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Research Article

The Complex Neural Network Model for Mass Appraisal and Scenario Forecasting of the Urban Real Estate Market Value That Adapts Itself to Space and Time

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In the modern scientific literature, there are many reports about the successful application of neural network technologies for solving complex applied problems, in particular, for modeling the urban real estate market. There are neural network models that can perform mass assessment of real estate objects taking into account their construction and operational characteristics. However, these models are static because they do not take into account the changing economic situation over time. Therefore, they quickly become outdated and need frequent updates. In addition, if they are designed for a specific city, they are not suitable for other cities. On the other hand, there are several dynamic models taking into account the overall state of the economy and designed to predict and study the overall price situation in real estate markets. Such dynamic models are not intended for mass real estate appraisals. The aim of this article is to develop a methodology and create a complex model that has the properties of both static and dynamic models. Moreover, our comprehensive model should be suitable for evaluating real estate in many cities at once. This aim is achieved since our model is based on a neural network trained on examples considering both construction and operational characteristics, as well as geographical and environmental characteristics, along with time-changing macroeconomic parameters that describe the economic state of a specific region, country, and the world. A set of examples for training and testing the neural network were formed on the basis of statistical data of real estate markets in a number of Russian cities for the period from 2006 to 2020. Thus, many examples included the data relating to the periods of the economic calm for Russia, along with the periods of crisis, recovery, and growth of the Russian and global economy. Due to this, the model remains relevant with the changes of the international economic situation and it takes into account the specifics of regions. The model proved to be suitable for solving the following tasks: industrial economic analysis, company strategic and operational management, analytical and consulting support of investment, and construction activities of professional market participants. The model can also be used by government agencies authorized to conduct public cadastral assessment for calculating property taxes.

1. Introduction

The authors of many recent publications, for example [1], emphasize that artificial neural networks (ANN) as complex nonlinear systems can take into account an unlimited number of external factors and dynamic interactions. Due to this, an ANN allows for solving multiple complex real problems that could not be solved by other methods. For example, the authors of this article created the world's first neural network lie detector [2]. The ANN technology ensured a unique diagnostic accuracy of 98 percent due to a comprehensive accounting of psychophysiological parameters of an individual such as personal data and signals coming from the sensors of a polygraph machine. The members of the same author's team developed a neural network system that helps detectives to investigate crimes, in particular, to identify people who can be serial maniacs and murderers [3]. This objective cannot be solved by other methods due to the need to analyze a large number of parameters and factors while many of them have an insignificant impact on the diagnostic result. The same authors created a medical system based on neural network technologies [4–6]. Due to a complex mathematical formulation of the problem, this system allows not only for diagnosing cardiovascular diseases, but also for making disease development forecasts for many years to come and for selecting the optimal courses of disease treatment and prevention (https://en.kardionet.ru). One more neural network system developed by the same team has a practical value enabling users to predict the future box office of a movie based on a set of various factors that have both a direct and an indirect impact on the result of forecasting [7]. Equally important in practice is a neural network system that predicts the bank failure probability and allows you to develop recommendations for preventing such bankruptcies [8]. The book in [9] by the author of this paper provides examples of neural network intelligent systems developed under his leadership and designed to diagnose complex technical devices, the economic position of enterprises, to predict political events, to identify the business and research skills of individuals, etc. Due to their complex formulation of mathematical problems, all these neural network systems enable users not only to diagnose and predict, but also to explore the simulated domains, as well as developing measures for active management of the behavior of these rather complex areas.

As noted by the authors in [1], the cutting-edge capabilities of neural networks make it possible to successfully apply them for modeling complex multifactor nonlinear systems such as a real estate system.

Many authors draw the attention to the great urgency of developing high-precision models for carrying out the mass valuation of real estate markets. For example, [10] presents the results of an analysis of international literature and interviews with statesmen of many countries. This analysis demonstrates that systems of mass valuation and real estate taxation are an important and viable basis for increasing government revenues. The authors of [1, 11–14] also note that high-precision methods of real estate valuation are a useful decision-making tool in the taxation and urban planning sectors. Such methods can be used by investors, buyers, and governments.

As noted in [15], until 1990, five standard recognized methods were mainly used for evaluating real estate such as the comparative method (comparison), contractor's method (cost method), residual method (development method), profits method (accounts method), and investment method (capitalization/income method).

In the 1990s, some researchers reported about successful attempts to create systems for mass appraisal of real estate objects based on a new mathematical apparatus, artificial neural networks (ANN). Apparently, one of the first papers in this direction was an article [16] published in 1991. Its author, Borst, defined a number of variables for designing an ANN-based model for evaluating New York real estate. He reported that the model can predict the price of real estate with an accuracy of up to 90%. It was a perceptron-type neural network.

In 1991, Tay and Ho in [17] reported on the use of a multilayer perceptron to determine the market price of real estate in Taiwan.

In the same year of 1991, Evans, James, and Collins in [18] reported on the use of neural networks for evaluating residential real estate in England and Wales. After testing several methods, the authors came to the conclusion that the neural network model is best suited for delivering real estate valuations.

In 1992, Do and Grudnitskiy [19] published a report on using a perceptron-type neural network to evaluate US real estate. Based on a test set of 105 houses, the neural network model had twice the accuracy of the predicted values as compared to the analogous regression model.

From the mid-1990s to the present, a series of research publications devoted to the development and application of neural network models for mass appraisal of real estate objects have been published. Many papers [12, 20–32] emphasize the advantages of this advanced technology as compared to regression modeling and other methods of real estate valuation.

Analyzing the papers devoted to neural network modeling of estate markets, it can be noted that few researchers (e.g., [33]) have paid attention to the specific problems of modeling this subject area and to the issues of overcoming these problems. When constructing a neural network system for assessing real estate, the authors in [33] faced the challenge of overcoming the negative impact of statistical outliers on the accuracy of the created models. For the real estate market, they tested a number of methods for detecting outliers such as Tukey's method, standard deviation method, median method, Z-score method, MAD method, and modified Z-score method. As a result, they concluded that the median method delivers the best results.

Looking ahead, we note that in our work we used an even more effective author's method for detecting statistical outliers [34] based on the neural network mathematical apparatus.

Summarizing the review of neural network models designed for mass real estate valuation [10, 12, 16–32], let us pay attention to their overall disadvantages:

(1) Developed for a specific city, these models cannot be applied to other cities because they do not take into account mesoeconomic factors.

(2) All these models quickly become outdated and require frequent updates because they do not take into account the changing economic situation in the world, some specific country, and region over time. Such models can be called static ones. This disadvantage of static models is particularly relevant for developing countries where markets are in the process of development. These markets depend on

time-varying oil prices, the dollar, GDP, stock indexes, government credit policies, and so on.

It should still be noted that there is a series of research papers, for example [1, 35], devoted to the development of economic and mathematical models of real estate markets that consider many macroeconomic parameters. However, these dynamic models are intended exclusively for modeling and studying market dynamics. They are not intended for the mass assessment of apartment prices that have a large variety of static characteristics. The apartment cost indices calculated in such models (the average unit cost of apartments assigned to a square meter) can, of course, be recalculated in the cost of specific apartments taking into account their construction, operational, environmental, and other parameters. However, such a recalculation can only be made using additional methods which are not used for mass appraisal of real estate objects due to their inefficiency. The fact is that the unit prices of apartments of the same type located in the same area and even in the same house may differ. Therefore, a more differentiated approach is required in this case.

Thus, on the one hand, we have a list of static models [10, 12, 16–32], etc., for mass appraisal of real estate objects. However, these models do not take into account the changing economic situation in the world, in the country, and in the region over time. Therefore, these models quickly become outdated and require frequent updates. These models are also not suitable for the medium-term forecasting of real estate markets.

On the other hand, there are dynamic models [1, 35] taking into account the general state of the economy and designed to forecast and investigate the overall price situation in the real estate market. Nevertheless, these models are not intended for mass appraisal of real estate.

In order to overcome these shortcomings, the authors of the article offered to your attention have recently published works [36, 37], in which attempts were made to develop methods for creating complex models that have the properties of both static and dynamic models. These new models take into account both construction and operational characteristics of real estate objects as well as some parameters characterizing the changing economic situation in some region, country, and the world. Due to this, such models have become self-adaptable to time; i.e., they have learned to maintain their predictive capabilities regardless of the changing economic situation over time.

The aim of this paper is to further expand and develop the results of the previous studies [36, 37]. Our goal is to create a model that can be self-adaptive not only to time but also to space.

2. Materials and Methods

When creating a model for mass assessment and scenario forecasting of residential real estate markets in Russian cities, geographical, construction, operational, time, and macroeconomic factors were taken into account as input parameters.

The model included the following geographical factors: the city index (1: Moscow; 2: Saint Petersburg; 3: Yekaterinburg; 4: Perm; etc.), the geographical coordinates of a specific apartment house (latitude, longitude) identified using the Yandex service at an address specified, and the level of prestige of the house's location on the geographical map of the city.

In this set of parameters, the city index, which links the estimated apartment to a specific city, is fundamentally new. The parameter that characterizes the degree of prestige of the house location on the geographical city map is also new. Let us look at this parameter in more detail, since this paper introduces it for the first time.

In order to take into account the house location prestige, professional appraisers often use the distance from a specific house to the city center. Sometimes, parameters that characterize transport accessibility, proximity to metro stations, parking lots, city squares, business and cultural centers, industrial enterprises, public toilets, etc. are considered as well. However, such parameters are subjective. For example, there are cities without some center. There are cities with several centers. Parking lots, squares, and cultural and business centers can vary in terms of their convenience and efficiency.

