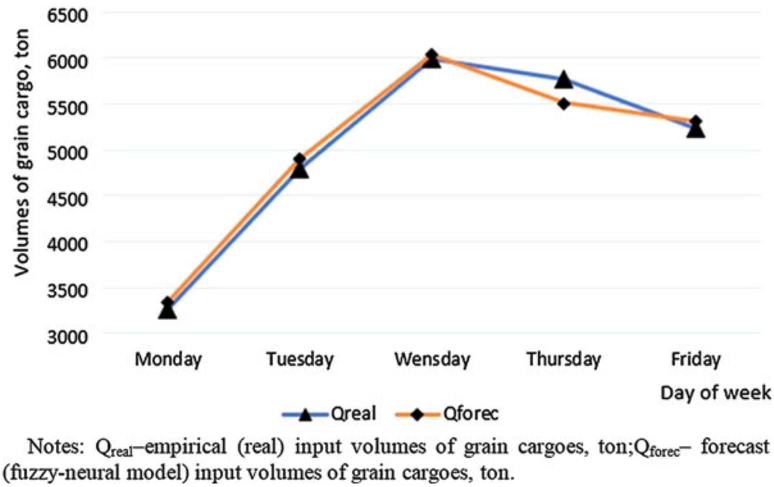


Fig. 8 Curves of empirical (real) and forecast (fuzzy-neural model) input signals. Notes: Q_{real}—empirical (real) input volumes of grain cargoes, ton; Q_{forec}—forecast (fuzzy-neural model) input volumes of grain cargoes, ton

Figure 8 proves that the deviation from the prediction results is less in actual units than when compared through the program. It further demonstrates the feasibility of using ANFIS to solve such forecasting problems.

Therefore, the prediction error will be even smaller with larger time-series sizes. It allows the researcher to better train and configure the network, especially if there are no significant fluctuations in the original database, which will make it possible to achieve an almost optimal result of forecasting.

4.1 Practical Aspects

The obtained forecast values allow planning the operation of overloading mechanisms and vehicles, which will carry grain to ports. Choosing transshipment mechanisms shall be at that time carried out based on technical parameters. Hourly capacity of the overloading mechanism must be first taken into account. This indicator will affect the following aspects of logistics processes:

- Sea ship service time (idle time under upload)
- Quantity of grain trucks required to provide combined work between vehicles and mechanization facilities
- Number of simultaneously used cargo mobile loaders
- Daily dispatch volumes, i.e., berth capacity

Mechanisms should possess a second specific feature. It is their mobility. This characteristic is particularly important when servicing several ships for a short time.

A trained neural network [44] was used to predict grain volumes that import into the port before the ship's arrival. The sample size for the experiment was six ships with a load capacity of up to 40,000 tons.

Predictive values are very important for making timely management decisions that must be consistent with Industry 4.0 policy. It is recommended to provide logistics nuances in the port when transferring cargo from one kind of transport to another based on three main factors related to port (terminal) capacities:

- Assessment of maximal port capacity in trucks at an hour according to technical features of infrastructure
- Definition of necessity port capacity in trucks at an hour based on coordinated interactions of vehicles and transshipment mechanisms
- Calculation of actual port capacity in trucks at hour based on results of cargo overload volumes forecast according to the fuzzy-neural model

4.2 *Assessment of Maximal Port Capacity in Trucks at an Hour According to Technical Features of Infrastructure*

The trucks' number is determined based on technical aspects according to terms of maximal quantities of vehicles that can accept by port zones per hour of operation. In this regard, the example of Mariupol seaport is one of the largest in quantities of trucks serviced. Port terminal can serve a maximum of 240-grain road-train trucks per day according to the maximum capacity. A comparison number of railway grain-carriages is 100 wagons in 24 h, which can be served by this port.

This study is ordered to determine the limitation of port capacity in management decision-making. It is assumed that trucks arrive at the port in an even flow. Grain overload occurs during an 8-h working day. Therefore, calculations of hourly capacities according to technical restrictions of the port are carried out by the next dependence:

$$\mathrm{CAP}_{\mathrm{tech}}^{\mathrm{hour}} = \frac{\mathrm{CAP}_{\mathrm{tech}}^{\max}}{T_{\mathrm{work}}^{\mathrm{port}}}, \tag{1}$$

where $\mathrm{CAP}_{\mathrm{tech}}^{\max}$—maximal port capacity in trucks at day according to technical aspects of loading infrastructures, trucks/day; $T_{\mathrm{work}}^{\mathrm{port}}$—operation time of transshipment mechanisms in the port during worker's duration, hour.

This condition shows that within an hour, no more than 30-grain road-train trucks can be serviced in the port. This nuance will be used in determining rational areas of management decisions regarding the organization of correct logistics in the port.

