THE ECONOMIC POTENTIAL GROWTH MANAGEMENT FOR REAL ESTATE DEVELOPMENT COMPANY THROUGH AUTOMATION AND ARTIFICIAL INTELLIGENCE TECHNOLOGIES

Andrii Rosynskyi[1]

[1]Postgraduate Student, Assistant Lecturer of the Department of Construction Economics, Kyiv National University of Construction and Architecture, Kyiv, Ukraine, e-mail: rosynskyi.av@knuba.edu.ua, ORCID: https://orcid.org/0000-0003-4119-7463

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Abstract. *Constant changes in the economic environment of development companies, as well as a large number of impact factors on the economic results of these companies, complicate the management processes of their economic potential formation and growth. Optimization of the management system for the economic potential growth of development companies requires the implementation of multifactorial models of informed decision-making, built on algorithms of fuzzy logical inference. Based on this, the article develops a multifactorial input-output model of fuzzy logical inference regarding the primary real estate price of the development project. The model is dynamic because it includes the time impact factors on the resulting values, thus it can be used throughout the entire cycle of the development project implementation. It grants obtaining of two output price values: full and with the maximum possible discount, depending on the input data for a specific real estate object, which is a tool both for increasing the company's pricing policy management effectiveness, as well as for developing of a system for profitability maximization of each development project. In addition, the algorithm of this model application in the economic potential growth management system of the development company is proposed, as well as the spheres of its practical utilization at different levels of managerial decision-making are considered. Analysis of the developed model disadvantages led to the development of methods for their minimization through automation and artificial intelligence technologies. The application of the Simulink environment of the MATLAB software complex made it possible to develop a software implementation of the developed model, which allows not only to minimize the identified disadvantages but also to apply artificial intelligence technologies for its further improvement. The software implementation, taking into account the features of the model, is presented in the form of a hierarchical system consisting of three subsystems, each of which is not only a component mechanism for obtaining the model resulting values but also allows for obtaining intermediate values for each separate subsystem, which favor multi-level result analysis to make informed management decisions.*

Keywords: *economic potential, potential growth, real estate development company, development management, primary real estate price, fuzzy logic multifactor model, management automation, artificial intelligence technologies, informed management decisions, digitalization.*

JEL classification: C67, L85, R31

Formulas: 4; fig.: 5; tabl.: 0; bibl.: 22

Introduction. To achieve stable economic potential growth for a real estate development company, it is necessary to constantly improve methods and approaches to managing its development. It can be achieved, in particular, through the development and implementation of universal multifactorial models in management processes, which can be used dynamically, that is, during all stages of the company's development project implementation. The application of such models in the company's operational activities can become a valuable tool in the economic potential growth management system of the development company. At the same time, the complexity of such models, as well as the large amount of input and output data, makes its high-quality application impossible without the integration of automation and artificial intelligence technologies into its implementation.

Literature review. Theoretical studies of the artificial intelligence technologies application impact on the economy's growth were conducted by Aghion, Jones B., and Jones C. (2018) and Wang, Sarker, Alam, and Sumon (2021). Bresnahan (2021) also investigated aggregate growth prospects through artificial intelligence technologies. At the same time, Strusani and Houngbonon (2019) focused on determining the role of artificial intelligence technology applications in the development of emerging markets. The issue of real estate price forecasting using artificial intelligence technologies at the methodological level is considered in (Rossini, 2000) and (Niu, J., & Niu, P., 2019) and is mainly researched in a regional context. While the article (Ćetković et al., 2018) focuses on the study of the European real estate market, Park and Bae (2015) use housing data from Fairfax County in Virginia.

There is a difference in approaches as well: while the study (Wang X., Wen, Zhang, & Wang Y., 2014) examines the support vector machine and its particle swarm optimization, Xu and Zhang (2022) in their article suggest using neural networks for real estate price forecasting. On the other hand, Guan, Shi, Zurada, and Levitan (2014) offer a neuro-fuzzy model for analyzing massive data sets for real estate property value prediction. For the Ukrainian real estate market, the principles of using rating modeling were studied in (Shaposhnikova, 2019).

Pieces of research (Akselrod, Shpakov, & Ryzhakova, 2022) and (Stetsenko, Tytok, Emelianova, Bielienkova, & Tsyfra, 2020) focus attention on how the digitalization of the economy influences the management processes of construction enterprises. The implementation of digital technologies and automation in the management systems of construction enterprises is considered in (Bolila, 2022). The use of fuzzy logic tools to increase the effectiveness of change management at construction enterprises was studied in (Shpakov, Stetsenko, Shpakova, Sorokina, & Akselrod, 2021).

Several research papers (Stetsenko et al., 2021; Bielienkova, 2019; Shaposhnikova, 2020) are devoted to the problem of management and assessment of the competitiveness of construction enterprises, in particular development companies, using automation and artificial intelligence technologies.

Important in the context of this study is the article by Stetsenko, Bolila, Sorokina, Tsyfra, and Molodid (2020), which proposes a monitoring mechanism for the resilience of the anti-crisis potential system of the construction enterprise in the long-term period.

The study by Bielienkova (2020) also deserves special attention, as it examines the competitive potential of a development company and proposes the use of artificial intelligence tools to improve its management mechanisms.

Despite many studies related to this research subject, the issue of using automation and artificial intelligence technologies for the economic potential growth management system of real estate development companies remains insufficiently disclosed. This study is a logical development and continuation of research (Rosynskyi, 2022), which considered the initial aspects of solving this complex problem.

Aims. This research aims to develop an optimizing mechanism for the development company's economic activity management and to find and implement possibilities for its improvement through automation and artificial intelligence technologies.

