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NEURAL NETWORK SYSTEM OF SALES VOLUME FORECASTING OF RESIDENTIAL REAL ESTATE IN THE PRIMARY REGIONAL MARKET

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When developing the economic part of a construction project, a cash flow model (CF model) is being built, in which it is necessary to take into account all the key factors affecting the overall project management system. An important component in building a CF model is knowing the volume of future sales. Forecasting the volume of sales allows you to predict the income from the implementation of the project and assess its profitability. Currently, construction companies assess sales volume expertly, and the results of the forecast depend on the expert's experience. In order to increase the efficiency of building the CF model, the authors propose a neural network model for predicting the volume of real estate sales, taking into account market factors. The model is based on the Loginom analytical platform, trained and has good predictive properties. The average relative error of forecasting is 6.89%. The model takes into account statistically significant external and internal factors affecting the volume of real estate sales in the conditions of shared-equity construction in the Chelyabinsk region market.

Keywords: equity construction; cash flow model; Loginom analytical platform; machine learning; neural network forecasting.

Introduction

Conducting building projects is a complex and time-consuming process, which is possible only if there are huge financial investments and a high level of professionalism of specialists. When developing the economic part of a construction project, it is extremely important to monitor the flow of funds, as this helps to avoid financial risks and achieve positive results. For this purpose, a cash flow (CF) model is being built, in which it is necessary to take into account all the key factors affecting the overall project management system.

Cash flow management is one of the key components of integrated project management, and building a cash flow model is a prerequisite for achieving successful results. The purpose of constructing a CF model is to assess the ability of an enterprise to generate cash in the required amounts and in the time required for the planned costs. In addition, this model will help to evaluate the effectiveness of the project, calculate revenue, profit / loss. An important component in building a CF model is knowing the volume of future sales. Forecasting the volume of sales allows you to predict the income from the implementation of the project and assess its profitability. Currently, construction companies assess sales volume expertly, and the results of the forecast depend on the expert's experience.

Among the forecasting methods, one can distinguish econometric methods that are based on formal mathematical models and heuristic methods based on intuition and expert experience [1]. Heuristic methods are informal methods for solving economic problems. They are mainly used to predict the state of an object in conditions of partial or complete uncertainty, when the influencing factors are set qualitatively.

Econometric models use quantitative statistical analysis of retrospective information and consist in constructing regression models that allow using extrapolation to obtain predictive estimates. The method is based on the assumption of the possible course of the simulated process, in connection with which significant modeling errors occur. Statistical models are effective for forecasts in a stationary environment and monotonous dynamics of processes [2].

An alternative approach to solving the forecasting problem is the use of neural networks. An alternative approach to forecasting is an approach that uses the apparatus of artificial neural networks. The set of problems, which are solved by the mathematical apparatus of artificial neural networks, largely coincide with the set of problems, which solving by traditional statistical methods.

Let's describe the advantages of models based on neural networks [3, 4].

1. The nonlinearity of the model, which allows you to display any nonlinear dependencies.

2. Locality of perception, which consists in the fact that each neuron perceives not the entire input vector, but only one of its coordinates.

3. During the training process, it is possible to configure the neural networks architecture. This allows the neural networks to perceive abstract features.

4. Well trained on the basis of a combination of different attributes.

Therefore, neural network forecasting algorithms are widely used. However, it should be noted that training neural algorithms often requires a large sample of retrospective training examples, which must meet certain quality criteria.

A study of published scientific papers in the field of forecasting the real estate market has shown that the publications of domestic authors are mainly devoted to the use of statistical methods for analyzing the value of real estate in the regional market [5, 6]. In the works of G.M. Sternik and his colleagues [7–10], macroeconomic factors are used in mathematical models for forecasting the indices of the value of residential real estate objects: indicators of GDP growth rate, % inflation, the amount of construction financing, household incomes, etc. In the foreign literature [11–14], the authors prove that the use of artificial neural networks is more effective in assessing the value of real estate compared to multidimensional regression models. In domestic publications, it is necessary to highlight the work of V.L. Yasnitsky [15–19] with colleagues who used neural network models to predict the market value of residential real estate. In all works, without exception, the dynamics of the market as a whole is modeled and studied, and they are not suitable for practical use at the level of a separate regional construction company.

