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Research Article

Evolutionary Neural Simulation of Import Substitution in the Radio Electronics Industry in the Regions Using Adaptive Network-Based Fuzzy Inference System

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Abstract: The aim of this study is evolutionary neural simulation concerning the possibility of import substitution in radio electronics industry (REI) in some specific regions. The process enables the analysis to identify regions that are leaders in terms of import substitution opportunities and regions with prospects for the future development of REI sector in the territory. During this study, a method of evolutionary neural simulation of import substitution opportunities in the regional radio electronics industry was developed. In the analysis, the target functions were, 1) export of technologies (receipt of funds), and 2) import of technologies (disbursement of funds), respectively. Concerning each target function, neural network for quasi-time series from 2012 to 2022 for 83 regions of Russia was built and trained in *Matlab* software program. The result showed that ANFIS-PSO algorithm produced a less mean absolute percentage error (MAPE=19.22% for target 1 and MAPE=13.25% for target 2. Similarly, the analysis showed the result on the new 2023 data compared to the conventional ANFIS (MAPE=20.88% for target 1 and MAPE=14.03% for target 2) as well as Lavenberg-Marquardt method (MAPE=40.3% for target 1), respectively. Neural network trained with ANFIS and PSO algorithms on the data from 2012 to 2022 allowed the study to conclude that the leading regions in terms of import substitution opportunities in REI sector were Moscow as well as St. Petersburg. At the same time, the Moscow and Nizhny Novgorod Regions had prospects for the development of this industry sector.

Keywords: Adaptive network-based fuzzy inference system; Particle swarm optimization; Radio electronics industry; Time series prediction

1. Introduction

Import substitution in major national industry is a process that plays a crucial role in driving societal development. Radio electronics industry (REI) in particular shows a significant imbalance, with technology exports exceeding import. This imbalance has far-reaching implications for REI and similar industry that depend on advanced radio-electronics and information technologies to

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drive innovation as well as progress. In this context, the study will examine several methods that offer effective ways to model the development of REI sector.

The study by Trofimov and Ganin (2019) shows the role of business accelerator as a tool for identifying and applying technological solutions in the field of radio electronics to improve the efficiency as well as competitiveness of industry members. As a variant of effective use of the existing situation in the radio electronics industry of St. Petersburg (the existing suboptimal distribution of the main equipment), Klushantsev (2020) proposed a software platform that incorporated the production equipment of enterprises into a single information network to optimize its load. Balychev et al. (2020) developed a model for optimizing the diversification program of REI enterprises producing civilian industry products. Additionally, the model was adapted to high-variety production and different types of market.

Simulating import substitution in REI sector is a challenging task due to the reliance on highly noisy data, where assessing the noise is a complex process (Kusumalestari et al., 2024). Conventional neural network methods such as Lavenberg-Marquardt method or Bayesian regularization (Yashin et al., 2023) do not allow the study to train neural network with sufficient quality. For this reason, the study will use Adaptive Network-Based Fuzzy Inference System (ANFIS). Since the invention of the model, it has passed through some useful modifications to refine the results of neural simulation.

Adebowale et al. (2019) introduced a strong ANFIS-based framework that incorporated features from text, images, and frames to detect as well as prevent web phishing, achieving an impressive accuracy of 98.3%. Building on the potential of adaptive neuro-fuzzy systems, (Yadav et al., 2022) discussed how such predictive soft computing methods specifically ANFIS could be effectively applied to estimate the health impacts of prolonged noise pollution exposure. In another application, Sareen et al. (2023) used ANFIS for solar irradiance forecasting. The study fed the system with inputs derived from three different decomposition algorithms, selected based on Pearson's Correlation Coefficient (PCC). This method led to highly accurate predictions, showing mean absolute percentage error (MAPE) of less than 2%.