Methods. The study applies general scientific research methods, such as the system-structural method, abstraction, analysis, synthesis, modeling, and forecasting. Simultaneously, specific research methods used in the study are input-output modeling, correlation-regression analysis, multifactor modeling, fuzzy inference modeling, and coefficient method.

Results. The study of impact factors on the primary real estate price (Rosynskyi, 2022) allows the formation of a fuzzy logic multifactor model suitable for usage in real time throughout the project development cycle. For modeling, the price of 1 m^2 of an apartment area P_{m2} is proposed to be expressed as a dependence:

$$P_{m2} = \Psi \cdot P_{base}, \qquad (1)$$

where P_{base} is the base (average) price of 1 m^2 of an apartment area, Ψ - the accumulated coefficient of transition from the base price of 1 m^2 of an apartment area to the actual one, which depends on the accepted impact factors on the price change during the project development cycle.

Meantime, the introduced accumulated coefficient Ψ is expressed as a dependence on group impact factors:

$$\Psi = BUILD \cdot APRTM \cdot TIME, \qquad (2)$$

where BUILD is the group building impact factor, APRTM is the group apartment impact factor, TIME is a group time impact factor.

The implementation of calculations according to formulas (1) and (2) allows getting the "desired" economically justified price value of 1 m^2 of an apartment area at a specific time moment, provided that there is an expected demand for particular residential premises. In the absence of expected demand, wishing to enter into an investment agreement, the developer should anticipate the maximum possible discount value that can be offered to a real investor.

At the same time, information about the presence or absence of expected demand for specific premises is internal information of the development company and unknown to investors. Therefore, the calculation of the price with a discount is offered not as a substitute for the main dependencies in formulas (1) and (2) but as an additional management tool that can provide sales department specialists with further options to support the level of sales and, as a result, the level of the development project economic potential.

Based on that, the presence of expected demand and consequently possible discount level are proposed to be estimated by introducing an additional group impact factor POSDISC. As a result, the price of 1 m^2 of an apartment area with the maximum permissible discount value $P_{m2,disc}$ can be expressed as a dependence:

$$P_{m2,disc} = \Psi^* \cdot P_{base}, \qquad (3)$$

where P_{base} is the base (average) price of 1 m^2 of an apartment area, Ψ^* - the accumulated coefficient of transition from the base price of 1 m2 of an apartment area to the actual one, which depends on the accepted impact factors on the price change during the project development cycle, considering the maximum allowable discount value.

The accumulated coefficient Ψ^* in this case is determined as follows:

$$\Psi^* = \Psi \cdot POSDISC = BUILD \cdot APRTM \cdot TIME \cdot POSDISC, \qquad (4)$$

where BUILD is the group building impact factor, APRTM is the group apartment impact factor, TIME is a group time impact factor, POSDISC is a group discount impact factor.

Every group impact factor is a defuzzified (clear) value of the logical fuzzy conclusion of the corresponding output linguistic variable, the analysis of which is of additional managerial interest when comparing different proposals, in particular, analyzing various development projects of one development company, or comparing offers of competing companies.

As a result, Fig. 1 displays the developed algorithm for determining the apartment (flat) price according to this model, which can serve as a tool for optimizing the management of the development company's economic activities. It allows obtaining not only the final result (the apartment price at a particular time moment) but also monitoring the influence degree of isolated impact factors (both individual and group) to obtain initial data for making strategic and operational management decisions both at the global level (the development company level) and the local level (the levels of an individual development project or its part).

The proposed algorithm (Fig. 1) is universal and flexible depending on its utilization tasks. From a practical point of view, the sequential execution of the first five steps of this algorithm allows an ordinary sales manager to get the necessary price characteristics of a particular apartment to present them to a potential investor. The sales manager concurrently receives two price values (full and maximum discounted, if possible) that allow building a corresponding communication strategy with the buyer with additional flexibility in formulating offers. Obtaining the value of $P_{m2,disc}$ or $P_{flat,disc}$ as a result of the algorithm utilization allows the manager to independently apply the proper discount without the need for coordination with supervisors, which increases the efficiency of working with clients and optimizes the working time of the development company management staff.

On the other hand, the economic department specialists and senior management staff can analyze the data obtained from the algorithm implementation, both resulting and intermediate. It allows both to carry out obtained values diagnostics for the development projects in progress and to receive forecast values for future development projects. This information is necessary for the further construction of the company's marketing strategies and is also a tool for monitoring the effectiveness of the company's activities.