In this regard, we suggest using the so-called heat maps to assess the location of real estate objects. These heat maps are constructed as follows. In each city, many properties of a similar type are selected, for example, many two-room apartments of approximately the same size sold over a certain period of time. The coordinates of apartments are put on the map, and their market value is shown on the map in different colors. The zones where the most expensive apartments are located are shown in red gradually changing to colder colors as the cost of the apartment decreases. An example of a heat map of Yekaterinburg constructed in this way is shown in Figure 1.

As you can see in Figure 1, Yekaterinburg has four distinct price centers located in different parts of the city.

At the next stage, a mathematical function is constructed that approximates the values of apartment prices shown on the heat map. This function depends on two arguments: the geographical latitude and longitude of the house location. The approximation is performed for each apartment. The value of the approximating function reduced to an interval from 0 to 1 in our method is the level of prestige of the apartment location.

The analysis has shown that the proposed parameter for evaluating the prestige of the real estate object location increases the model accuracy by 3–7 percent.

Below are the construction and operational input parameters of the model: type of house walls (1: block; 2: cinder blocks; 3: wood; 4: monolith; 5: concrete; 6: panel; and 7: brick), rooms, floor, number of floors, total apartment square area, and living area and kitchen area.

The year and season (1: winter; 2: spring; 3: summer; and 4: autumn) on the date of the apartment price estimation were selected as time-factor parameters.

The following macroparameters were selected to characterize the external economic situation in the world,

Figure 1: Heat map of price zones of the city of Yekaterinburg. The zones where the most expensive apartments are located are shown in red gradually changing to colder colors as the apartment price decreases.

country, and region: the US dollar exchange rate against the ruble; the price of Brent oil, the country's GDP; the volume of urban housing construction in the year preceding the assessment; and the volume of mortgage loans issued to city residents in the year preceding the assessment.

The output variable of the model corresponds to the declared market price of the real estate.

The statistical basis for training and testing the neural network was the data of real estate markets in a number of Russian cities for the period from 2006 to 2020. Thus, the training database included data during the periods of the economic calm for Russia (2006), the economic growth (2007–mid-2008), the crisis and turning point of the Russian and world economy (2008–early 2010), the recovery after the crisis (2010–2012), the slowing growth (2013–early 2014), the weakening of the ruble, the introduction of Western sanctions, a sharp drop in oil prices and the ruble against the US dollar, and the financial blockade and no access to the international capital (2014–2020).

The data were collected and processed for 10 Russian cities: Moscow, Saint Petersburg, Nizhny Novgorod, Yekaterinburg, Novosibirsk, Khabarovsk, Rostov-on-Don, Pyatigorsk, Kazan, and Perm. For each city, the data was collected on an average of 30,000 real estate properties.

Thus, the model included all cities that are the centers of Russia's federal districts.

As said above, a characteristic feature of the real estate market is a large amount of unreliable data called statistical outliers [33]. To search for such outliers, we used the median method recommended by the authors of [33] and the factual-graphical search method [38]. The results were compared to show that the neural network method proposed in [34] is the most effective one. This method is based on the capability of some neural networks to learn poorly from examples which are statistical outliers. For instance, if a perceptron-type neural network with sigmoid activation functions has a small number of hidden layer neurons and there are relatively few outliers in the training set, the neural network usually shows a higher learning error for examples that are statistical outliers as compared to those examples that are not outliers after applying the training procedure.

In our case, a two-layer perceptron with sigmoid activation functions was used to search for outliers. The number of hidden neurons was calculated using the formulas proposed in [34]:

$$
\begin{aligned}
N &= N_{\min} + \xi\left(N_{\max} - N_{\min}\right),\\
N_{\min} &= \frac{N_y Q}{\left(1 + \log_2(Q)\right)\left(N_x + N_y\right)},\\
N_{\max} &= \frac{N_y}{N_x + N_y}\left(\frac{Q}{N_x} + 1\right)\left(N_x + N_y + 1\right) + N_y.
\end{aligned}
\tag{1}
$$

In these formulas, N_x is the number of neurons in the input layer; N_y is the number of neurons in the output layer; Q is the number of elements of the training set; and $\xi = 0,1$ is the empirical coefficient.

In total, about 3.2% of the collected information was discovered and deleted.

The set of examples was divided into the training, testing, and confirming sets as follows: 70 : 20 : 10. The optimal structure of the neural network was a three-layer perceptron with linear input and output neurons, three sigmoid neurons on the first hidden layer, and two sigmoid neurons on the second hidden layer. The neural network was trained using the resilient backpropagation algorithm [39]. According to this algorithm, the correction of the weight coefficients of the neural network was performed using mathematical formulas:

$$
\begin{aligned}
w_{ij}(t+1) &= w_{ij}(t) + \Delta w_{ij}(t),\\
\Delta w_{ij}(t) &= -\eta_{ij}(t)\cdot \operatorname{sign}\left(S_{ij}(t)\right),\\
S_{ij}(t) &= \frac{\partial \varepsilon(t)}{\partial w_{ij}},\\
\varepsilon(t) &= \frac{1}{2}\sum_{i=1}^{I}\left(d(t) - y(t)\right)^2,\\
\eta_{ij}(t) &= \begin{cases} 1,2 \times \eta_{ij}(t-1), & \text{if } S_{ij}(t)\times S_{ij}(t-1) > 0,\\ 0,5 \times \eta_{ij}(t-1), & \text{if } S_{ij}(t)\times S_{ij}(t-1) < 0,\\ \eta_{ij}(t-1), & \text{if } S_{ij}(t)\times S_{ij}(t-1) = 0. \end{cases}
\end{aligned}
\tag{2}
$$

In these formulas, t is the iteration number (number of the training epochs); $w_{ij}(t+1)$ is the weight coefficient of the neural network in the new training epoch; $w_{ij}(t)$ is the weight coefficient of the neural network in the previous training epoch; $d(t)$ and $y(t)$ are the required and resulting perceptron output signals; and $\eta_{ij}(t)$ is the learning rate coefficient.

To assess the quality of the neural network, we used the standard-square relative error calculated using the following formula:

$$E = \frac{\sqrt{\left(\sum_{n=1}^{N} \left(d_n - y_n\right)^2 / N\right)}}{\left|\max\left(d_n\right) - \min\left(d_n\right)\right|} 100\%, \quad (3)$$

in which N is the number of sample elements, d_n is the declared cost of the n-th apartment, and y_n is its cost estimated using a neural network.

The error of the neural network calculated by formula (3) on the training set was 5.2% and 6.2% for the test set and 6.3% for the confirmation set.

In order to visualize the error of the resulting neural network model, Figure 2 shows a histogram built on a fragment of the test set, showing the difference between the actual and projected models of the cost of apartments.

It is important to note that the data about the parameters of the test set and confirmation set were not used in training the neural network; i.e., the neural network has never "seen" them. Based on the results obtained using formula (3) and shown in Figure 2, we can conclude that the trained neural network has learned to predict the cost of apartments with an acceptable degree of accuracy. The neural network has mastered the laws of the simulated subject area and is adequate to it. This means that the neural network behaves in the same way as the simulated subject area would behave in a given situation. Therefore, the neural network can be used both for the mass appraisal of apartment prices and for studying the patterns of real estate markets in Russian cities by performing scenario forecasts. In other words, virtual computer experiments can be performed on a neural network model.

3. Results and Discussion

Studies of the behavior of urban real estate markets were conducted on the example of five virtual apartments, which differ in the number of rooms and square area as shown in Table 1.

It is assumed that the virtual house where the virtual apartments are located is originally located in the central part of Moscow and has the following geographical coordinates: the latitude is 55.75211 degrees; the longitude is 37.59398 degrees. The prestige level in this part of the city is 0.95. The house has brick walls. The apartments are located on the 10th floor. The number of floors in the apartment house is 16. The year of evaluation of apartments is 2020; the season is winter. At the time of the assessment, the US dollar exchange rate was 63.62 Russia roubles; the price of Brent oil is 3,530 roubles per barrel; Russia's GDP is 109,361 billion roubles. In the year preceding the assessment, the volume of the housing construction in Moscow amounted to 5,025 thousand square meters, and the volume of mortgage lending was 389.842 billion roubles. This set of parameters describing the geographical location of the house, its construction data, and the time of assessment and the corresponding economic situation in the world, country, and region is summarized in Table 2.

The results of the evaluation of the five apartments selected for experiments are presented graphically as a group of five columns placed on the left in Figure 3. To the right, the same figure shows the results of evaluating the same apartments located in the same virtual house when the house is virtual moved to the central part of St. Petersburg and then to the central parts of Yekaterinburg and Perm. In a computational experiment, virtual house relocation is performed by replacing the values of the model's input parameters shown in Table 2 with the values of the input parameters shown in Table 3 and then in Tables 4 and 5 for Saint Petersburg, Yekaterinburg, and Perm, respectively.

As you can see in Figure 3, in all cities, apartment prices fall with a decrease in the number of rooms (square). The difference in the cost of a five-room Moscow apartment and a similar five-room Perm apartment is 196 percent. For four-room apartments, this difference is 263 per cent, for three-room apartments it is 270 per cent, for two-room apartments it is 267 percent, and for one-room apartments it is 250 percent.

Discussing the results of scenario forecasting presented in Figure 3, we note that they, in general, correctly reflect the specifics of the cities selected for the research. Moscow is the capital of the Russian Federation with a population of 12.5 million people (according to the 2019 data). In terms of wealth, income, investment, and other indicators, Moscow is significantly superior to all other cities in Russia. Saint Petersburg is the second largest city in the Russian Federation with a population of 5.4 million people. Yekaterinburg and Perm are lesser administrative and commercial and industrial centers with a population of 1.5 million people and 1.0 million people, respectively. Therefore, the cost of apartments in these cities is much lower than that in Moscow.