Imran and Alsuhaibani (2019) used ANFIS to classify retinal damage caused by diabetic retinopathy (DR) into four categories, namely low, moderate, high, and not damaged. The study found that selecting only the most highly correlated features improved performance, with the model reaching 84.09% accuracy, a root-mean-square error (RMSE) of 0.476, and a Kappa coefficient of 0.79. Consequently, when principal component analysis (PCA) was used for feature reduction, performance dropped to 65.9% accuracy, with an RMSE of 0.738 and a Kappa of 0.544. Focusing on industry applications, Nwanwe and Duru (2023) proposed a white-box ANFIS model for real-time prediction of multiphase flowing bottom-hole pressure (FBHP) in wellbores. The study first optimized a black-box ANFIS model and then translated it into a white-box format with Gaussian as well as linear output membership functions. By tuning the premise and consequence parameters, the model successfully emulated the expected influence of input parameters on FBHP in trend analyses. In another hybrid method, Mohammadi et al. (2020), combined ANFIS with the shuffled frog-leaping algorithm (SFLA). The ANFIS-SFLA model outperformed the traditional ANFIS setup across multiple metrics, achieving $R^2 = 0.88$, NS = 0.88, RMSE = 142.30 m^3/s, MAE = 88.94 m^3/s, and MAPE = 35.19%. In comparison, the classic ANFIS model produced a lower performance with $R^2 = 0.83$ and MAPE = 45.97%.

Rajabzadeh et al. (2023) evaluated the use of ANFIS for diagnosing coronary artery disease and compared its performance with flexible discriminant analysis (FDA) and logistic regression (LR). The results showed ANFIS as the most accurate method among the three. Relating to this discussion, Semih (2020) explored the application of ANFIS in environmental modeling by predicting sea surface temperatures (SST) in the Çanakkale Strait. Among several models tested, ANFIS-SC4 variant delivered the highest correlation (0.96) between observed and predicted SST values. Both the grid partitioning (ANFIS-GP) and subtractive clustering (ANFIS-SC) methods were applied using Gaussian membership functions to build the fuzzy inference systems. Turning to financial technology, Asemi et al. (2023) designed an adaptive neuro-fuzzy inference recommender system that used customer feedback to provide personalized investment recommendations. The model offered a fresh perspective for investment firms, individual investors, and fund managers in making informed decisions. In the renewable energy sector, Kaur et al. (2021), applied ANFIS to maximize power extraction from non-linear photovoltaic (PV) modules. The simulation results showed efficient and reliable power-tracking performance.

Kamal et al. (2018) proposed a novel architecture combining ANFIS with long short-term memory (LSTM), a form of recurrent neural network, for improved prediction tasks. This architecture incorporated rule-based simplification and constrained learning, which (Rajab, 2019) later showed to significantly improve the balance between accuracy and model interpretability. Yaseen et al. (2018) also contributed to hybrid model development by incorporating ANFIS with Firefly optimization algorithm (ANFIS-FFA) for monthly rainfall prediction. The results confirmed the superior performance of the hybrid model over standard ANFIS. Lastly, Abbas et al. (2022) showed the effective use of ANFIS in non-intrusive load monitoring (NILM). The hybrid method offered better accuracy than existing procedures, marking a significant advancement in smart energy monitoring systems. However, the most accurate results with ANFIS learning algorithm are obtained when network it is augmented through an evolutionary algorithm to optimize error.

Chopra et al. (2021) observed that the performance of a standard ANFIS architecture improved significantly when increased with metaheuristic methods, particularly when these were moderated by natural algorithms through careful calibration and parameter tuning. Similarly, Oladipo and Sun (2023) introduced a hybrid model named GA–ANFIS–FCM—which incorporated fuzzy c-means clustering, a genetic algorithm (GA), and ANFIS to model electricity consumption across districts in Lagos, Nigeria. The study showed the potential of the model as a reliable energy forecasting tool. Karaboga and Kaya (2018) explored both heuristic and hybrid methods for training ANFIS, aiming to guide authors in selecting effective procedures. In another significant analysis, Khosravi et al. (2018) proposed three novel hybrid optimization models for flood control in Kharaz watershed of Iran. These models combined ANFIS with cultural algorithms (ANFIS-CA), bee colony algorithms (ANFIS-BA), and invasive weed optimization (ANFIS-IWO), signifying improved control and prediction capabilities.