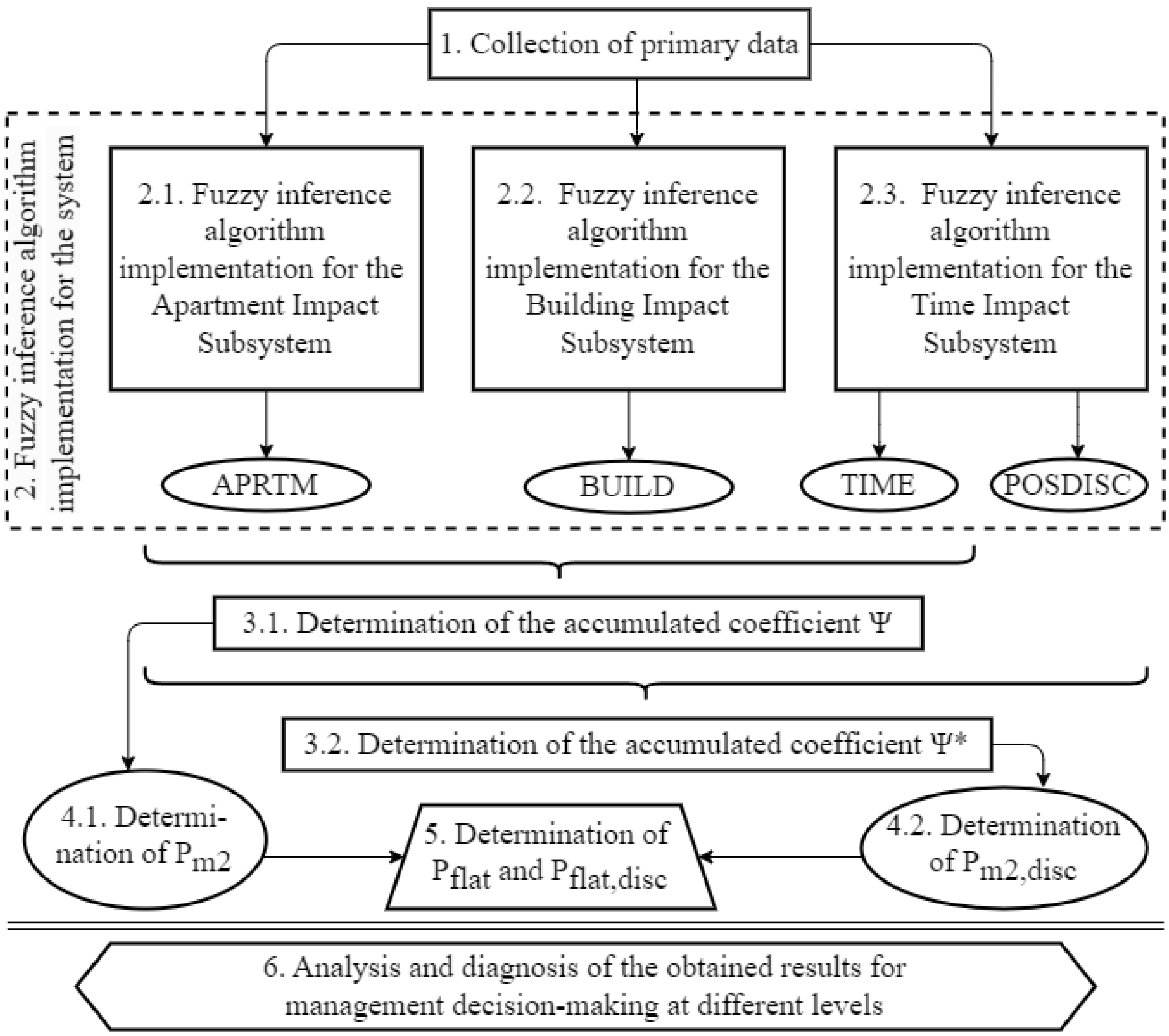

Figure 1. The apartment price determination algorithm following the multifactor model of fuzzy inference as an optimizing mechanism for the development company economic activity management

Source: developed by the author

In the meantime, if it is necessary to analyze and study only the building location and technical characteristics impact on the apartment price, step 2 of the algorithm can be limited only to the sub-step 2.2 execution with immediate proceeding to step 6. It allows not only to reduce the time for processing a large amount of information and to concentrate exclusively on the set tasks but also to perform them under conditions of limited initial data, which are either not relevant to this task (input variables of other subsystems) or are not the subject of research and are deliberately excluded from the calculation (for example, the absence of a subway in the city or the absence of final information regarding the energy efficiency class of the designed building).

At the same time, algorithm utilization for forecasting also allows expanding the list of received fuzzy conclusion results. The IV stage of the fuzzy inference algorithm covered in (Rosynskyi, 2022) provides for obtaining only the centroid value of the accumulated figure obtained at the III stage of the corresponding algorithm as the desired clear value of the corresponding output variable. At the same time, prospective forecasting implementation following the algorithm makes it possible to expand the range of values obtained at this stage due to additional research and analysis of the accumulated figure for local maxima and minima. These values are economically justified limits of the corresponding output variable and suitable for modeling various scenarios ("most optimistic", "most expected", "most pessimistic", etc.) of the development project growth and their impact on the company's economic indicators. The same approach allows modeling and evaluating the impact of various management decisions on the development company's economic indicators.

Additionally, the model can be used for marketing research and as a supplementary tool in the marketing strategies construction and implementation. The obtained defuzzified values of each subsystem output variable allow the determination of linguistic descriptions of each output variable, depending on the terms that their defuzzified value satisfies. Thus, the analysis of the calculated values set for the apartment and building group impact factors allows for establishing a justified classification of buildings and apartments according to the degrees of accessibility and prestige, which should be considered when building marketing strategies and highlighting additional characteristics of the target audience.

The set of time impact group factor values is suitable for analysis in the context of planning and implementation of various marketing approaches to intensify demand in the most profitable periods of the development project and make appropriate decisions regarding real estate that does not enjoy the expected demand. The results of such an analysis allow the clustering of both the company's development projects and the totality of apartments to develop appropriate strategies for managing their development for different isolated clusters. This approach allows working more locally with each real estate cluster, thereby increasing the effectiveness of decisions and development strategies.

However, the developed models and algorithms, due to a relatively large number of input variables along with their universality and flexibility, have several characteristic disadvantages.

The developed model has a limited geography of use because it is based on a sample of development projects in Kyiv. In such a way, if it is necessary to expand its geography to several settlements or to adapt it to another one, an appropriate representative sample must be formed and analyzed, which will allow to single out the relevant impact factors, based on which, according to the described methodology, it will be necessary to build a new model.

A similar problem arises since the primary real estate market is dynamic and sometimes quite volatile, which necessitates periodic screening and clarification of the actual data that became the model basis. Even if the list of impact factors remains constant, the influence degrees of these factors may change in response to market demands or changes in legislation.