The next series of computer experiments is shown in Figures 4–7. Figure 4 shows the change in the cost of all five Moscow apartments with a virtual increase in their total square area while simultaneously increasing the proportion of living space and kitchen area. At the bottom of the same figure, it is shown how the unit cost per square meter of the total area of the apartments under consideration changes. As you can see from the picture, the cost of all five apartments increases with an increase in their square. However, the unit cost per square meter of apartment space is subject to slightly different laws. As can be seen from the lower graph of Figure 4, the highest specific cost per square meter in Moscow has a one-room apartment of minimum size–16 sq. m. It is also seen that the maximum cost of a two-room apartment is achieved with its area of 90 sq. m., that of three-room apartment is 100 sq. m., that of four-room apartment is 110 sq. m., and that of five-room apartment is 120 sq. m.

This interesting experimental fact seems to make sense for business representatives involved in planning housing construction in Moscow and should be taken into account in this respect.

Analyzing the following figures (Figures 5–7), which show the results of similar computational experiments related to St. Petersburg (parameters of Table 3), Yekaterinburg (Table 4), and Perm (Table 5), we can see that, for all these cities, a one-room apartment with a square area of 16 sq.m. is still a winner from the point of view of the developer. The cost per square meter of its square area is still the maximum.

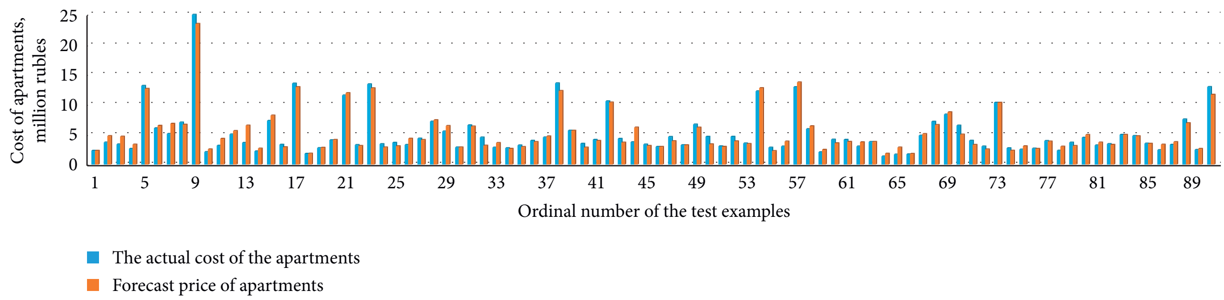


FIGURE 2: Neural network testing results: comparison of declared (actual) and estimated apartment values using the neural network.

TABLE 1: Input parameters of the model that characterize the apartments under consideration.

Apartment number	Number of rooms	Total square, sq. m	Living square, sq. m	Kitchen square, sq. m.
1	1	30	18	6
2	2	55	32	9
3	3	80	50	12
4	4	106	70	14
5	5	145	75	16

TABLE 2: Input parameters of the model that characterize a house in Moscow, its geographical location, evaluation time, and the corresponding economic situation in the world, country, and region.

Parameter	Value
City index	1
Latitude	55.75211 degrees
Longitude	37.59398 degrees
Prestige level	0.95
Type of house walls	7
Floor	10
Number of floors in the house	16
Season	1
Dollar rate	63.62 roubles
Brent oil price	3,530 roubles
GDP	109,361 billion roubles
Housing construction in the year preceding the assessment	5,025 thousand square meters
Mortgage loans in the previous year	389.842 billion roubles

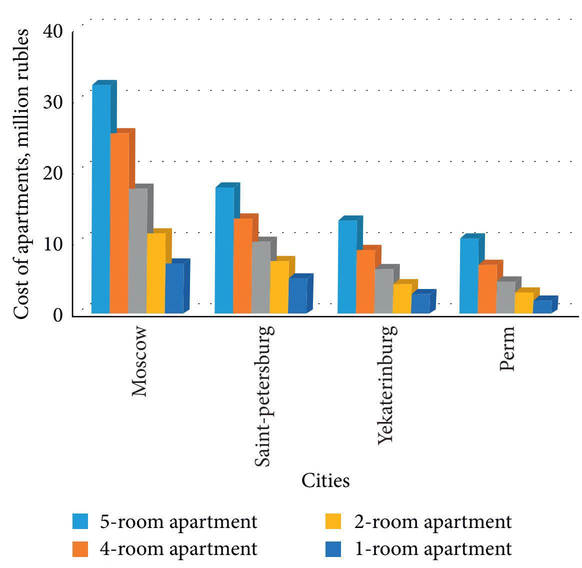


FIGURE 3: Results of computer experiments on virtual relocation of a residential building from Moscow to St. Petersburg, Yekaterinburg, and Perm.

Table 3: Input parameters of the model that characterize a house in Saint Petersburg, its geographical location, evaluation time, and the corresponding economic situation in the world, country, and region.

Parameter	Value
City index	2
Latitude	59.936927 degrees
Longitude	30.315257 degrees
Prestige level	0.95
Type of house walls	7
Floor	10
Number of floors in the house	16
Season	1
Dollar rate	63.62 roubles
Brent oil price	3,530 roubles
GDP	109,361 billion roubles
Housing construction in the year preceding the assessment	3,471.2 thousand square meters
Mortgage loans in the previous year	193.359 billion roubles

Table 4: Input parameters of the model that characterize a house in Yekaterinburg, its geographical location, evaluation time, and the corresponding economic situation in the world, country, and region.

Parameter	Value
City index	3
Latitude	56.839114 degrees
Longitude	60.606952 degrees
Prestige level	0.95
Type of house walls	7
Floor	10
Number of floors in the house	16
Season	1
Dollar rate	63.62 roubles
Brent oil price	3,530 roubles
GDP	109,361 billion roubles
Housing construction in the year preceding the assessment	2391.1 thousand square meters
Mortgage loans in the previous year	89.816 billion roubles

Table 5: Input parameters of the model that characterize a house in Perm, its geographical location, evaluation time, and the corresponding economic situation in the world, country, and region.

Parameter	Value
City index	4
Latitude	58.013225 degrees
Longitude	56.2459 degrees
Prestige level	0.95
Type of house walls	7
Floor	10
Number of floors in the house	16
Season	1
Dollar rate	63.62 roubles
Brent oil price	3,530 roubles
GDP	109,361 billion roubles
Housing construction in the year preceding the assessment	1112.929 thousand square meters
Mortgage loans in the previous year	44,908 billion roubles

It can also be noted that, in the conditions of the city of St. Petersburg, the cost of one square meter of two-, three-, four- and five-room apartments does not depend much on their total square area and differs by no more than 25 percent. For Yekaterinburg and Perm, this difference is significantly greater and reaches 50 percent. For these two cities, the two-room apartments with the highest cost of square meter are the apartments with a total square area of 30 square meters. Among three-room apartments, the highest price is for apartment of 110 square meters; among