The experience of building models that allow predicting the volume of real estate sales in the primary market is not presented in the literature. Currently, when compiling the CF model, an expert subjective assessment of future sales volumes based on past periods is used, which does not take into account changing environmental factors. Therefore, the planned financial indicators are inaccurate and largely indicative. Therefore, the task of forecasting the volume of real estate sales based on the methods of analyzing retrospective sales data is relevant. The purpose of the study is to build a model for forecasting the volume of real estate sales in the primary market, taking into account the influence of external economic factors for a regional construction company.

1. Application of Neural Network Apparatus to Forecasting Problems

For solving forecasting problems, as a rule, researches use a multilayer perceptron (Fig. 1) [20].

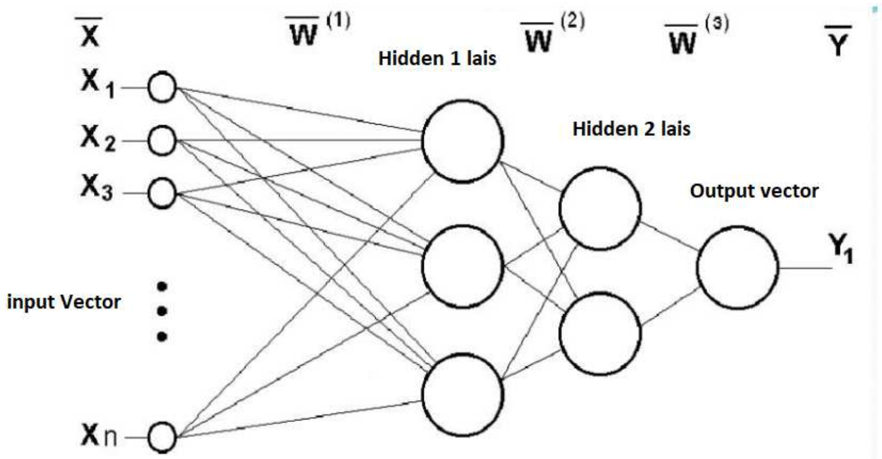

Fig. 1. Perceptron containing two hidden layers

A multilayer perceptron consists of a set of sensory (input) neurons, one or more hidden computational layers (two hidden layers in Fig. 1) and an output layer. Neural network models are built on the basis of machine learning methods, which allow using various factors influencing the behavior of the process under study to build a model [3, 4].

The general formulation of the learning task is as follows. There are many objects and many possible answers (a set of object–response pairs is called a training sample). The training sample is a function defined by table of input-output pairs $[(X_1; Y_1), (X_1; Y_1), \dots (X_k; Y_k)]$, between which there is some functional dependence, which is unknown. Based on the training sample, it is required to build a model with which you can get a fairly accurate answer. To measure the accuracy of the response, an accuracy criterion is introduced. The model transforms the input data using a function of many variables $Y = F(X)$. The magnitude of the quadratic error E is determined by the next formula

$$E = \frac{1}{2} \sum_{i=1}^{N} \left(Y^{(i)} - Y_d^{(i)} \right)^2,$$

where N is a number of training examples;
$Y^{(i)}$ is a value at the output of the model for the i-th example;
$Y_d^{(i)}$ is a target value for the i-th example.

To train a model means to set it up so that for all pairs $(X^{(i)}, Y^{(i)})$ the error function E is minimal. A correctly trained model acquires the ability to generalize, which means that for each input vector $X = (X_1, X_2, \ldots, X_n)$, the correct response vector $Y = (Y_1, Y_2, \ldots, Y_m)$ is always formed at the output.

The multilayer perceptron is trained using gradient learning algorithms with a teacher. The learning process consists in minimizing the error function $E = E(w_{ij})$, which depends on the values of the weighting coefficients w_{ij} from the gradient algorithm. The number of neurons in the input layer is equal to the size of the input vector X, which determines the characteristics of the external environment in which the company operates. The external environment is the sphere in which an organization carries out its vital activities, it is a set of factors that affect its activities and exist outside the organization.

Macroenvironment analysis is an important component in the development of a company's strategy. It allows you to take into account the impact of the external environment on the company's activities and take appropriate measures to achieve your goals. As a result of the analysis, 3 groups of external factors were identified that probably influence the dynamics of the volume of real estate purchases: external macroeconomic indicators determined at the federal level (federal), regional macroeconomic indicators (regional) and individual factors related to buyer preferences (Fig. 2).