In the case of the need to analyze a large amount of data, many results sets are obtained based on the outputs of the calculations, which require a competent storage structure development with the possibility of separating data that may require additional attention.

From the applied point of view, the results of calculations according to the algorithm have a limited shelf life because the output values are affected by constantly dynamic time factors. It requires conducting new estimations for the same apartment almost every time a potential buyer is interested in it or when it becomes the subject of analysis and diagnostics to make appropriate management decisions.

It is possible to neutralize or at least dramatically minimize the identified shortcomings by the automation of calculations and the involvement of artificial intelligence tools in their implementation. The advantage of the developed model is that it is suitable for this and, in addition to eliminating the shortcomings highlighted above, it significantly reduces the risks of human factor influence on the obtained results.

The developed model is a partial reflection of the life cycle simulation model of each development project concerning its price values, particularly their dynamics in time and space.

By setting the initial indicators obtained from the estimated construction documentation of the real estate object and dynamically changing them in case of changes, the model generates quantitative price indicators suitable for use by development companies in their operational activities.

The specified modeling implementation through automation and artificial intelligence allows not only to change the initial data but also to make corrections in the simulation of the resulting values, including in the analysis of the data obtained from the newly implemented development projects. In other words, it enables the model to "live", "learn" and "evolve" by increasing its base of raw data, as well as by aggregating data on "its" previous experience.

Thus, an essential step towards further improvement of the development company growth management is the automation and programming of the developed model. It can be achieved, for example, by using the functionality of the Simulink environment of the MATLAB software complex.

Figure 2 shows the software implementation front-end view of the developed multifactor model of fuzzy inference with an automated calculation based on input data described in (Rosynskyi, 2022).

The program implementation uses colored indicators, which do not affect the calculation process or its result, but serve as supplementary tools for analyzing the program structure and additionally visualize individual components of the program system concerning the developed algorithms and grouping methods.

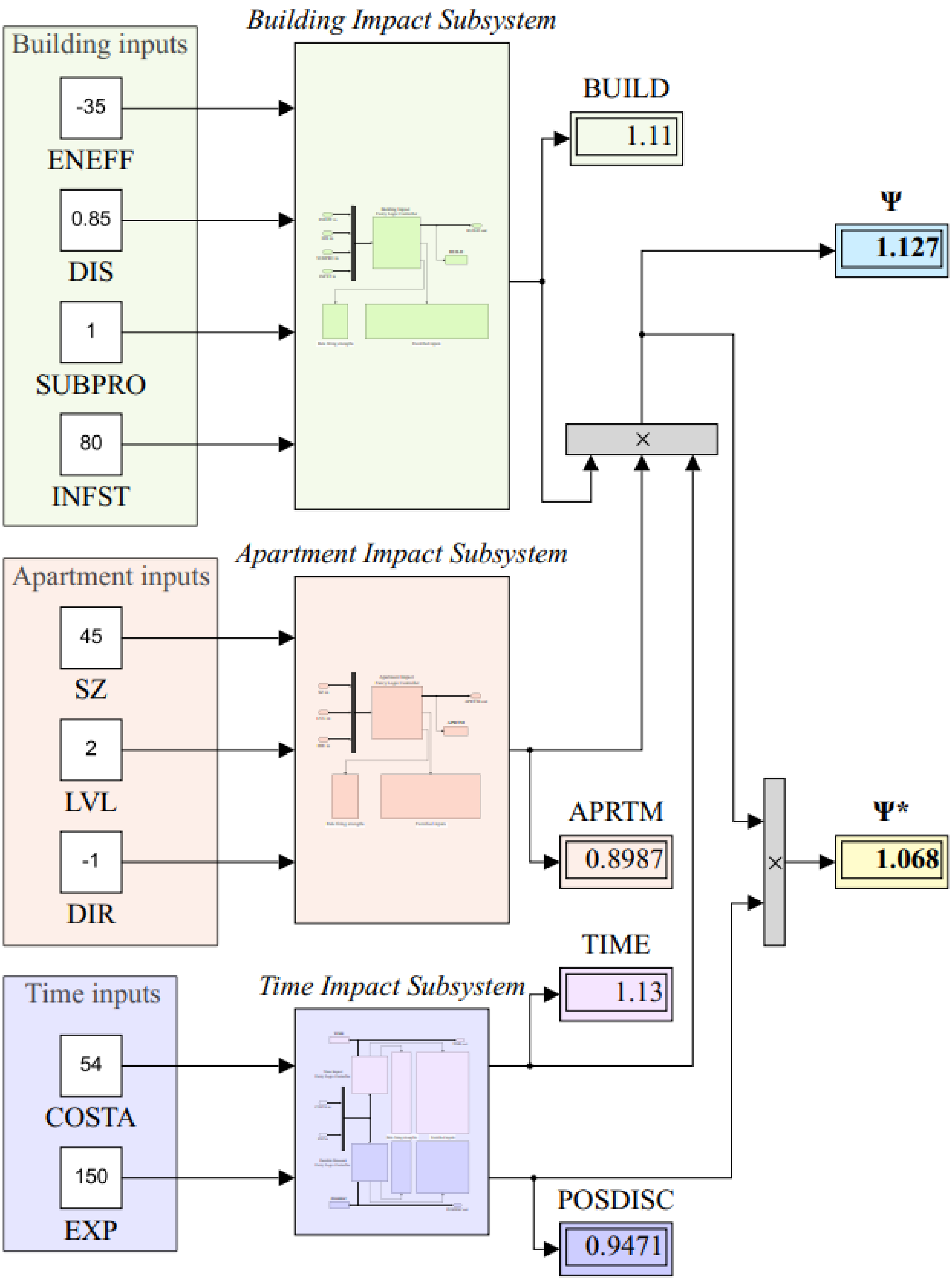

Figure 2. Software implementation of a multifactor model of fuzzy inference in the Simulink environment of the MATLAB software complex

Source: developed by the author

In particular, each subsystem has its own color indicator: the Building Impact Subsystem is painted in green, the Apartment Impact Subsystem - in peach color, and the Time Impact Subsystem - in light purple. The resulting values of the accumulated coefficients Ψ and Ψ* are colored in blue and yellow, respectively.