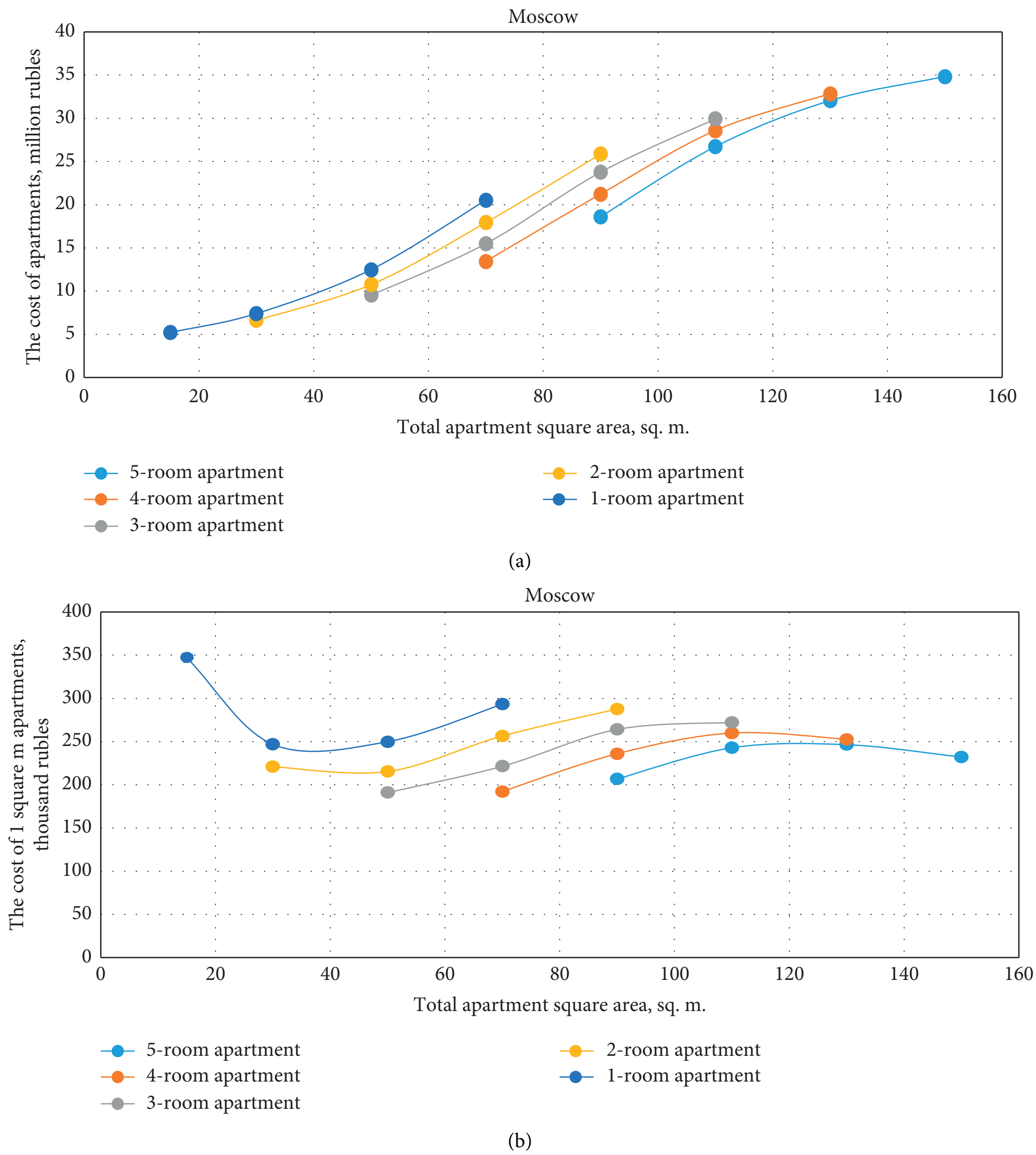


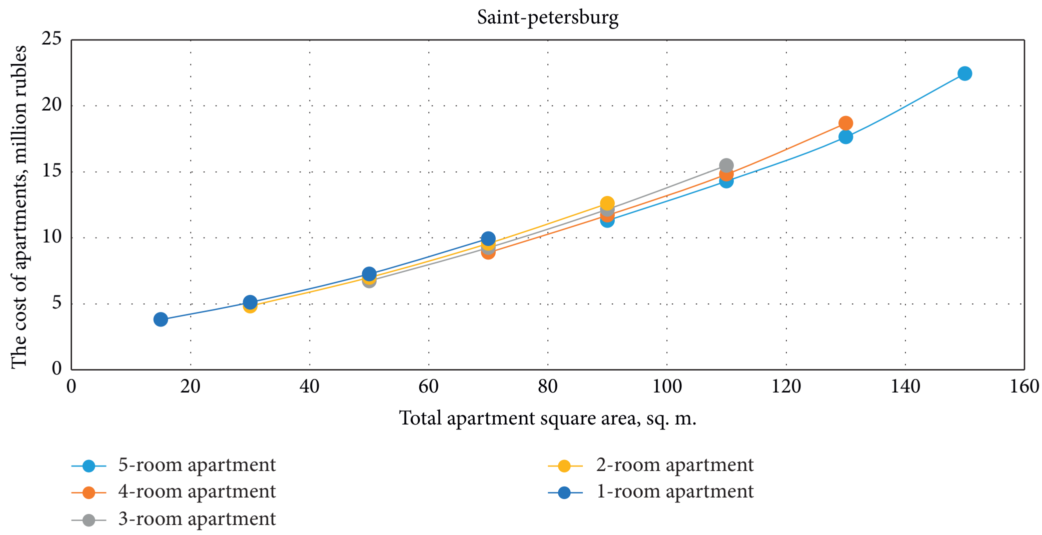
Figure 4: Influence of the square area of Moscow apartments on their cost (a) and on the unit cost of one square meter (b).

four-room apartments the highest price is 130 sq. m.; and among five-room apartments it is 150 sq. m.

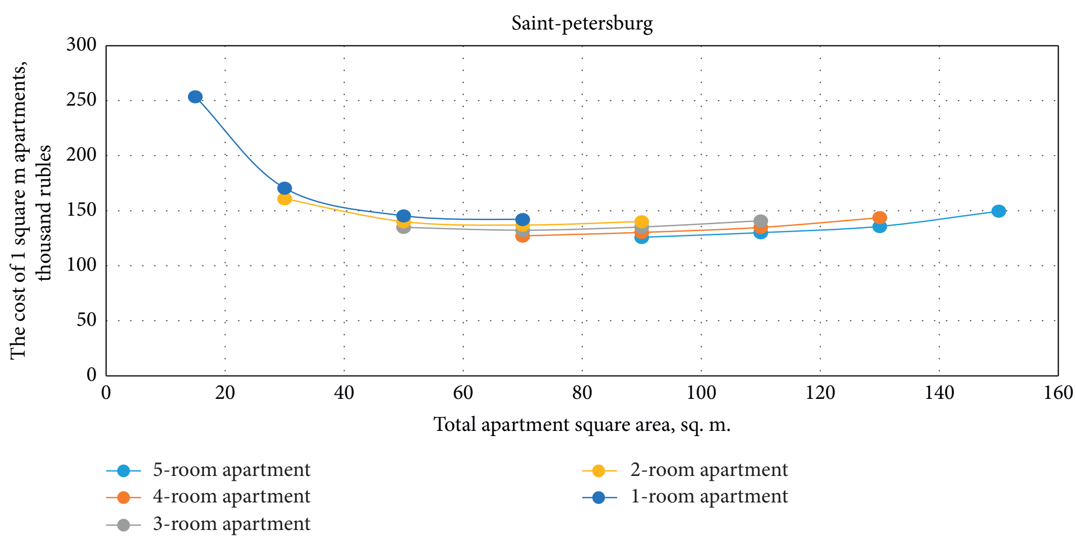
This experimental fact is of practical interest to developers in Yekaterinburg and Perm.

As already mentioned, the results of our research can be useful in the design of urban housing construction. However, it should be emphasized that the presented analysis was performed only for some urban apartments in the Russian Federation and only for the houses located in the central districts of Moscow, St. Petersburg, Yekaterinburg, and Perm. Naturally, the results will be different for apartments demonstrating different characteristics and locations in other cities. However, they can be obtained using the proposed neural network model which can be accessed by the following link: http://myann.uk.host1381882.serv68.hostland.pro/en.html.

The next series of computer experiments, the results of which are presented in Figure 8, is devoted to the study of the impact of mortgage lending on the cost of residential real estate in the four cities of the Russian Federation considered above. These experiments were performed by virtually increasing of the input parameter “mortgage loans in the year preceding the assessment” when observing the output parameter of the model, i.e., when observing the projected cost



(a)



(b)

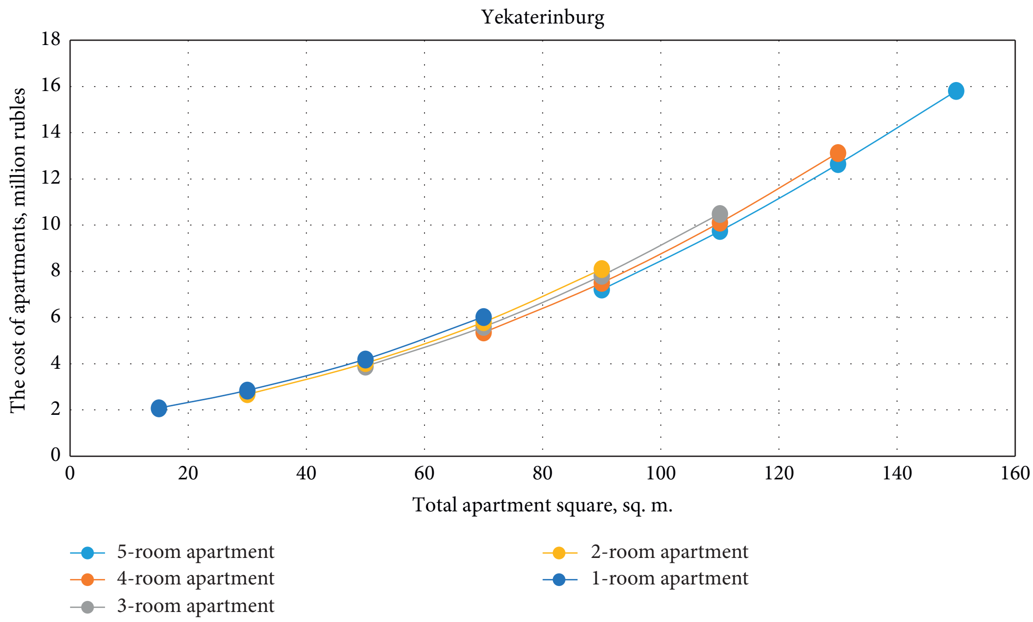
Figure 5: Influence of the square area of St. Petersburg apartments on their cost (a) and on the specific cost of one square meter (b).

of apartments. All other input parameters of the model, shown in Tables 1–5, remained unchanged.

