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Studies on the ANN implementation in the macro BIM cost analyzes
O możliwościach zastosowania SSN w analizach kosztowych „macro BIM”

Key words: BIM, macro BIM, cost analyzes, neural networks, ANN
Słowa kluczowe: BIM, macro BIM, analizy kosztów, sieci neuronowe, SSN

Introduction

Growing relevance of BIM (building information modelling) for construction industry on a global basis is a fact. BIM is discussed in many aspects both by researchers and academics as well as professionals. Fundamentals of BIM can be found both in foreign and Polish literature, e.g. Eastman, Teicholz, Sacks and Liston (2011), Tomana (2015). Current trends, reported and potential benefits, risks and challenges of BIM for the construction industry are discussed by Azhar (2011). Sunil, Pathirage and Underwood (2015) presented a thorough state-of--the-art review of literature in order to examine significance and importance of BIM in the UK construction sector with a specific focus on cost management.

BIM models serve as repositories of information about buildings. Components of a model, (parametric “objects” that are defined in the course of a design process), carry the geometric and non-geometric information and rules for creating relationships between these components within the building's model – compare with Eastman et al. (2011). Use of BIM models in a construction project results in analyzes and decisions based on an information-rich, virtual model of a building. According to Sacks, Koskela, Dave and Owen (2010) the components of a model can be attributed cost information that can be used by the cost managers. In consequence BIM models constitute a basis for cost analyzes. Broadly defined field of BIM-based cost analyzes in construction projects is the domain of a wide variety of current publications. Goucher and Thurairajah (2012) presented studies on the advantages, challenges and usability of BIM for cost consultants, and its likely impact during cost estimating. This research investigated BIM capacity to influence the operations throughout the construction industry. Kogut and Tomana (2013) presented the issue of integration of design, costing and scheduling within a BIM workflow. In the work mentioned above Sunil et al. (2015) investigated potential improvements in area of BIM-based cost management. In another paper Fan, Wu and Hun (2015) proposed a model to link cost and schedule data on an automatic manner with BIM elements.

Artificial neural networks can be defined as mathematical structures, inspired by and modeled after a human brain, and their software or hardware implementations, performing calculations or signal processing. Theory of artificial neural networks is widely presented both in foreign and Polish literature – e.g. Tadeusiewicz (1993), Haykin (1994), Bishop (1995), Osowski (2013). Applications of ANNs in the field of construction management are reported in many publications. In particular some examples of ANNs application in problems of construction cost management can be given. Williams (2002) presented studies on application of ANN for prediction of project cost on the basis of using bidding data. Attalla and Hegazy (2003) investigated the issue of cost deviation prediction in reconstruction projects with the use of ANNs and regression analysis. Modelling of highway construction costs using neural networks was presented by Wilmot and Mei (2005). Juszczyk and Leśniak (2016) reported the research results on the application of RBF neural networks in predicting site overhead cost index. Apart from ANNs some other examples of applications of mathematical methods in the field of construction cost management can be given. For instance Chan and Park (2005) analyzed the problem of construction project cost estimation with the use of principal component regression. Other work by Zima (2015) presents case-based reasoning approach for cost estimation in the early phase of a construction project.

The literature review presented above allows for conclusion that both BIM-based cost analyses and application of mathematical methods (especially ANNs) in construction cost management are significant and current topics. The aim of this paper is to combine and discuss the issues of: BIM-based cost analyzes performed on the macro-level and application of neural networks as artificial intelligence tools in these analyzes. On this background results of some studies in this field are reported – namely a case study which depicts the ANN application for BIM-based cost analysis. The subject of the analysis is a part of a buildings' structural frame.

Macro BIM analyzes and artificial neural networks

Depending on the stage of a construction project – especially advancements in the design works – BIM models can offer different levels of aggregation of buildings elements, and thus different level of information aggregation. In consequence cost analyzes done on the basis of BIM models can offer estimates accuracy that depends on how aggregated information stored in the model is. Moreover the applied method of estimation must be adequate to the level of information aggregation. According to Tomana (2015) the term "macroBIM" was introduced by Beck Technologies to distinguish between conceptual and detailed analyzes based on BIM models. "Macro" refers to the higher level building's elements – for which the level of information aggregation is high. The idea of macro BIM cost analyzes is close to the conceptual cost estimation approach performed on the basis of models assembled of elements for which level of detail is either low or medium.