The input variables for each subsystem are combined into blocks titled "Building/Apartment/Time inputs" and specified by “Constant” type blocks, which involve setting values in the block options.

Despite the use of this block type for input variables being quite limited and relatively unautomated, it was adopted deliberately as it offers the best visibility, which is most desirable when demonstrating the principles of the software product.

In the case of non-demonstration software product use, information for input variables should be filled automatically from pre-formed databases by linking the latter as sources for filling the corresponding blocks and/or creating the corresponding signals. In such case, the software product front-end view should not include the display of the list and values of each input variable, being limited only to the application of a single block type, e.g. "From File" or "From Spreadsheet".

Each subsystem in this program window is grouped separately to simplify the main interface of the software product, but if necessary, the structure of each subsystem can be expanded. Rather, using "Display" type blocks, the main screen shows output variables clear values of each subsystem, calculated by the entered input variables values. For instance, the value of the group apartment impact factor APRTM = 0.8987, which corresponds to the value obtained in the Rule Viewer dialog box of the Fuzzy Logic Designer environment in (Rosynskyi, 2022, Fig. 5). These blocks are informative, displaying only the final clear output values of fuzzy inference algorithm implementation for each subsystem.

Further, the obtained values are combined into the "Product" type blocks (marked in gray in Fig. 2) following formulas (2) and (4), the implementation results of which allow obtaining signals with the values of the calculated accumulated coefficients Ψ and Ψ*, the visualization of which in the software environment is ensured by the "Display" type blocks usage.

So, for the apartment under consideration, according to the results shown in Fig. 2, the value of Ψ = 1.127, and the value of Ψ* = 1.068. The software calculation results based on the entered values of the input variables make it possible to offer the buyer a discount of about 5%. The time and building group factors influenced the increase of the accumulated coefficient output value and, therefore, the price of the apartment. On the contrary, the apartment group factor influenced the decrease of the corresponding resulting values. If the building is in the design stage, it makes sense to check all apartments for the value of the relevant apartment group impact factors and, through their analysis, try to find opportunities to change the essential characteristics of each apartment, which will lead to increase of the APRTM factor value and, accordingly, this real estate object price.

Let us consider in more detail the software implementations of each subsystem. Fig. 3 shows the software implementation front-end view of the Building Impact Subsystem in an expanded form, that is, in a separate dialog box. All subsystem components have a corresponding coloring.