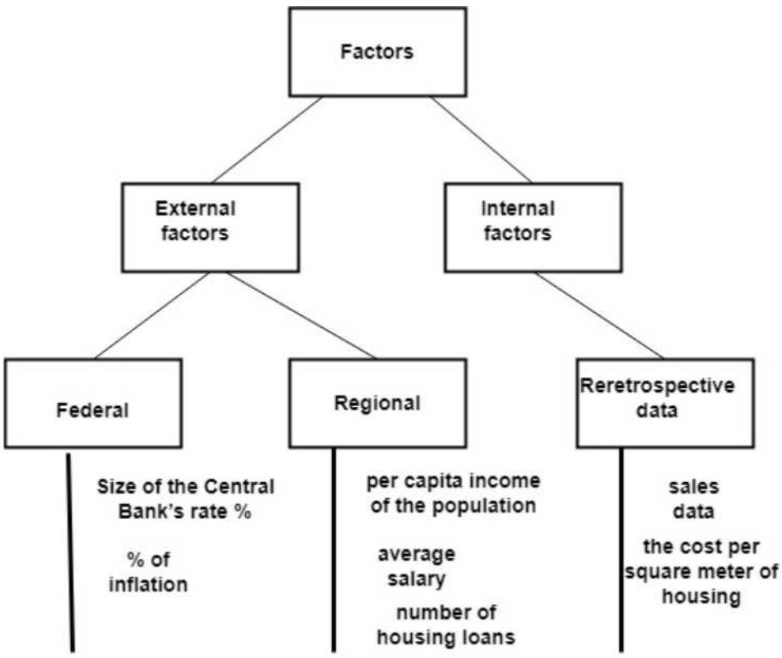

Fig. 2. Structure of the analyzed factors

Regional factors can be quantified by sources representing official information and which are characteristic of the Chelyabinsk region. For example, the number of housing and mortgage loans, the number of people who used maternity capital to buy real estate in new buildings, the average per capita monetary income of the population, the average monthly salary. External macroeconomic factors established at the state level (conditionally called federal) that significantly affect the size of housing loans, household incomes and average monthly salary in work include: the size of the Central Bank's rate % and the inflation rate. The values of external indicators can be obtained on the next official websites.

• Unified Interdepartmental Information and Statistical System (EMISS) [21]. The site contains official statistical information generated by the subjects of official statistical accounting within the framework of the Federal Statistical Work Plan.

- The Central Bank of the Russian Federation [22, 23].
- Social Fund of Russia [24].
- Ministry of Economic Development of the Russian Federation [23].

Individual factors influencing the decision to purchase residential real estate are of great importance. Usually buyers evaluate the location of real estate, the development of social institutions: kindergartens, schools, shops, accessibility of transport, the prestige of the developer and many others. However, such information is usually inaccessible to the researcher, and it is impossible to quantify it.

Thus, to predict the volume of transactions, the following groups of external factors will be used, quantified: the number of housing and mortgage loans, the number of persons who used maternity capital to buy real estate in new buildings, the average per capita monetary income of the population, the average monthly salary, the amount of the Central Bank's rate %, the inflation rate. Internal retrospective data is a time series of real estate sales for an already implemented project and the cost of 1 sq.m. of living space. The choice of retrospective data is significantly influenced by the technical and economic characteristics of the project. The model was used to forecast sales volumes of the second stage of a certain project based on real retrospective monthly sales data of the first stage of the same project for 2018–2022. The volume of the training sample is 4219 records. The forecast horizon is 1 year.

The model implies that the characteristics of the apartments of the first and second stages are similar and, consequently, the cost of sq.m. has not changed significantly. In the real estate market, the existing offers are heterogeneous and buyers can choose an apartment based on their tastes and income. The developed model can be applied in an area where the uniformity properties of an object are fulfilled, for example, apartments in a certain area or city built according to projects with similar technical and economic indicators.

2. Implementation of the Forecasting Model

The construction of a neural network forecasting model was carried out on the domestic Loginom platform. The Loginom analytical low-code platform contains a visual constructor that allows you to build analysis models without programming knowledge [25]. The model has a modular structure (Fig. 3).