The use of ANNs as mathematical tools cover diversity of problems such as: predicting, approximating, association, classification, pattern recognition, sequential decision making, data clustering, data filtering, data processing and numerical control. Applicability of ANNs to the regression analysis and the feature of generalization (ability to handle unseen data), as well as previous works and research of the author, became a motivation to consider an approach that combines the idea of macro BIM cost analyzes and the use of neural networks.

An ideogram of the proposed approach is presented in Figure 1. The blocks of the ideogram drawn with the dashed line represent the initial analysis and assumptions formulation made on the three levels. One of the blocks depicts the general assumptions on the level of the cost analyzes as a whole. As the term "higher level elements" is ambiguous and there is no one generally approved paradigm how to define such elements in the BIM model during the design process two key assumptions need to be made. The first assumption concerns the definition of the higher level elements, their identification and classification, for the purposes of macro BIM cost analyzes. This assumption should follow an investigation of a BIM models developed in the conceptual design stage. The second assumption should be made to clarify the expectations about the expected accuracy and reliability of the cost analyzes. On the level of the BIM models identification of key parameters for the identified earlier elements is necessary. Values of the parameters are to be used in the process of neural modelling. Respectively, the third block refers to the collecting and ordering training data sets and actual training ANNs as the artificial intelligence tools that support cost estimation of identified building's higher level elements. The three parts of the process, that are represented by the three blocks, are interrelated. They influence each other. The blocks of the ideogram which are drawn with the solid lines refer to the estimates built upon the set of higher level building's elements and corresponding ANNs. On the left side of the scheme there is a BIM model which serves as a source of information about a building's and certain higher level elements. On the right side of the scheme there is a set of trained ANNs – each of the ANNs acts as a tool supporting cost estimation of a certain higher level element. Moreover, each of the ANNs supports regression function for a certain higher level element. The data that is essential in the cost estimation of certain element can be easily derived from a model and presented to the trained ANN.

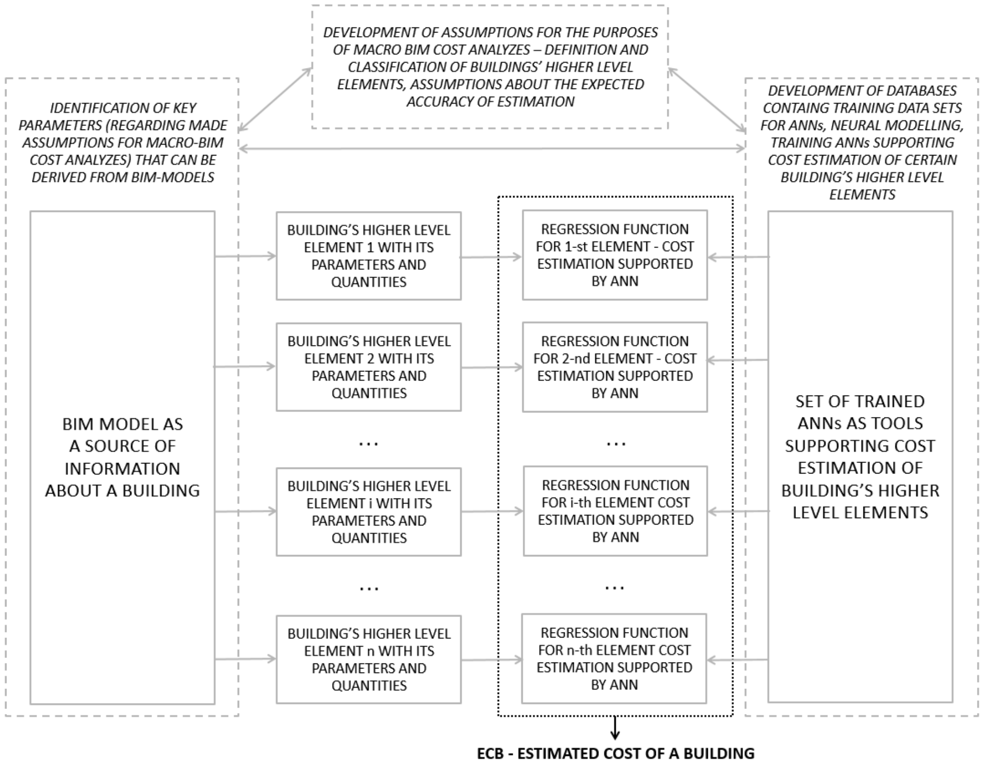

FIGURE 1. Ideogram of the ANNs use in macro BIM cost analyzes (own study)
RYSUNEK 1. Ideogram zastosowania SSN w analizach kosztowych macro BIM (opracowanie własne)