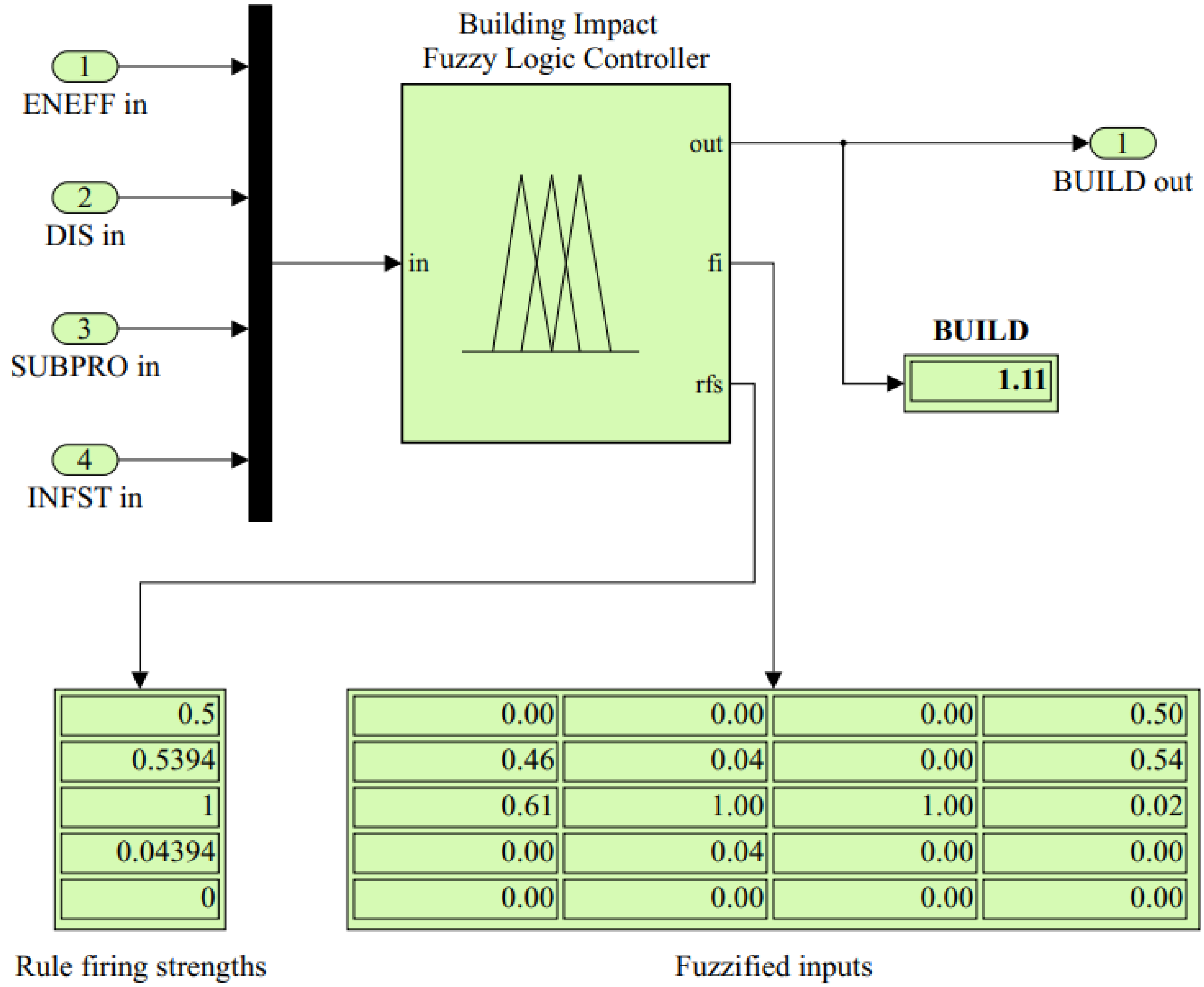

Figure 3. Software implementation of a multifactor model of fuzzy inference for the Building Impact Subsystem in the Simulink environment of the MATLAB software complex

Source: developed by the author

Hierarchically, any subsystem is a component of the overall system hence it must have inputs and outputs that link the system components with the corresponding subsystem blocks.

The input function is implemented by "Inport" type blocks, which carry signals from the corresponding blocks of the overall system (in this case, from the blocks with the input variables values of this subsystem). These blocks have an internal numbering for the subsystem (in this case, from 1 to 4) and are numbered and arranged in such a way that the signal of each input block gets to its designated place.

"Outport" type blocks transmit the output signal from the subsystem to the overall system. They also have their own end-to-end numbering. According to Fig. 3, the subsystem has only one "Outport" type block, which transmits to the overall system a signal with the value of the building group impact factor BUILD calculated in the subsystem. The numerical value of this factor is additionally duplicated inside the subsystem using a "Display" type block.

The main mechanism of the subsystem is a fuzzy logic controller represented by a "Fuzzy Logic Controller" block type. The presence of only one input port in this block ("in") requires the use of a "Mux" type block (shown by a black vertical rectangle in Fig. 3), which is designed to combine all input signals into a common one. Settings of the "Fuzzy Logic Controller" block provide for assigning to it the appropriate Fuzzy Inference System (FIS), an example and an algorithm for its development using the Fuzzy Logic Designer environment is discussed in (Rosynskyi, 2022). In addition, configuring a "Fuzzy Logic Controller" block consists of assigning which output signals the block will produce.

For example, the fuzzy logic controller in Fig. 3 produces three output signals. The first mandatory "out" one, which carries information about the calculated clear value of the output variable, is combined directly with the "Outport" type block discussed above. In addition, the controller is configured to provide additional output signals "fi" and "rfs", which are connected to the corresponding "Display" type blocks to analyze the received data arrays.

The "fi" signal transmits numerical information in matrix form with fuzzified values of all input variables following each knowledge base rule of the fuzzy logical inference subsystem. The matrix has dimension $n \times m$, where n is responsible for the number of the matrix rows and depends on the knowledge base rules number of the fuzzy inference subsystem, and m is responsible for the number of the matrix columns and depends on the number of input variables. In the fuzzy logical inference Building Impact Subsystem (Fig. 3), the knowledge base consists of 5 rules for 4 input variables. That is why the matrix «Fuzzified inputs» has the dimension $n \times m = 5 \times 4$. Numerical values that make up the matrix are nothing but the significance degree values of the input variables.

In turn, the "rfs" signal creates similar information but for the output variables. The matrix "Rule firing strength" will always have the same number of rows as the matrix "Fuzzified inputs", because it also displays the values for each knowledge base rule of the subsystem, which are common to the input and output variables. Meantime, the column number of the matrix "Rule firing strength" will correspond to the number of output variables. For example, the matrix «Rule firing strength» in Fig. 3 has only one column corresponding to the single output variable BUILD. The numerical values that make up this matrix are similarly the significance degree values of the output variables concerning every rule of the fuzzy inference knowledge base.

Figure 4 displays the Apartment Impact Subsystem software implementation in its expanded form. Its structure and construction principle correspond to the Building Impact Subsystem software implementation (Fig. 3). The values displayed in the corresponding data arrays of the "Display" blocks correspond to and, in a certain way, complement the graphic display of the execution of the fuzzy inference algorithm in the Rule Viewer dialog box of Fuzzy Logic Designer environment performed for this subsystem in (Rosynskyi, 2022). Thus, the software implementation of the algorithm makes it possible to obtain all the necessary results exclusively in its own environment, which removes the urgent need to use additional applications.