The modular structure gives the model a universal character due to the allocation of independent modules in the model structure, which allow taking into account regional, federal and corporate input factors. The modules "Data preparation", "Correlation analysis" and the module "Sales forecasting" are universal. The Neural Network Model module is a trained neural network that is configured on the retrospective data entered in the Data Preparation module.

The developed model can be used repeatedly to create a forecast for three different scenarios of economic development: optimistic, pessimistic and realistic.

1. The optimistic forecast assumes the preservation of the current indicators of the real estate market development with the stability of the macroeconomic situation.

2. In a pessimistic scenario, the deterioration of any macroeconomic indicators is modeled.

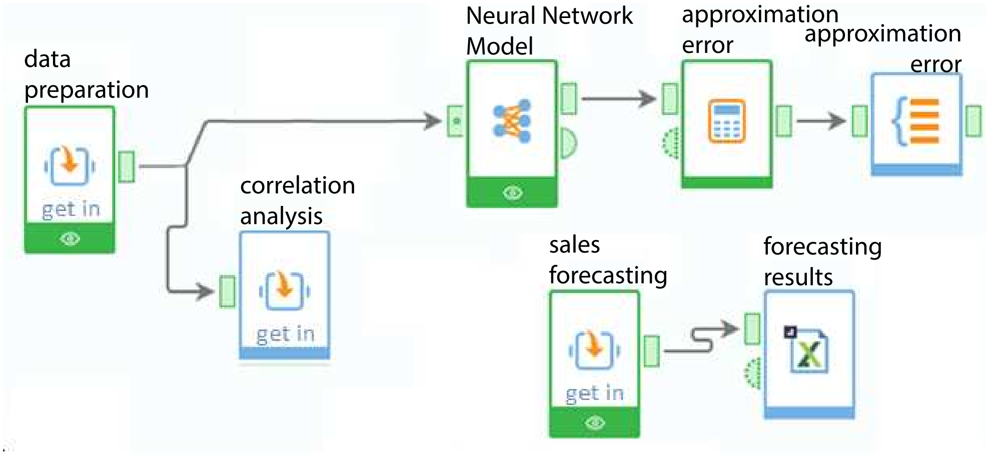

Fig. 3. Implementation of the model on the Loginom platform

3. A realistic scenario provides for the preservation of macroeconomic parameters.

We describe in more detail some important for us features of the implementation of the model.

4219 records are submitted to the input of the model, including indicators characterizing the dynamics of sales of apartments of the first stage of the project, as well as indicators characterizing the external environment. The module «Data Preparation» includes two modules: «Preparation of external factors» and «Preparation of internal factors», as well as the node «Data Consolidation» (Fig. 4).

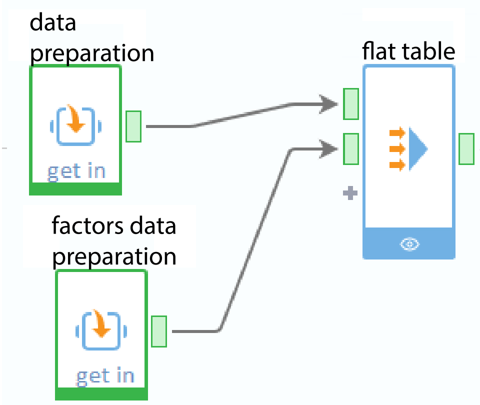

Fig. 4. Structure of the «Data Preparation»

In the module «Preparation of internal factors»(Fig. 5) the input of initial data on monthly sales for the periods from 2018 to 2022 is performed. In the ETL process, uninformative factors are not loaded. The data is then consolidated into one flat table. The data is grouped by year and month, the monthly number of sales and the average cost of sq.m. are calculated.

The structure of the module «Preparation of external factors» is similar. In this module, factors determined by federal and regional indicators are introduced and processed.