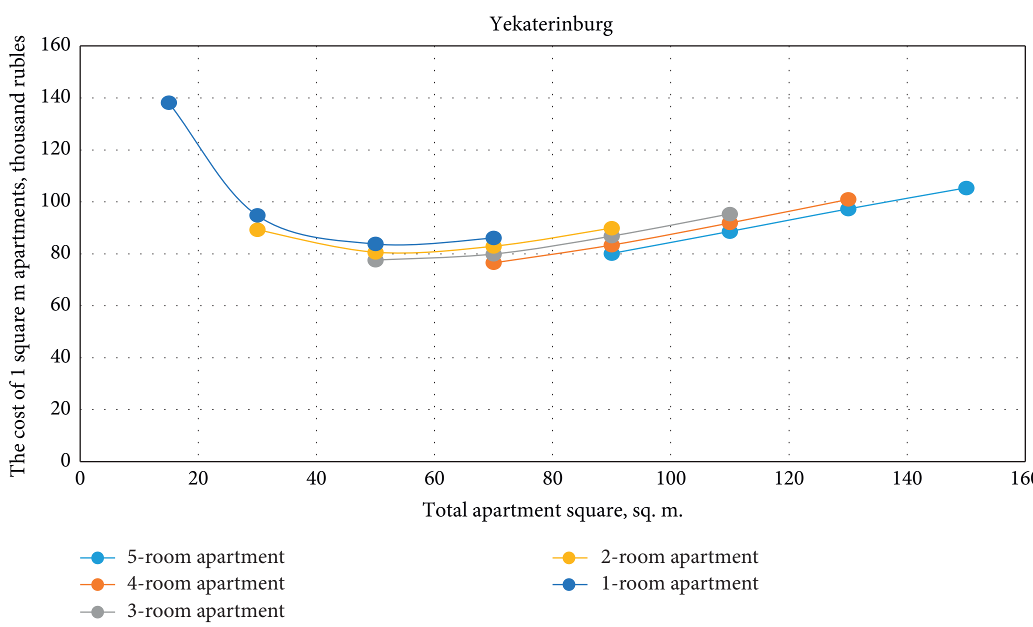
As can be seen in Figure 8, the virtual increase in mortgage lending in all cities demonstrates an increase in the cost of all types of apartments. However, the nature and rate of growth of their cost in different cities differ significantly. So, according to the figure, the increase in the volume of mortgage lending by 20% in Moscow leads to an increase in the cost of a five-room apartment by 4%, four-room apartment by 15%, three-room apartment by 37%, two-room apartment by 55%, and one-room apartment by 58%. The same increase in the volume of mortgage lending in St. Petersburg will increase the cost of the five-room apartment by 7%, four-room apartment by 4%, three-room apartment by 3%, two-room apartment by 2%, and one-room apartment by 1%. In Yekaterinburg and Perm, the increase in mortgage lending will have virtually no effect on the cost of the apartments under consideration.

Based on these forecasts, we can conclude that, in Moscow, there is an urgent need for residents with relatively low incomes to purchase apartments. Having purchased mortgage loans, they will massively buy cheap apartments, thus raising the demand and prices. The presence of the described demand in Moscow is a consequence of the process of mass migration of the young part of the working-age population of Russia to its capital.

Figure 9 shows the results of scenario forecasting of the impact of the country's GDP on the housing market of the cities under consideration. As can be seen from the figure, projected apartment values increase with the GDP growth,



(a)



(b)

Figure 6: Influence of the square area of Yekaterinburg apartments on their cost (a) and on the specific cost of one square meter (b).

with the lowest growth rate observed in Moscow and the highest growth rate observed in Perm.

Figure 10 shows the results of scenario forecasting of the housing market in Russian cities in the event of a change in the exchange rate of the US dollar against the Russian ruble. As you can see in the figure, the behavior of the curves differs slightly for different cities. However, in all cases, fluctuations in the US dollar exchange rate slightly affect the apartment values of Russian cities.

If the apartment values are not expressed in the national currency and converted to US dollars, the picture is completely different. The apartment values fall with the growth of the US dollar as shown in Figure 11. Besides, as the US dollar exchange rate increases, the rate of falling apartment prices gradually slows down, which is especially noticeable in the case of one-room, two-room, and three-room apartments.

Summing up the discussions on the results of virtual experiments shown in Figures 3–11, it should be noted that for

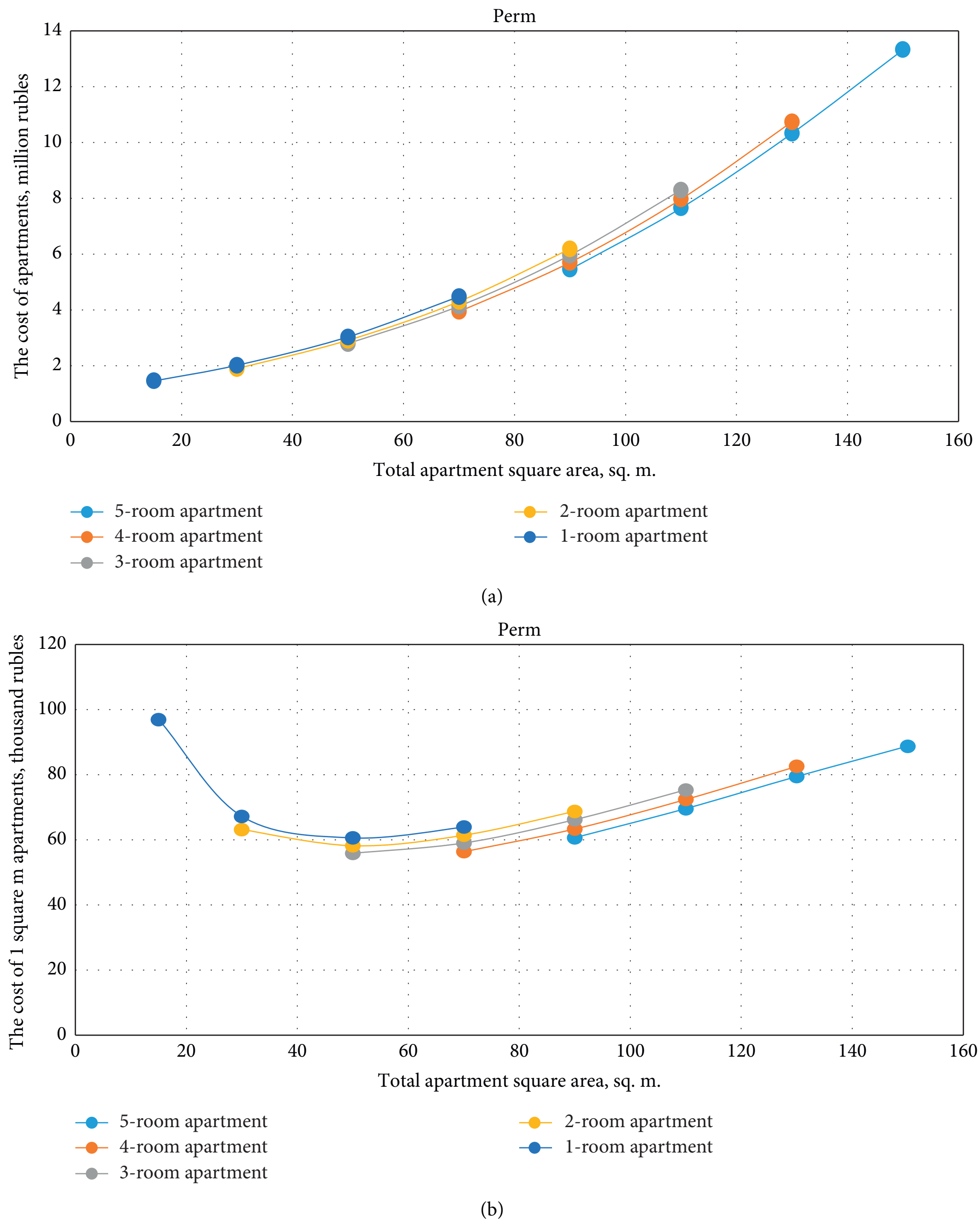


FIGURE 7: Influence of the square area of Perm apartments on their cost (a) and on the specific cost of one square meter (b).

the revealed peculiarities of the behavior of real estate markets do not always manage to give simple explanations, especially to confirm their reliability through natural experiments. However, it can be stated that the discovered regularities do not cause any objections from the expert practitioners. In addition, the relatively low mathematical error of the neural network calculated by formula (3), as well as the verification of the results of the neural network model on the test set (see Figure 1), confirms the real existence of the revealed regularities.

It should be added that in the practice of neural network modeling (e.g., [2–9]) the author's team repeatedly revealed regularities of different subject areas and made predictions that were explained and experimentally confirmed only some time after the publication of the results.