4.3 Definition of Necessity Port Capacity in Trucks at an Hour Based on Coordinated Interactions of Vehicles and Transshipment Mechanisms

Following condition must be met in order to ensure coordinated operation of transshipment mechanisms and vehicles:

$$\text{INTERVAL} = \text{OPERATION RHYTHM}, \tag{2}$$

where INTERVAL—trucks arrival time interval to the port, trucks/hour; OPERATION RHYTHM—operation rhythm of transshipment mechanisms, operation/hour.

It should be noted that two parameters play a key role in determining the required number of trucks to be serviced by the port. They are cargo capacity of grain road-train trucks and hourly operational productivity of overloading mechanisms. Mathematical dependency was derived to determine the required port capacity considering uninterrupted operation condition:

$$\text{CAP}_{\text{neces}}^{\text{hour}} = \frac{T_{1\text{ h}}^{\text{parking}} \cdot \text{TRANSCAP}_{\text{oper}}^{\text{total}}}{\text{LCAP}_{\text{truck}}^{\text{average}}}, \tag{3}$$

where $T_{1\text{ h}}^{\text{parking}}$—the time during which port achieve necessity volumes of grain cargoes for beginning to overload process, hour; $\text{TRANSCAP}_{\text{oper}}^{\text{total}}$—total cargo overloading capacity of transshipment mechanisms per hour, ton/hour; $\text{LCAP}_{\text{truck}}^{\text{average}}$—average loading capacity of trucks, ton.

The total cargo overloading capacity of transshipment mechanisms was calculated per hour by the following formula:

$$\text{TRANSCAP}_{\text{oper}}^{\text{total}} = \sum_{i=1}^{k} N_i^{\text{mech}} \cdot \text{TECHCAP}_i^{\text{mech}} \cdot K_i^{\text{ustime}}, \tag{4}$$

where N_i^{mech}—number of transshipment mechanisms of ith type, unit; $\text{TECHCAP}_i^{\text{mech}}$—technical cargo overloading capacity of transshipment mechanisms of ith type, ton/hour; K_i^{ustime}—coefficient of operation time using by ith type of transshipment mechanisms which load a ship, percent.

The distribution surface of the number of vehicles has been built based on calculations results of formulas (3) and (4) to ensure coordinated work between elements of grain supply chains to ports (Fig. 9).

Results of empirical observations of using mechanisms and trucks, which are operating for transshipment of grain cargoes to ships, were used in order to build the distribution surface of required port capacities in automobiles.

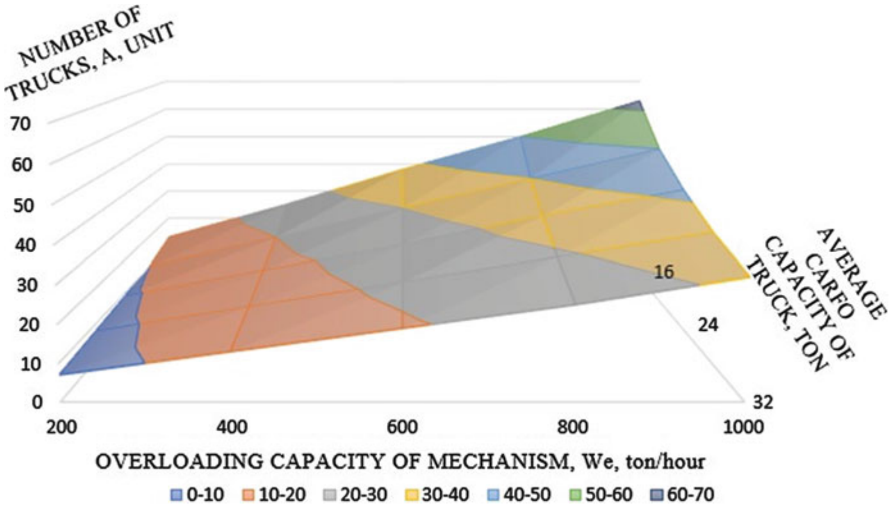


Fig. 9 Necessity port capacity in trucks at an hour based on coordinated interactions of vehicles and transshipment mechanisms

4.4 Calculation of Actual Port Capacity in Trucks at Hour Based on Results of Cargo Overload Volumes Forecast According to Fuzzy-Neural Model

The most important parameter is the actual port capacity in trucks. This factor helps design the flexible solutions at time management decision-making during cargo transshipment processes at the port. This indicator is determined by forecasting results (Fig. 8) derived from a trained fuzzy-neural network.

Conversion of classical dependency is used in this case to calculate actual port capacities to find the value of this indicator in trucks per hour. The final formula is presented as follows:

$$\mathrm{CAP}^{\mathrm{hour}}_{\text{fuzzy-neural}} = \frac{Q_{\mathrm{forec}}}{T^{\mathrm{idle}}_{\mathrm{unload}} \cdot \mathrm{TRANSCAP}^{\mathrm{total}}_{\mathrm{oper}} \cdot K^{\mathrm{arrival}}_{\mathrm{uneven}}}, \tag{5}$$

where Q_{forec}—forecast volumes got by using fuzzy-neural model, ton; $T^{\mathrm{idle}}_{\mathrm{unload}}$—truck idle time under unloading, hour; $K^{\mathrm{arrival}}_{\mathrm{uneven}}$—coefficient of vehicles uneven arrival at the port.