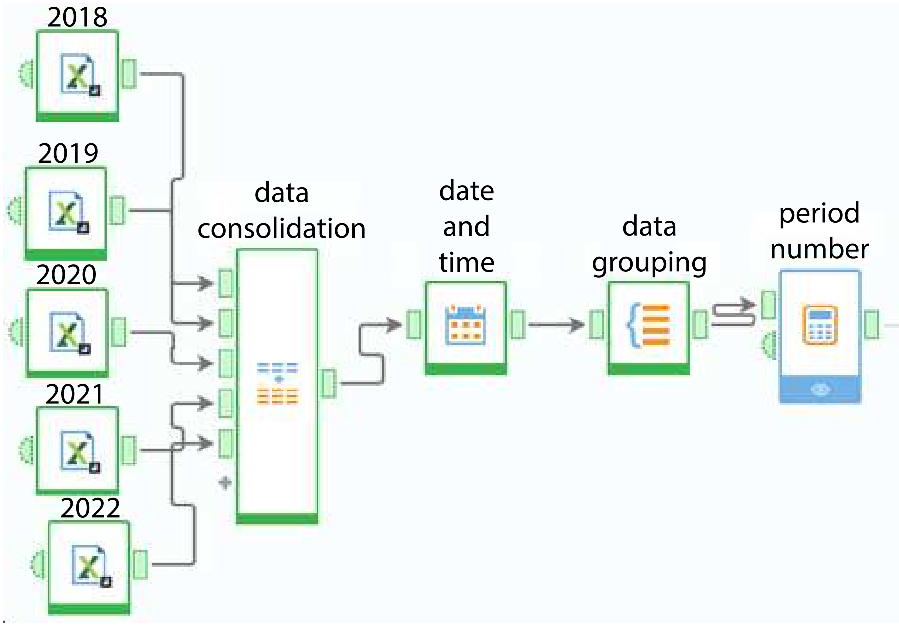

Fig. 5. Structure of the module «Preparation of internal factors»

These factors include:

- regional factors: the number of housing and mortgage housing loans; average monthly salary; average per capita income; the number of family loans spent on improving housing conditions;
- federal factors (factors whose values are determined at the federal level): inflation % in the country and the Central Bank rate %.

Since the forecasting model is based on the results of machine learning, the quality of data and their suitability for analysis have a significant impact on the result of forecasting. Therefore, before building the model, after data collection, their preparation is performed (Fig. 6).

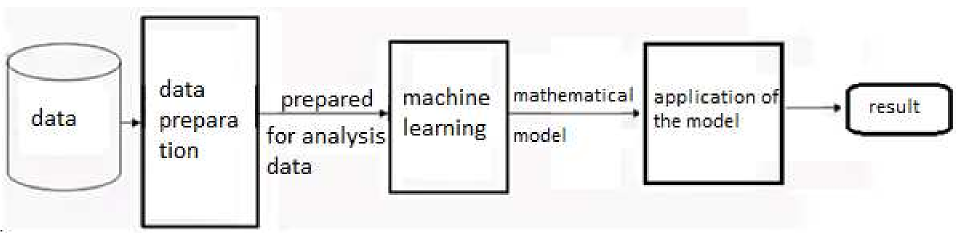

Fig. 6. The data preparation in the overall analysis structure

The analysis uses that data
1) are structured, i.e. ordered and organized in the form of flat two-dimensional tables;
2) are presented in a specific format;
3) informative;
4) have a certain quality.

The primary assessment of data quality implies, first of all, the identification and processing of objective errors and deviations – duplicates, contradictions, omissions, anomalies. In data preparation modules, each factor is entered from a separate file. This gives the model versatility, because if we change the value of any of the external indicators then we should change the data in only one file. When the retrospective data is changed, only the module «Preparation of internal factors» is subject to change.

The module «Correlation analysis» determines the presence of a linear relationship between the parameters of the model (Fig. 7). There is a weak negative linear relationship of the dependent variable number of sales with the size of the annual interest rate and with inflation %. This is natural, because both indicators affect the interest rates of banks when taking out loans for the purchase of housing.

field1	field2	coefficient
sales quantity	average price	0,09
sales quantity	revenue	0,90
sales quantity	quantity of housing loans	0,64
sales quantity	quantity of mortgage housing loans	0,64
sales quantity	average salary	0,07
sales quantity	central bank interest rate	-0,32
sales quantity	inflation	-0,12
sales quantity	maternal capital, used on flat buying	0,39
sales quantity	average per capita income	-0,01

Fig. 7. Correlation matrix

The relationship with the other independent factors is positive. There is a weak relationship between the volume of real estate purchases with the price of sq.m., per capita monetary income and the average monthly salary of the buyer. There is a weak relationship between the dependent variable number of sales and the variables that determine the financial capabilities of the buyer. Buying an apartment is an expensive investment and, as a rule, buyers take out housing loans.