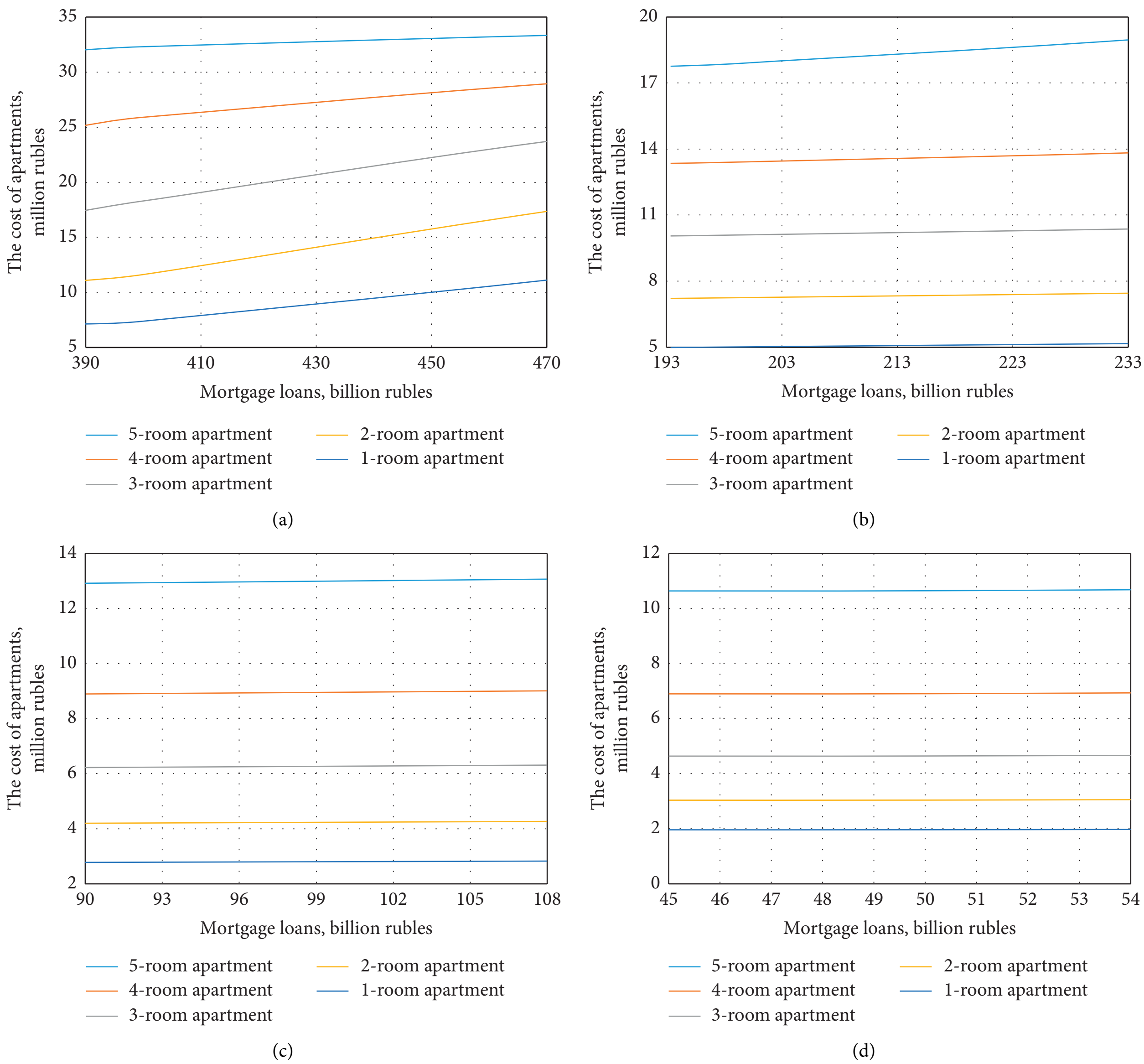


Figure 8: Forecast of the dependence of apartment costs in Russian cities on the volume of mortgage lending. (a) Moscow, (b) Saint Petersburg, (c) Yekaterinburg, and (d) Perm.

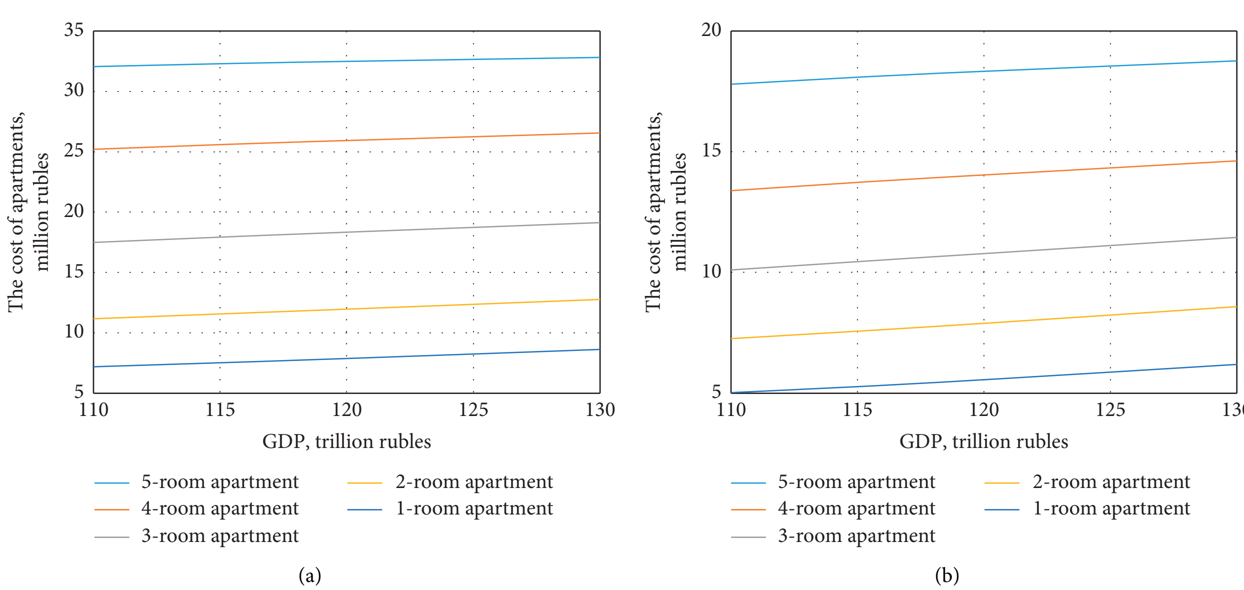


Figure 9: Continued.

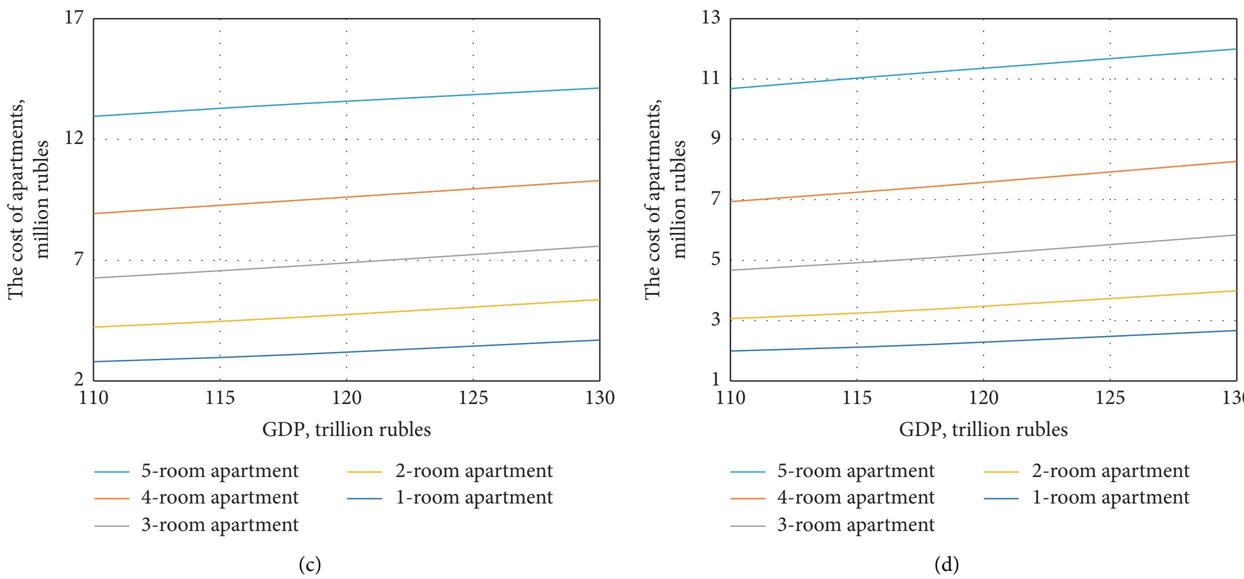


Figure 9: Forecast of the dependence of apartment costs in Russian cities on the country's GDP. (a) Moscow, (b) Saint Petersburg, (c) Yekaterinburg, and (d) Perm.

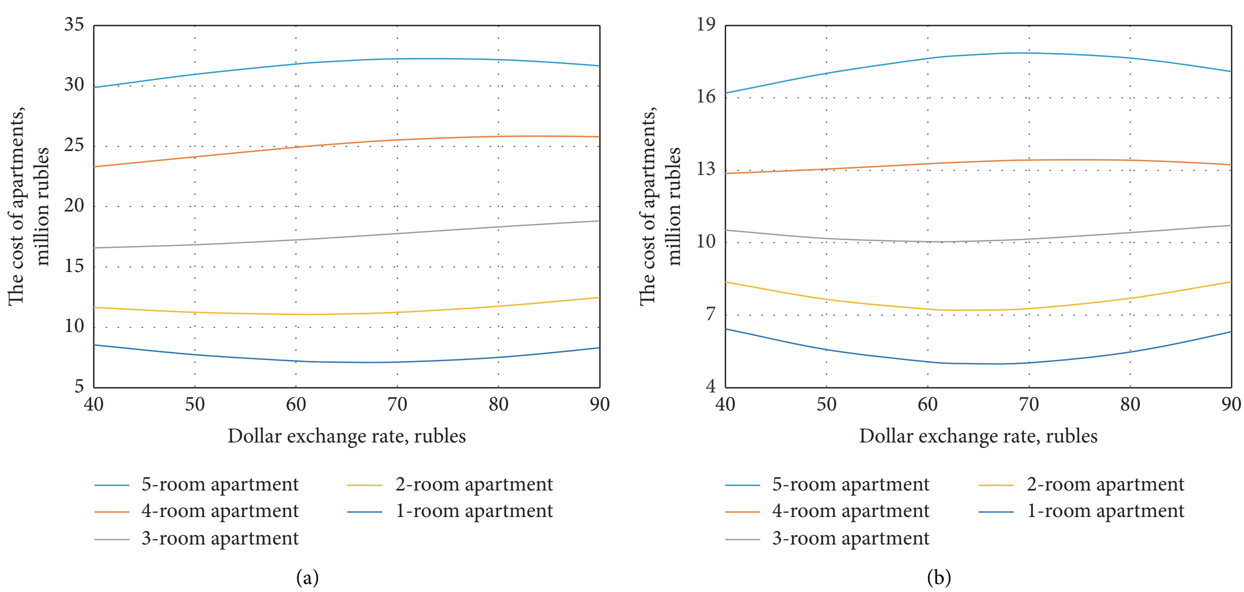


Figure 10: Continued.