Ahmadlou et al. (2019) also leveraged hybrid methods by combining ANFIS with biogeography-based optimization (BBO) and bee colony algorithm (BA) to map flood susceptibility in parts of Iran. Equally, Elaziz et al. (2019) introduced an improved ANFIS model using Crow Search Algorithm (CSA) to predict heat transfer fluctuation coefficients. The results showed that ANFIS-CSA was particularly effective in modeling non-linear relationships between input and output variables. Jaafari et al. (2019) proposed two hybrid intelligence models that combined ANFIS with grey wolf optimizer (GWO) and BBO algorithms for strong landslide susceptibility estimation. Moreover, the strength of the model was validated through extensive testing across different training and validation datasets. In the field of robotics, Lazreg and Benamrane (2019) developed an intelligent navigation system for mobile robots, combining ANFIS with ant colony algorithm (ACOr). The system showed adaptive navigation capabilities in varied and dynamic environments.

Abdullah et al. (2019) introduced a predictive model called WT-ANFIS-HFPSO, which combined wavelet transform (WT), ANFIS, and a hybrid of firefly and particle swarm optimization (HFPSO). In comparative performance analyses, this hybrid model showed superior results in statistical error metrics. Karaboga and Kaya (2019), expanded ANFIS training methods by applying an adaptive and hybrid artificial bee colony algorithm (aABC), a variant of the standard ABC algorithm. The results showed that aABC outperformed traditional optimization methods, including GA and PSO, in training ANFIS to identify non-linear static systems.

Kumar et al. (2020) proposed a feature extraction method using neural network, classified through a hybrid bat algorithm combined with an ANFIS classifier (HBA–ANFIS). Farzaneh (2020) developed an ANFIS model optimized using a modified firefly algorithm (MFO), improved with perturbation and observation (P&O), to track the maximum power point (MPP) in photovoltaic systems. This method significantly increased MPP tracking speed across varying illumination conditions. Lastly, Azad et al. (2021) used two heuristic algorithms, namely GA and ant colony optimization for continuous domains (ACOR) to adjust the parameters of two soft computing models including ANFIS and least squares support vector machine (LSSVM).

This study improves ANFIS algorithm by incorporating the model with Particle Swarm Optimization (PSO) method to minimize neural network error more effectively. Moreover, several valuable advancements have been made in the development of the PSO method, which further supports the application in this context.

Ahmadianfar et al. (2022) introduced an incorporated method that combined an Adaptive Differential Evolution and Particle Swarm Optimization hybrid (A-DEPSO) with ANFIS model to predict electrical conductivity (EC). The results showed that the wavelet-based ANFIS-A-DEPSO model significantly improved the accuracy of EC predictions. In particular, the version using the Dmey wavelet—W-ANFIS-A-DEPSO outperformed other models, achieving strong results (R = 0.988, RMSE = 53.841, PI = 0.485). Building on similar optimization concepts, Jiang et al. (2024) developed a novel framework that incorporated ANFIS with a Bi-objective Particle Swarm Optimization (BOPSO) algorithm and sentiment analysis methods. The model was better able to identify optimal input parameters and address the limitations typically associated with ANFIS systems by incorporating BOPSO. In another related effort, Adhikari and Srirama (2019) proposed an energy-efficient, container-based scheduling strategy (EECS) designed for the rapid processing of both IoT and non-IoT tasks. The method used Accelerated Particle Swarm Optimization (APSO) algorithm to match tasks with the most suitable containers despite minimizing delay. Similarly, Al-Thanoon et al. (2019) introduced a hybrid algorithm combining Firefly Algorithm with Particle Swarm Optimization to modify parameters in Penalty Support Vector Machine (PSVM). This hybrid method leveraged the strengths of both algorithms, enabling the selection of the most relevant descriptors and achieving high classification performance. Lastly, Gad (2022) conducted a comprehensive review of studies published between 2017 and 2019, focusing on improvements, hybrid models, and variants of PSO. The technical taxonomy of the results covered a range of practical applications across sectors such as healthcare, environmental management, industry, commerce, and smart cities. In evaluating different PSO models, the stochastic inertia weight variant (Sto-IW PSO) is outstanding, consistently performing well across multiple evaluation metrics—different from several other algorithms that showed strength in only an area (De Guzman et al., 2024).

This study presents a method based on evolutionary neural network simulation to explore import substitution opportunities in the regional radio electronics industry (REI) in Russia. The model replicates the dynamics of import substitution across different regions by using neural network, enabling the identification of both current leaders and regions with strong potential for future development in REI sector.