Neural network training is carried out in the module «Neural network model» (see Fig. 3) based on real market data. The training consists in finding the weighting coefficients of the connection between neurons. The list of input variables that were used to train the neural network model is shown in Fig. 8.

field	name	data type	purpose
year	Data_Y_1	district	input
month	Data_M_1	district	input
sales quantity	Vyruchka_Count	continuous	output
average price	tsena_za_kvadrat	continuous	input
total revenues	Vyruchka_Sum	continuous	input
quantity of housing loans	Kolichestvo_zhilischnykh_kreditov	continuous	input
quantity of mortgage housing...	Kolichestvo__ipotechnykh_zhilisc...	continuous	input
central bank interest rate	Razmer_stavki___godovykh	continuous	input
inflation	__inflyatsii	continuous	input
maternal capital used on flat b...	CHislennost_lits__rasporyadivshi...	continuous	input

Fig. 8. Input data for model training

All real data has been normalized and brought to the range $0 - 1$. The use of normalization increases the quality and speed of neural network learning. The neural network architecture is configured automatically during the learning process.

To control the quality of training, three errors are displayed.

1. The root-mean-square error on the training set (MSE)

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \overline{y}_i)^2 . \tag{1}$$

2. Average absolute error on the training set (MAE)

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \overline{y}_i| . \tag{2}$$

3. Average relative error on the training set ($MAPE$)

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - \overline{y}_i|}{y_i}\cdot 100\%. \tag{3}$$

Formulas (1)–(3) use the following notation:
n is the number of observations of the data set;
y_i is the actual value of the independent variable for the i-th observation;
$\overline{y}_i$ is the value predicted by the model for the i-th observation.

Similar errors are calculated on the test set (Fig. 9).

mean square error on the training set	1,86
mean absolute error on the training set	1,51
mean relative error on the training set	0,03
mean squared error on the test set	14,23
mean absolute error on the test set	11,88
mean relative error on the test set	0,24

Fig. 9. Education and test errors

The average relative error on the training set is the training error shows the difference between the actual and predicted values. The standard error on the test set is within 15%, which indicates good predictive abilities of the model.

A graphic illustration of the model learning process is shown in Fig. 10.

The forecast was carried out for an optimistic scenario, i.e. it was assumed that the current trend in the development of the real estate market and the stability of macroeconomic indicators, both at the federal and regional levels, would be maintained. The forecast results are exported to an excel file.

The monthly results of the forecast for 2023 are shown in Fig. 11. The average relative error of the model was 6.89%.

To obtain a forecast under other conditions, you should enter input data characterizing the new situation without rebuilding the neural network model. Input data characterizing