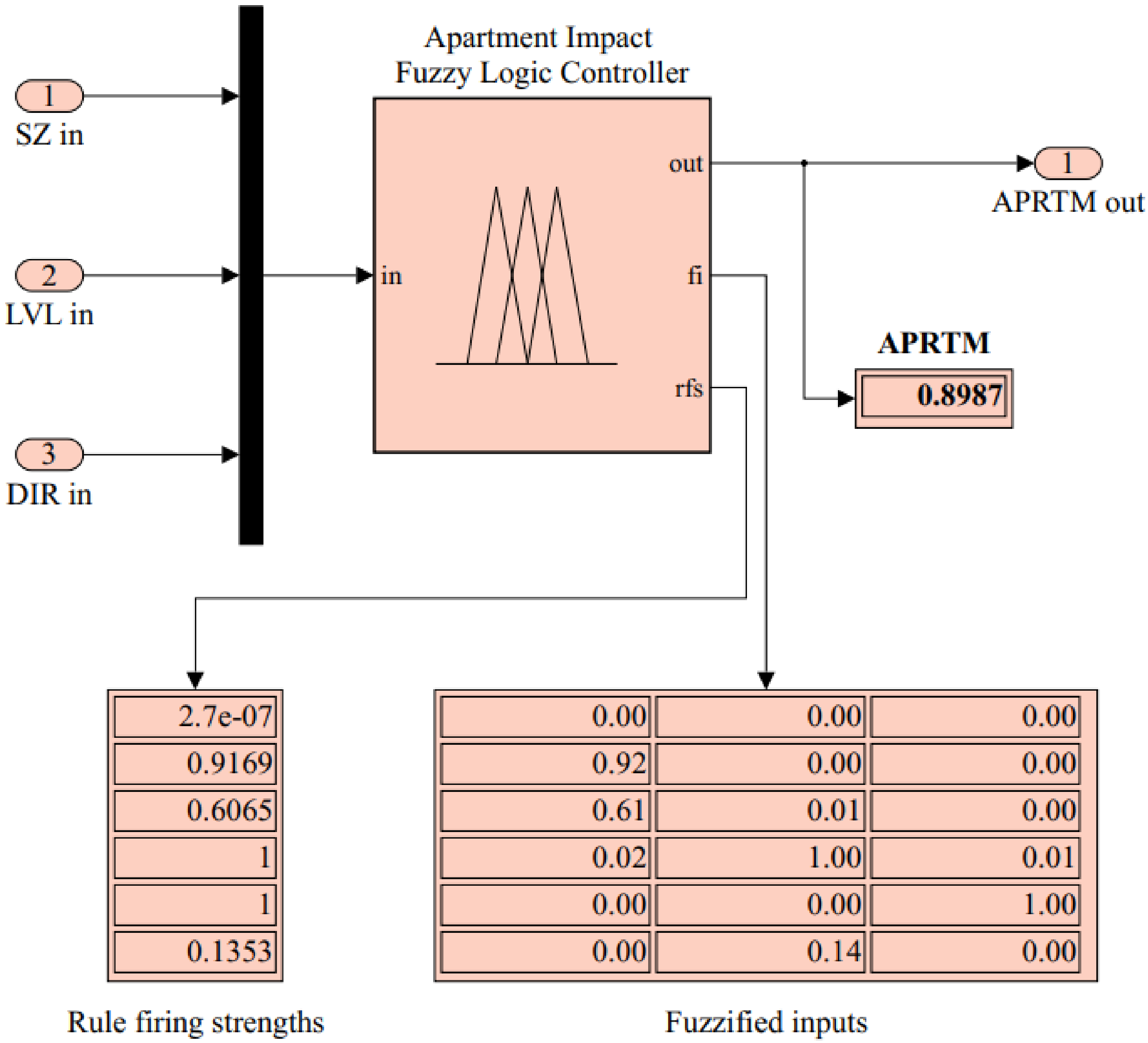

Figure 4. Software implementation of a multifactor model of fuzzy inference for the Apartment Impact Subsystem in the Simulink environment of the MATLAB software complex

Source: developed by the author

Time Impact Subsystem software implementation in expanded form deserves additional attention and is shown in Fig. 5.

Structural elements and the general principle of its construction coincide with previously considered subsystem software implementations but the appearance and structure are slightly different due to the peculiarities of the knowledge base construction of this subsystem described in (Rosynskyi, 2022). Thus, the Time Impact Subsystem software implementation (Fig. 5) includes two separate fuzzy logic controllers for each output variable. Visually, they are separated by color: the blocks related to the TIME output variable are colored pink, and the POSDISC output variable blocks are purple. These shades are preserved for the "Display" type block corresponding to clear values of this subsystem output variables in the overall system software implementation (Fig. 2). As expected, each fuzzy logic controller has its own output signal, that is, the subsystem, unlike the others, has two "Outport" type blocks.