2. Methods

In this study, import substitution process in REI sector across various Russian regions was simulated using neural network. Specifically, ANFIS and PSO algorithms were used for this purpose. The different stages included in neural simulation process were shown in Figure 1.

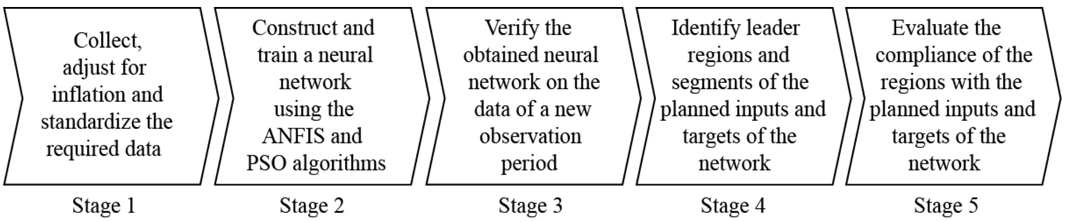


Figure 1 Stages of Neural Simulation of Import Substitution in the Regional Radio Electronics Industry

Stage 1 – Collect, adjust for inflation, and standardize the required data. At this stage, data covering the period from 2012 to 2023 including input variables and target functions for 83 Russian regions (based on figures from 2012-2013) were initially collected from the official website of Federal State Statistics Service (*www.gks.ru*):

a) Input 1 – value of fixed assets (informatization and communication) (RUB million) (x_1);
b) Input 2 – commissioning of fixed assets (informatization and communication) (RUB million) (x_2);
c) Input 3 – degree of wear and tear (informatization and communication) (%) (x_3);
d) Input 4 – turnover of organizations (informatization and communication) (RUB billion) (x_4);
e) Input 5 – costs of implementation and use of digital technologies (total) (RUB million) (x_5);
f) Input 6 – internal current expenditures on R&D (fundamental study) (RUB million) (x_6);
g) Input 7 – internal current expenditures on R&D (applied study) (RUB million) (x_7);
h) Input 8 – internal current expenditures on R&D (developments) (RUB million) (x_8);
i) Input 9 – expenditures on innovation activities (total) (RUB million) (x_9);
j) Input 10 – advanced manufacturing technologies used (total) (units) (x_{10});
k) Target 1 – technology exports (receipt of funds) (USD thousand) (y_1);
l) Target 2 – technology import (disbursement of funds) (USD thousand) (y_2).

The study had a data matrix of 996×12 dimension, where variables x_1 to x_4 were direct and the rest were indirect.

The ruble and US dollar figures were then adjusted for inflation. As a result, these figures were obtained in 2023 prices.

Following the process, the study recalculated the values of all input variables according to the formula

$$\tilde{x}_i = \frac{x_i - \mu}{\sigma},$$

where x_i was the previous value of i-th variable,
μ represented its mean value, and
σ signified its mean-square deviation.

This process was to ensure that the weights of variables in neural network were not distorted by different scales of variables. After the analysis, the data of the last year 2023 for model verification was not used but only the data from 2012 to 2022, i.e. the matrix of 913×12 dimension (83 regions multiplied by 11 years).

Stage 2 – Construct and train neural network using the ANFIS and PSO algorithms. During this phase, the study constructed and trained neural network for the quasi-time series from 2012 to 2022 for 83 regions of Russia. This process was performed in *Matlab* software program using software code of Heris (2015). This code included augmenting ANFIS algorithm with the evolutionary PSO algorithm to minimize the model training error. During the process, the study compared the results with the conventional ANFIS using software code of the previously mentioned author, Nonlinear Regression using ANFIS (URL: *https://yarpiz.com/301/ypfz101-nonlinear-regression-using-anfis*), Yarpiz, 2015. All these processes were conducted for both target functions, namely technology exports and import (y_1 and y_2).

Stage 3 – Verify the obtained neural network on the data of a new observation period. Data from 83 regions in 2023 were obtained as the data of the new observation period. According to study, each target function was predicted and the prediction was compared to the actual values in 2023. The quality of the prediction was assessed by using MAPE, which was expected to be minimal. Additionally, the performance of the model was evaluated by comparing the plots of target and predicted values for each target function.