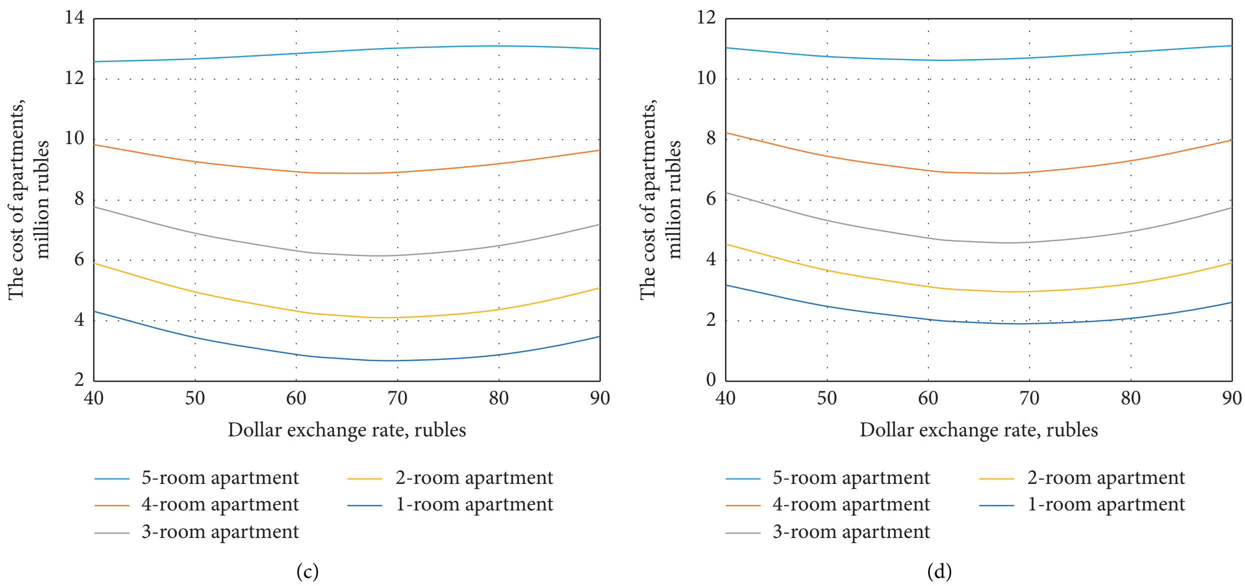


Figure 10: Scenario forecast of the dependence of apartment costs in Russian cities on the exchange rate of the US dollar against the Russian rubble. (a) Moscow, (b) Saint Petersburg, (c) Yekaterinburg, and (d) Perm.

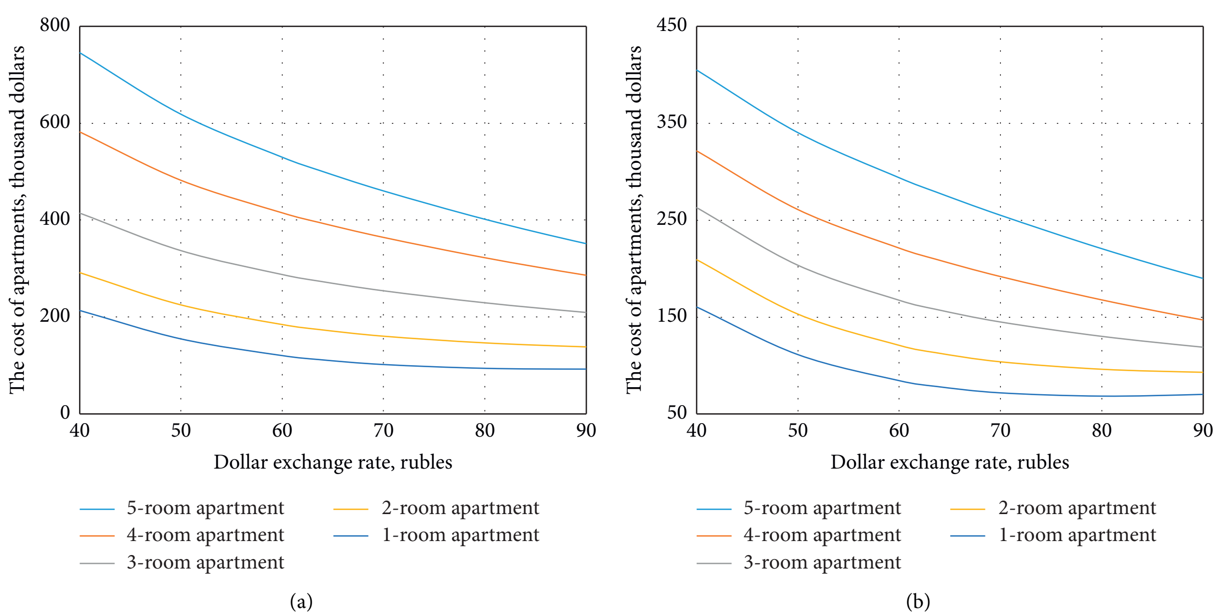


Figure 11: Continued.

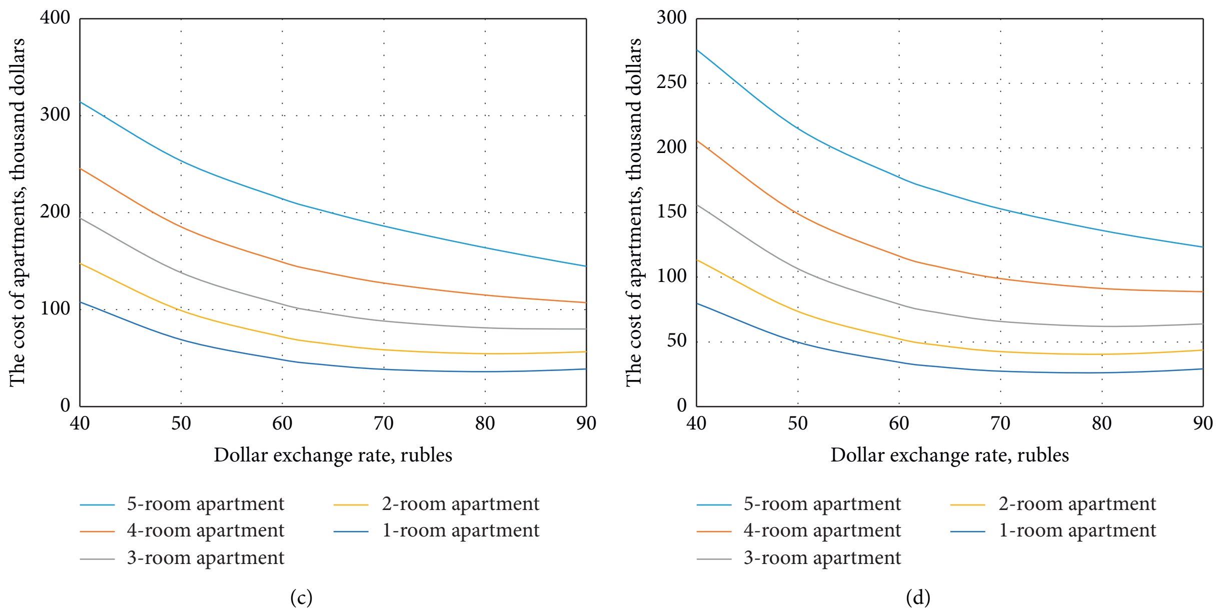


Figure 11: Scenario forecast of the dependence of apartment costs expressed in US dollars on the exchange rate of the US dollar against the Russian ruble. (a) Moscow, (b) Saint Petersburg, (c) Yekaterinburg, and (d) Perm.

4. Conclusion

A method is proposed, and a comprehensive economic-mathematical model is developed for the mass appraisal of residential real estate in Russian cities, taking into account their geographical location, construction, and operational parameters and economic parameters that change over time, characterizing the economy in the region, country, and the world. A distinctive feature of the model is the capability of applying to many cities at once, as well as the capability of self-adapting to the constantly changing economic situation, which eliminates the need for updating the model frequently. This is the scientific novelty and the competitive advantage of the approach we are developing.

The model-based scenario forecasting of the Russian urban real estate markets has shown that the market value of various apartments located in different cities reacts differently to virtual changes in their area, the volume of mortgage lending in the regions, the country's GDP, and the changes in the exchange rate of the US dollar against the local currency.

The model can be useful for government agencies involved in managing the urban real estate market and property tax issues and for construction companies enabling them to perform market forecasts and optimize their construction business. In the future, it is planned to expand the scope of the model to other cities and other countries.

Data Availability

Data for training neural networks was collected from various open sources, for example, https://upn.ru/newspaper.htm. Neural networks were generated, optimized, trained, and tested using software found in [40]. This software is created by the authors of this article. This software is freely downloadable as part of laboratory works from the website http://www.LbAi.ru. The results of the real estate market research presented in Figures 3–11 can be obtained by contacting our service: http://myann.uk.host1381882.serv68.hostland.pro/en.html. In addition, the reader can use this service to evaluate the value of the apartment of interest, as well as performing additional research on the behavior of real estate markets, similar to those shown in Figures 3–11.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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References

[1] J. Ćetković, S. Lakić, M. Lazarevska et al., "Assessment of the real estate market value in the European market by artificial neural networks application," *Complexity*, vol. 2018, 10 pages, 2018.