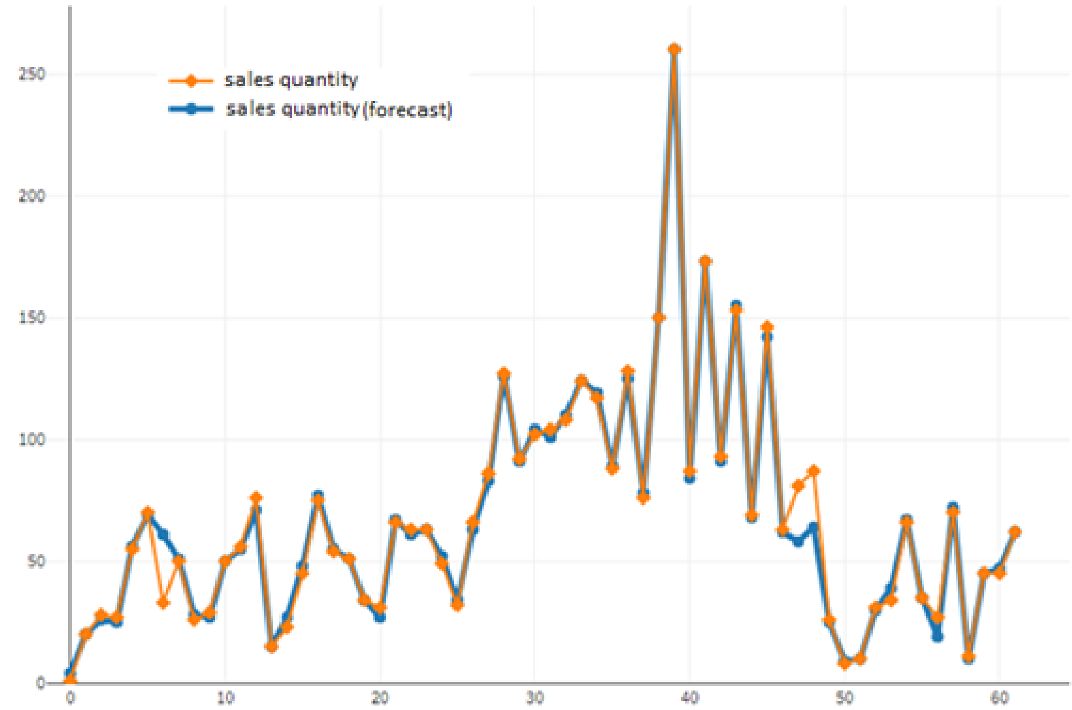

Fig. 10. Graphic illustration of the model learning process

year	month	forecast
2 023	1	10
2 023	2	42
2 023	3	46
2 023	4	60
2 023	5	55
2 023	6	50
2 023	7	55
2 023	8	53
2 023	9	56
2 023	10	53
2 023	11	63
2 023	12	55

Fig. 11. Forecast results

the change in the economic situation are entered in the module "Preparation of external factors". The forecasting model is universal and allows you to forecast the volume of sales of real estate in a new building with changing macroeconomic indicators. At the time of writing, the real data for the period January–April 2023 were known (Fig. 12).

As Figure 12 shows, the model has good predictive properties and can be usefull in practice.

12 year	12 month	12 sales quantity (forecast)	12 sales quantity
2 023	1	10	11
2 023	2	42	45
2 023	3	46	45
2 023	4	60	62

Fig. 12. Comparison of real data and predicted

Conclusions

1. Data from diverse sources have been identified, collected and prepared for analysis. The data is structured, optimized, and stored in one flat table.

2. The model is trained and has good predictive properties. The average relative error of modeling is 6.89%.

3. The model takes into account statistically significant external and internal factors of the volume of real estate sales in the conditions of shared-equity construction in Chelyabinsk region market.

4. The constructed model is universal and allows you to make a forecast with changing macroeconomic indicators within three different scenarios of economic development: optimistic, pessimistic and real.

Input data characterizing the change in the economic situation are entered in the module ≪Preparation of external factors≫. In their study, the authors are fully aware that the quality of the estimates obtained in the modeling process significantly depends on the completeness and adequacy of the information collected. However, the approximate estimates obtained will be due to external economic factors, which is of practical importance for any construction company.

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НЕЙРОСЕТЕВАЯ СИСТЕМА ПРОГНОЗИРОВАНИЯ ОБЪЕМА ПРОДАЖ ЖИЛОЙ НЕДВИЖИМОСТИ НА ПЕРВИЧНОМ РЕГИОНАЛЬНОМ РЫНКЕ

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При разработке экономической части строительного проекта строится модель движения денежных средств (ДДС), в которой необходимо учесть все ключевые факторы, влияющие на общую систему управления проектом. Важным компонентом в построении модели ДДС является знание объема будущих продаж. Прогнозирование объема продаж позволяет спрогнозировать доходы от реализации проекта и оценить его рентабельность. В настоящее время строительные компании оценивают объем продаж экспертно, причем результаты прогноза зависят от опыта эксперта. С целью повышения эффективности построения модели ДДС в статье предлагается нейросетевая модель прогнозирования объема продаж недвижимости с учетом рыночных факторов. Модель построена на базе аналитической платформы Loginom, обучена и имеет хорошие прогностические свойства. Средняя относительная погрешность прогнозирования 6,89%. Модель учитывает статистически значимые внешние и внутренние факторы, влияющие на объем продаж недвижимости в условиях долевого строительства на рынке Челябинской области.

Ключевые слова: долевое строительство; модель движения денежных средств; аналитическая платформа Loginom; машинное обучение; нейросетевое прогнозировании.

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