Stage 4 – Identify leader regions and segments of the planned inputs and targets of network. During this stage, leader regions were identified for each target function. The actual (Target) and network-projected (Output) values were ranked for the entire quasi-time series from 2012 to 2022 to perform the process. The study selected those regions throughout the series that had a rank value less than 10 and had a low absolute percentage error (APE) – preferably less than 50%.

For the resulting leader regions, the standardized values of input parameters ($\overline{x_1, x_{10}}$) were converted back to the actual values by considering the inflation as the lowest, and the best values were then determined. These values were also determined for the target functions y_1 and y_2. Therefore, the analysis assigned the segments of the planned inputs and targets of the model.

Stage 5 – Evaluate the compliance of the regions with the planned inputs and targets of network. This stage determined how actual ranks of constituent entities of Russian Federation in 2022 and 2023 corresponded to segments of the planned parameters of the model. During the process, the regions whose actual values of technology exports as well as import were high and at the same time less than those of the leader regions in 2023 were determined first. The actual values of both target functions were then used to identify regions where technology exports exceeded imports and where these corresponded to segments related to the planned targets of the model.

Following the analysis, the analysis examined how the identified regions showed any potential for the future development of REI sector. This process was conducted by comparing the actual input parameter values ($\overline{x_1, x_{10}}$) in 2023 with the planned segments. When there were several such correspondences, such regions had designated prospects. Consequently, the task of assessing the opportunities for import substitution and development of REI sector in regions of the country was solved at this last stage.

3. Results and Discussion

This study assessed import substitution opportunities in REI sector in the Russian regions using the presented neural network model. For this purpose, the analysis used data from Federal State Statistics Service (*www.gks.ru*) from 2012 to 2023.

Stage 1. Having performed these procedures, all data from the last year 2023 were left for model verification and only data from 2012 to 2022 were analyzed. For example, the matrix of 913×12 dimension was shown in Table 1.

Table 1 Data for Neural Simulation

Regions	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	y_1	y_2
						2012						
Belgorod Region	-0.31	-0.27	-1.06	-0.15	-0.13	-0.22	-0.18	-0.27	-0.3	-0.45	0	0
Bryansk Region	-0.25	-0.22	-0.02	-0.1	-0.16	-0.25	-0.23	-0.29	-0.38	-0.51	0	471
…	…	…	…	…	…	…	…	…	…	…	…	…
Chukotka Area	-0.36	-0.24	-1.97	-0.17	-0.17	-0.26	-0.24	-0.29	-0.42	-0.82	0	0
						…						

Stage 2. This study trained neural network in *Matlab* software program for target 1 (technology exports, y_1) and target 2 (technology import, y_2), respectively. At the same time, the analysis reduced the dimension of the problem from 10 variables to 3 or 5 clusters to reduce the number of rules in ANFIS system. This significantly improved the accuracy of ANFIS system and allowed neural network to be trained in a better way.

Stage 3. Table 2 compared the results of pure ANFIS and ANFIS combined with PSO in minimizing network error during the verification stage using 2023 data that were new to network. The results of the classical Levenberg-Marquardt method for training neural network were also presented there. From the data in Table 2, the study showed that ANFIS-PSO algorithm was the best quality algorithm for training network.