[2] L. N. Yasnitsky, Z. I. Sichinava, and F. M. Cherepanov, *Neyrosetevoy Detektor Lzhi: Printsipy Postroyeniya I Opyt Razrabotki [Neural Network Lie Detector: Principles and Development Experience]*, Lap Lambert Academic Publishing GmbH & Co. KG., Saarbrucken, Germany, 2012.

[3] L. N. Yasnitsky, S. V. Vauleva, D. N. Safonova, and F. M. Cherepanov, "The use of artificial intelligence methods in the analysis of serial killers' personal characteristics," *Criminology Journal of Baikal National University of Economics and Law*, vol. 9, no. 3, pp. 423–430, 2015.

[4] L. N. Yasnitsky, A. A. Dumler, and F. M. Cherepanov, "Dynamic artificial neural networks as basis for medicine revolution," *Advances in Intelligent Systems and Computing*, vol. 850, pp. 351–358, 2019.

[5] L. N. Yasnitsky, A. A. Dumler, A. N. Poleshchuk, C. V. Bogdanov, and F. M. Cherepanov, "Artificial neural networks for obtaining new medical knowledge: diagnostics and prediction of cardiovascular disease progression," *Biology and Medicine*, vol. 7, no. 2, p. 8, 2015.

[6] L. N. Yasnitsky, "Artificial intelligence and medicine: history, current state, and forecasts for the future," *Current Hypertension Reviews*, vol. 16, no. 3, pp. 210–215, 2021.

[7] L. N. Yasnitsky, I. A. Mitrofanov, and M. V. Immis, "Intelligent system for prediction box office of the film," in *Lecture Notes in Networks and Systems*, vol. 78, pp. 18–25, Springer, Berlin, Germany, 2020.

[8] L. Yasnitsky, D. Ivanov, and E. Lipatova, "Neural network designed to estimate probability of bank bankruptcies," *Biznes Informatika-Business Informatics*, vol. 29, no. 3, pp. 49–56, 2014.

[9] L. N. Yasnitsky, *Intellektualnyye Sistemy [Intelligent Systems]*, Laboratory of knowledge, Moscow, Russia, 2016.

[10] M. J. Hefferan and T. Boyd, "Property taxation and mass appraisal valuations in Australia - adapting to a new environment," *Property Management*, vol. 28, no. 3, pp. 149–162, 2010.

[11] P. Davis, W. J. McCluskey, T. V. Grissom, and M. McCord, "An empirical analysis of simplified valuation approaches for residential property tax purposes," *Property Management*, vol. 30, no. 3, pp. 232–254, 2012.

[12] B. Manganelli, P. Pontrandolfi, A. Azzato, and B. Murgante, "Using geographically weighted regression for housing market segmentation," *International Journal of Business Intelligence and Data Mining*, vol. 9, no. 2, pp. 161–177, 2014.

[13] O. S. Oshodi, W. D. Thwala, T. B. Odubiyi, R. B. Abidoye, and C. O. Aigbavboa, "Using neural network model to estimate the rental price of residential properties," *Journal of Financial Management of Property and Construction*, vol. 24, no. 2, pp. 217–230, 2019.

[14] R. B. Abidoye, A. P. C. Chan, F. A. Abidoye, and O. S. Oshodi, "Predicting property price index using artificial intelligence techniques: evidence from Hong Kong," *International Journal of Housing Markets and Analysis*, vol. 12, no. 6, pp. 1072–1092, 2019.

[15] Y. Xiao, *Hedonic Housing Price Theory Review*, Springer Geography, Berlin, Germany, 2017.

[16] R. A. Borst, "Artificial neural networks: the next modelling/calibration technology for the assessment community," *Property Tax Journal*, vol. 10, no. 1, pp. 69–94, 1991.

[17] D. P. Tay and D. K. Ho, "Artificial intelligence and the mass appraisal of residential apartments," *Journal of Property Valuation and Investment*, vol. 10, no. 2, pp. 525–540, 1991.

[18] A. Evans, H. James, and A. Collins, "Artificial neural networks: an application to residential valuation in the UK," *Journal of Property Valuation and Investment*, vol. 2, no. 11, pp. 195–204, 1991.

[19] A. Q. Do and G. Grudnitski, "A neural network approach to residential property appraisal," *The Real Estate Appraiser*, vol. 58, no. 3, pp. 38–45, 1992.

[20] R. A. Borst, "Artificial neural networks in mass appraisal," *Journal of Property Tax Assessment & Administration*, vol. 1, no. 2, pp. 5–15, 1995.

[21] W. J. McCluskey, K. Dyson, D. McFall, and S. Anand, "The mass appraisal of residential property in Northern Ireland," in *Computer Assisted Mass Appraisal Systems*Gower Publishers, London, UK, 1997.

[22] J. Greenwood and Z. Hercowitz, "The allocation of capital and time over the business cycle," *Journal of Political Economy*, vol. 99, no. 6, pp. 1188–1214, 1991.

[23] J. Guan, J. Zurada, and A. S. Levitan, "An adaptive neuro-fuzzy inference system based approach to real estate property assessment," *Journal of Real Estate Research*, vol. 30, no. 4, pp. 395–422, 2008.

[24] L. N. Yasnitsky, V. V. Bondar, S. N. Burdin et al., "Permskaya nauchnaya shkola iskusstvennogo intellekta I yeye innovatsionnyye proyekty [perm scientific school of artificial intelligence and its innovative projects]," in *Regular and Chaotic Dynamics*Scientific Publishing Center, Moscow-Izhevsk, Russia, 2008, https://cloud.mail.ru/public/8V5o/VShaP3Tey.

[25] V. Kontrimas and A. Verikas, "The mass appraisal of the real estate by computational intelligence," *Applied Soft Computing Journal*, vol. 11, no. 1, pp. 443–448, 2011.

[26] Y. H. Mao, M. B. Zhang, and N. B. Yao, "Hangzhou housing demand forecasting model based on BP neural network of genetic algorithm optimization," *Applied Mechanics and Materials*, vol. 587-589, pp. 37–41, 2014.

[27] J. Guan, D. Shi, J. M. Zurada, and A. S. Levitan, "Analyzing massive data sets: an adaptive fuzzy neural approach for prediction, with a real estate illustration," *Journal of Organizational Computing and Electronic Commerce*, vol. 24, no. 1, pp. 94–112, 2014.

[28] H. Zhang, S. Gao, M. J. Seiler, and Y. Zhang, "Identification of real estate cycles in China based on artificial neural networks," *Journal of Real Estate Literature*, vol. 23, no. 1, pp. 67–83, 2015.

[29] R. B. Abidoye and A. P. C. Chan, "Modelling property values in Nigeria using artificial neural network," *Journal of Property Research*, vol. 34, no. 1, pp. 36–53, 2017.

[30] W. Mccluskey, P. Davis, M. Haran, M. Mccord, and D. Mcilhatton, "The potential of artificial neural networks in mass appraisal: the case revisited," *Journal of Financial Management of Property and Construction*, vol. 17, no. 3, pp. 274–292, 2012.

[31] W. J. McCluskey, M. McCord, P. T. Davis, M. Haran, and D. McIlhatton, "Prediction accuracy in mass appraisal: a comparison of modern approaches," *Journal of Property Research*, vol. 30, no. 4, pp. 239–265, 2013.

[32] R. B. Abidoye and A. P. C. Chan, "Improving property valuation accuracy: a comparison of hedonic pricing model and artificial neural network," *Pacific Rim Property Research Journal*, vol. 24, no. 1, pp. 71–83, 2018.

[33] S. Sandbhor and N. B. Chaphalkar, "Impact of outlier detection on neural networks based property value prediction," *Advances in Intelligent Systems and Computing*, vol. 862, pp. 481–495, 2019.

[34] L. N. Yasnitsky, "Algorithm for searching and analyzing abnormal observations of statistical information based on the Arnold–Kolmogorov–Hecht-Nielsen theorem," *International*

Journal of Advanced Trends in Computer Science and Engineering, vol. 9, no. 2, 2020.

[35] C. M. Becker and A. R. Morrison, "Chapter 43 urbanization in transforming economies," *Handbook of Regional and Urban Economics*, vol. 3, pp. 1673–1790, 1999.

[36] A. O. Alexeev, I. E. Alexeeva, L. N. Yasnitsky, and V. L. Yasnitsky, "Self-adaptive intelligent system for mass evaluation of real estate market in cities," *Advances in Intelligent Systems and Computing*, vol. 850, pp. 81–87, 2019.

[37] L. N. Yasnitsky and V. L. Yasnitsky, "Technique of design for integrated economic and mathematical model for mass appraisal of real estate property. study case of Yekaterinburg housing market," *Journal of Applied Economic Sciences*, vol. 11, no. 8, pp. 1519–1530, 2016.

[38] S. D. Kulik, "Factographic information retrieval for biological objects," *Advances in Intelligent Systems and Computing*, vol. 948, pp. 277–282, 2020.

[39] M. Riedmiller and H. Braun, "A direct adaptive method for faster backpropagation learning: the RPROP algoritm," in *Proceedings of the IEEE International Conference on Neural Networks (ICNN-93)*, pp. 586–591, IEEE, San Francisco, CA, USA, April 1993.

[40] F. M. Cherepanov and L. N. Yasnitsky, *Neurostimulator 5.0: Certificate of Rospatent on State Registration of Computer Programs No. 2014618208 Dated 12.07.2014*, Cloud.Mail.Ru, Moscow, Russia, 2020, https://cloud.mail.ru/public/Jr29/RzgouF6b9.