The coefficient of vehicles uneven arrival in the port was defined from observation of statistical data. It has an average value distributed in interval 1.1–1.8.

5 Discussion

The port capacity value was modeled in trucks per for different conditions based on the calculation of the dependencies (1), (3), and (5). The calculations results are presented in Table 2.

The graph of port capacity was designed to find dependency for different conditions from total cargo overloading capacity of transshipment mechanisms per hour (Fig. 10) and to define the management decision area.

Logistic operators should use a hatched area to develop management solutions, which is limited to three curves that describe the port operation based on different conditions.

System of making decisions on serviced trucks quantity in a specific time of reloading front operation can be represented by the following mathematically:

Table 2 Calculated results of port capacity according to various aspects

Maximal port capacity in trucks, trucks/hour	Necessity port capacity in trucks, trucks/hour	Actual port capacity in trucks, trucks/hour
30	13	28
30	25	33
30	38	34
30	50	26
30	63	23

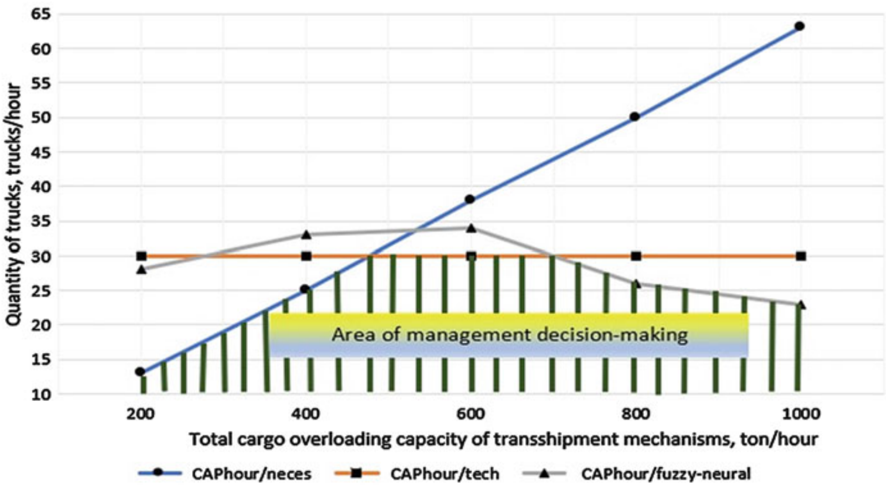


Fig. 10 Scheme for finding an area of management decision-making

$$\text{MAN DEC}\,(Q_{\text{trucks}}) = \min \begin{cases} \text{CAP}^{\text{hour}}_{\text{tech}}, & \text{technical condition,} \\ \text{CAP}^{\text{hour}}_{\text{neces}}, & \text{technological condition,} \\ \text{CAP}^{\text{hour}}_{\text{fuzzy-neural}}, & \text{actual condition,} \end{cases} \tag{6}$$

where MAN DEC(Q_{trucks})—management decision-making about logistics aspects of port functioning based on maximal potential quantities of trucks which can be serviced at the port during an hour, truck/hour.

Management decisions on this methodology allow port and carrier resources to be allocated in a manner that minimizes losses of time and financial resources. This approach is fully correlated with the Industry 4.0 concept on the appropriate allocation of resources to achieve the maximum possible profit while maintaining the high efficiency of manufacturing processes.

6 Conclusions

The methodology of management decision-making on logistics aspects organization in the port was presented based on the research results. The approach considers peculiarities of technical arrangements of overload fronts, technological aspects during the interaction between two kinds of transport, as well as prediction results obtained from the fuzzy-neural model. Obtained results of forecast about transshipment volumes have a lower average error (not more than 4.99%) due to using the ANFIS self-learning system than when using probabilistic methods.

The methodology presented advantages of management decision-making, as the actual calculation of truck quantities that will supply grain to the port is used. Therefore, planning with this indicator allows rational allocation of port resources, which is consistent with Industry 4.0 manufacturing policy.

The presented field of management solutions allows developing technological aspects in subsequent studies, in which logistics of port elements functioning will be the most optimal. It will, firstly, reduce ship service time, which will not exceed 2—3 days. It is in line with world standards and will improve supply chain efficiency in wholes.

The next step of the study will be the determination of the reasonable time of ships in port during loading considering management decisions-making based on the presented methodology.

The study will be aimed at reducing ship serviced time not only by organizing at a high level the interaction between two kinds of transport to ensure grain overload according to the direct option but also by determining the necessary grain reserves on port elevators, which should ensure the ship's loading in continuous mode.

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