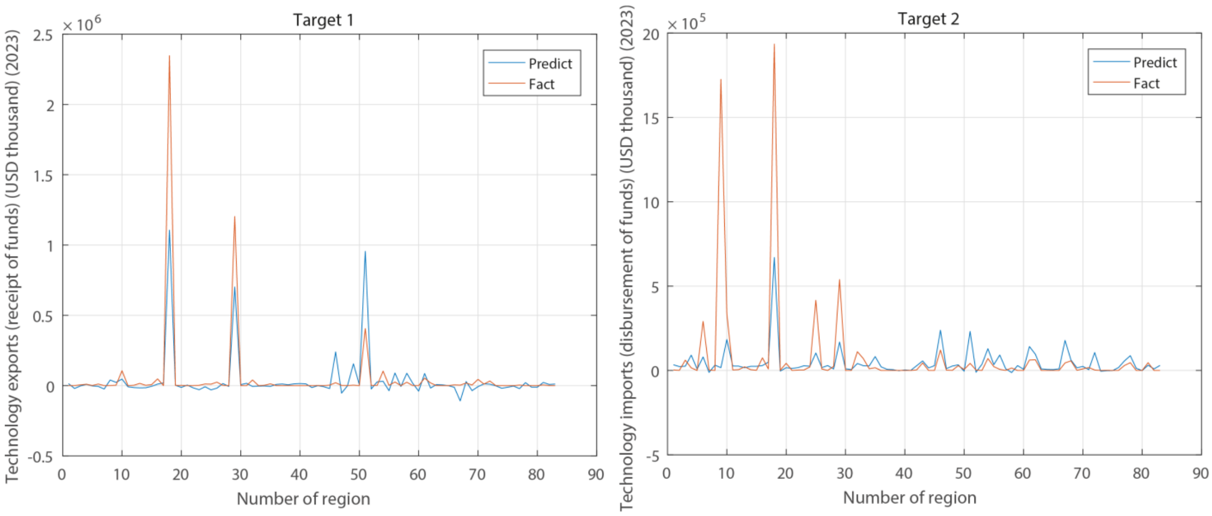
Table 2 Comparison of MAPE Error of Different Models on New 2023 Data (%)

Neural network model	Technology exports (y_1)	Technology import (y_2)
Levenberg-Marquardt method	40.3	Unable to train network (R^2<0.5 on test)
ANFIS	20.88	14.03
ANFIS-PSO	19.22	13.25

The comparison of the plots of target and predicted values of the target functions y_1 and y_2 in Figure 2 showed the good prediction quality of network trained with the ANFIS-PSO algorithm.

Stage 4. According to the data of Table 1 and the predicted values of the two target functions, the leader regions with technology exports exceeding technology import were selected, as shown in Figure 3. APE of the model relative to actual data was also considered, as it should preferably be less than 50% and the results were shown in Table 3. Relating to the discussion, the leading regions were Regions 18 as well as 29 according to Figures 2 and 3, i.e. Moscow and St. Petersburg.

The lowest and best values of the target functions (y_1 and y_2) and input parameters ($\overline{x_1, x_{10}}$) were determined in Table 3. Consequently, the study assigned the segments of the planned inputs and targets of the model.



a) b)

Figure 2 Comparison of Plots of Target and Predicted Values for Target Function 1 (a) and for Target Function 2 (b)

Stage 5. Figures 2 and 3 showed that the following regions had relatively large values of both target functions in 2023, including Region 6–Kaluga, 10–Moscow, 25–Leningrad, 46–Republic of Tatarstan, and Region 51 – Nizhny Novgorod, respectively.

This study assessed import substitution opportunities in REI sector in the regions mentioned earlier according to the data in Table 3. For this purpose, the analysis compared the values of the target functions with the planned segments by considering only those regions where technology exports exceeded import. Table 3 showed that only Nizhny Novgorod Region met these requirements. Therefore, the process showed that only Nizhny Novgorod had import substitution opportunities in REI sector.

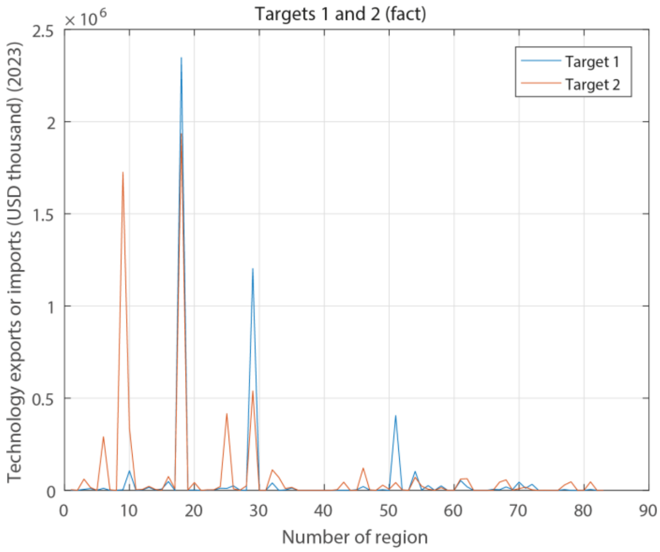


Figure 3 Comparison of Plots of Actual Values of Technology Exports and Import in 2023

The assessment of compliance of the model input parameters with the planned segments showed that the most promising in terms of future development was Moscow Region, while Nizhny Novgorod Region was less promising. Kaluga, Leningrad Region, and Republic of Tatarstan were the least promising.