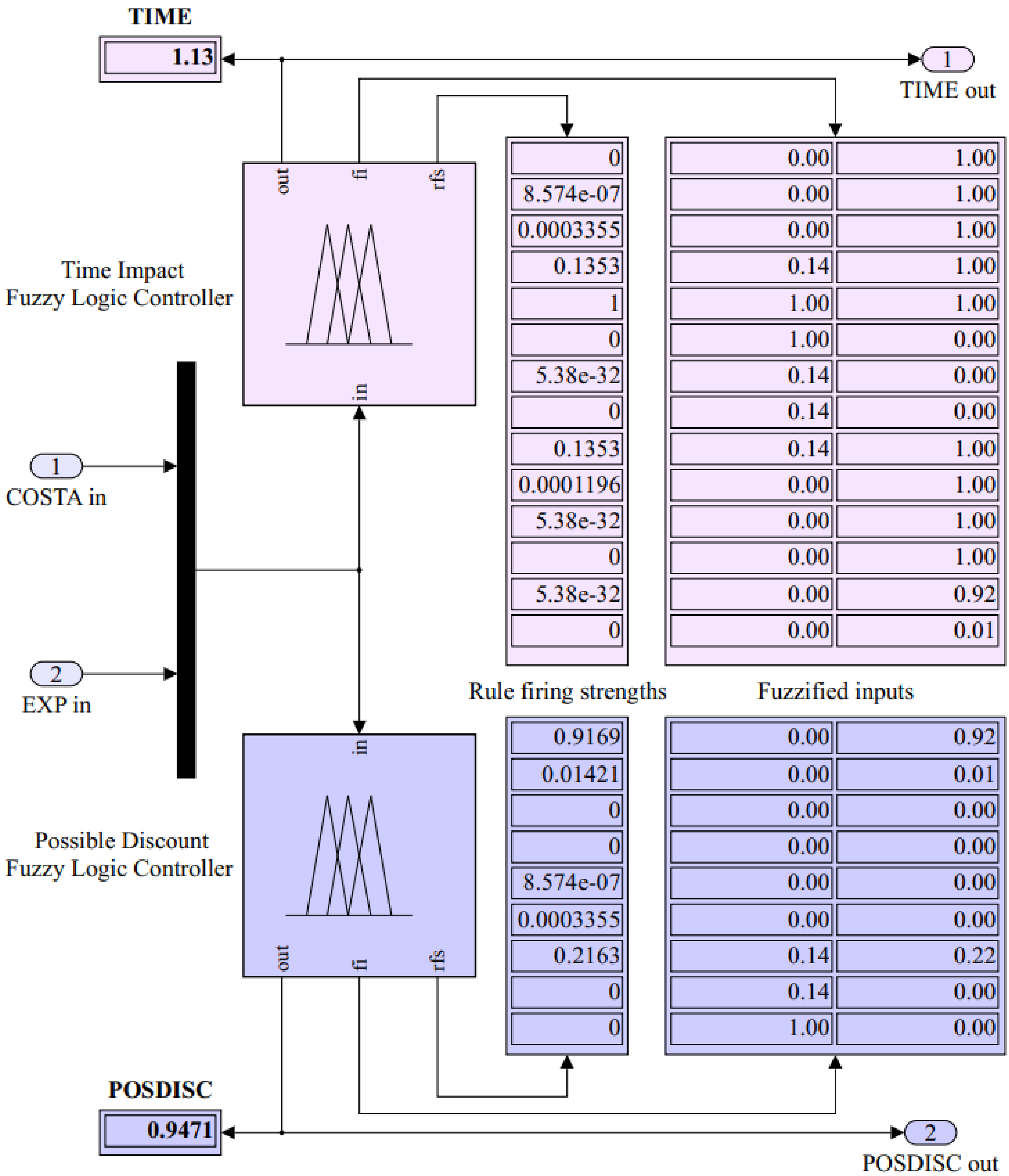

Figure 5. Software implementation of a multifactor model of fuzzy inference for the Time Impact Subsystem in the Simulink environment of the MATLAB software complex

Source: developed by the author

Input subsystem variables are common to both controllers and are represented by "Inport" type blocks, the signals of which are combined using a "Mux" type block into a single signal simultaneously branched to both controllers.

The number format and precision of values in all "Display" type blocks are customizable. For example, in Fig. 5, the number format in data arrays «Fuzzified inputs» is limited to the decimal system with two decimal places, while to demonstrate the functionality and the level of calculation accuracy, the corresponding setting was deliberately not performed for the values of the data arrays titled «Rule firing strength». The setting of these options depends on how the analysis of the obtained results is carried out, as well as how they are planned to be aggregated, segmented, and stored in the future.

The values obtained in automated calculation outputs can be sent to the corresponding blocks of the "Sinks" category, which allow, for example, visualization of numerical information in graphics of the same format and content that can be obtained in the Surface Viewer dialog box in Fuzzy Logic Designer environment (Rosynskyi, 2022, Fig. 6). For this, "Scope" or "XY Graph" block types can be used. It is also possible to redirect the resulting data signals to the appropriate databases for further processing. For this, it is worth using the "To File" block type.

Computerized maintenance of performed calculations' registers, sequential data accumulation, and their mutual exchange between the input and output databases of the model software implementation allows taking into account changes in trends and indicators and the software environment usage experience during modeling.

The artificial intelligence technologies integration into the proposed software stimulates model stable development and its independent updating due to the introduction of machine learning algorithms, as well as increasing the efficiency of management processes.

In particular, artificial intelligence technologies can perform analysis of databases and calculation results and notify the development company's management of identified trends and potential risks that require additional attention and deeper analysis. Retrospective analysis of implemented development projects' indicators allows artificial intelligence to distinguish the operational activity specifics of the respective development company, as well as to identify potential problems and risk areas. The results of such analyses, which artificial intelligence can conduct with a given frequency, are the basis for making informed management decisions.

Creating registers of decisions made in response to identified problematic trends is the next stage of artificial intelligence machine learning, which can create appropriate management decision-making systems that are able not only to highlight information about potential threats to management personnel but also to provide recommendations on optimal strategies for their resolution.

Given that the developed model is suitable for use in real-time, the functionality of artificial intelligence technologies can also be used for automatic continuous monitoring, analyzing input and calculated data in real-time. It allows quick response to any threats and predicts potential consequences.

In particular, the described monitoring system can be configured to detect signs of abuse and/or fraud by all development project stakeholders. The monitoring system's access to bank transactions on the company's accounts allows the detection of potentially threatening actions and even fraudulent schemes.

Discussion. The developed multifactor model of fuzzy inference and its improvement through automation and artificial intelligence technologies is an indispensable step towards further improvement of the development company growth management in a digitalized economic environment. At the same time, the use of artificial intelligence and automated calculations requires human supervision and expert analysis to prevent the presence of actual errors in the programmed system and to respond appropriately to possible failures and technical errors that can lead to information distortion that can serve as a basis for making incorrect management decisions.

Conclusion. The developed algorithm following the multifactor model of fuzzy inference in addition to the operational application, can be used as an optimizing mechanism for flexible economic forecasting and increasing the efficiency of construction development management.

Its improvement through automation and artificial intelligence technologies results in the minimization of human involvement in the calculation, analysis, and diagnosis processes, which reduces the risks of making incorrect management decisions, which is a positive factor influencing the economic potential growth of a real estate development company.

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