Table 3 Actual (Inflation-Adjusted) Parameters for Leader Regions and Regions (2023)

Region	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	y_1	y_2
SPb. (2014)	130,260	34,279	38.1	354	66,205	14,525	21,809	106,210	108,685	7,924	318,053	294,011
Moscow (2015)	625,531	67,092	31	1,644	600,664	64,034	100,646	233,726	251,245	18,838	1,103,701	374,815
SPb. (2016)	171,108	69,576	38.5	310	93,205	15,130	20,771	97,943	120,185	9,026	723,177	355,920
SPb. (2017)	296,132	22,694	64.1	546	82,049	14,380	20,687	104,735	112,252	8,933	1,101,239	526,273
SPb. (2018)	304,317	27,370	64.4	601	84,365	15,403	20,957	101,501	110,337	9,553	735,033	351,876
SPb. (2019)	347,059	30,337	66.2	620	99,921	18,598	26,511	110,675	141,616	9,972	816,403	479,728
Moscow (2020)	2,979,518	342,628	61.2	3,651	1,650,415	96,423	99,540	241,263	571,645	11,022	2,737,770	1,878,760
SPb. (2020)	400,744	52,578	66.5	652	129,355	19,120	25,410	93,563	138,932	9,399	890,712	544,926
Worst Value	*130,260*	*22,694*	*66.2*	*310*	*66,205*	*14,525*	*20,687*	*93,563*	*108,685*	*7,924*	*318,053*	*1,878,760*
Best Value	*2,979,518*	*342,628*	*31*	*3,651*	*1,650,415*	*96,423*	*100,646*	*241,263*	*571,645*	*18,838*	*2,737,770*	*294,011*
Kaluga Region	27,310	1,166	*59.8*	3	9,346	609	2,314	3,716	7,733	3,514	11,012	290,810
Moscow Region	*328,647*	22,131	*46.8*	58	*100,967*	*15,601*	*33,778*	90,192	*207,162*	*16,190*	106,008	338,007
Leningrad Region	*39,053*	4,824	*63.1*	2	24,726	602	2,959	5,519	*25,044*	2,830	10,051	416,121
Republic of Tatarstan	*134,806*	8,326	69.8	69	39,732	3,060	2,989	14,799	*203,076*	6,729	20,444	120,917
Nizhny Novgorod Region	*145,063*	12,524	*64.7*	25	35,187	5,778	11,933	61,366	*146,563*	*8,711*	*405,655*	42,213

Neural network trained with ANFIS and PSO algorithms allow the conclusion that the leading regions in terms of import substitution opportunities in REI sector were Moscow as well as St. Petersburg. At the same time, Moscow and Nizhny Novgorod Regions had prospects for the development of this industry sector.

4. Conclusions

In conclusion, this study used neural network to simulate the process of import substitution opportunities in REI sector in Russian regions. This process enabled the analysis to identify leader regions in terms of import substitution and regions that had prospects for the future development of REI sector in the territory. The following steps were performed to achieve this objective. 1) The necessary data were collected, adjusted for inflation, and standardized. 2) Neural network was constructed and trained using ANFIS and PSO algorithms. Additionally, 3) trained network was verified on the data of a new observation period. 4) Leader regions and segments of the planned inputs as well as targets of network were determined. Finally, 5) compliance of the regions with the planned inputs and targets of network was assessed. Neural network trained with ANFIS and PSO algorithms on the data from 2012 to 2022 allow this study to conclude that the leading regions in terms of import substitution opportunities in REI sector were Moscow as well as St. Petersburg. At the same time, Moscow and Nizhny Novgorod Regions had prospects for the development of this industry sector. The obtained results would be useful for government agencies to plan import substitution process in REP industry in the specified regions. These results would also be used by investors to select the directions of capital investments of funds.

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