The block of the ideogram, which is drawn with the dotted line, represents the association of the element's cost estimates (1):

$$ECB = \sum_{i=1}^{n} ECE_i = \sum_{i=1}^{n} \hat{Y}_i \tag{1}$$

where:
ECB – estimated cost of a building,
ECE_i – estimated cost of an i-th higher level element,
$\hat{Y}_i$ – predicted cost of an i-th higher level element of a building with the use of regression function performed implicitly by ANN.

Macro BIM cost analyzes can be performed on the different levels that depend on: the assumptions made for the analyzes, how detailed the BIM models are and the selected input for ANNs training. The approach depicted in Figure 1 presents general concept of the combination of macro BIM cost analyzes and ANNs application. Next part of the paper includes a case study – ANN-based macro BIM cost analysis for selected higher level element of a building.

Case study

The exemplary analysis was carried out on the level of typical floor structural frame as a higher level element. The floor structural frame as a part of building's superstructure includes structural elements required for support of floor construction – both horizontal (slabs, beams, landings and stair flights) and vertical (walls and columns) structural members. According to the paradigm of the development of structural BIM models each floor contains the horizontal structures above and the vertical structures that support them as presented in Figure 2.

that support cost analyzes. Case study included investigation of two variants (later referred to as variant 1 and variant 2) that differed in the selection of describing variables. The regression models can be represented formally with the following equations (2) and (3):

$$Y = F(Z_j; \varepsilon) \tag{2}$$

$$Y = G(X_j; \varepsilon) \tag{3}$$

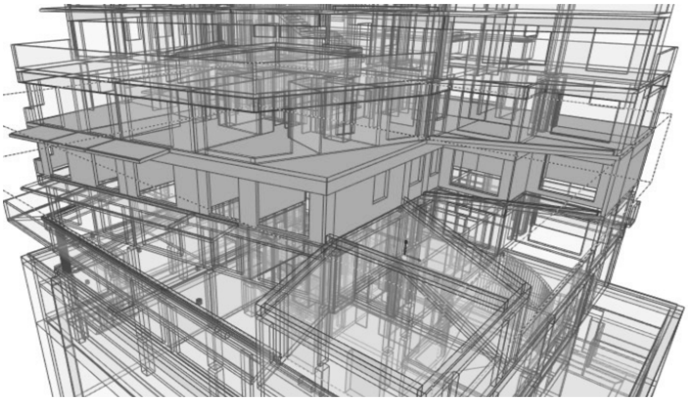

FIGURE 2. Floor structural frame highlighted in a BIM/IFC (own study)
RYSUNEK 2. Uwydatniona konstrukcja kondygnacji budynku w modelu BIM/IFC (opracowanie własne)

Analysis of several BIM models of buildings and review of the requirements for modelling, that explain how the modelling is done and how detailed is the information about the elements from which models are assembled, allowed to decide what kind of parameters can be obtain. The parameters are type of structural element, basic information about material solutions (e.g. cast-in-place concrete or masonry unit) and approximate geometry of structural elements.

According to the previous discussion, neural networks were assumed to be applied in regression models as tools

where:
Y – described variable (model baseline) – the cost of the building's floor structural frame,
Z_j, X_j – describing variables (input of the model) selected respectively for variant 1 and variant 2,
F, G – correlation functions binding the describing variables and the described variable, respectively for of the model for variant 1 and variant 2,
ε – models' errors.

Variables of the two considered variants of regression models are set together in Table 1. In the course of the

TABLE 1. Variables of the two considered variants of the model (own study)
TABELA 1. Zmienne dwóch rozważanych wariantów modelu (opracowanie własne)

Variables Zmienne	Descriptions Opisy	Type of input data for modelling Typ danych wejściowych do modelowania
Described variable		
Y	the cost of the buildings' storey structure	numerical (net cost – excluding value added tax, discounted for a base year [PLN])
Describing variables		
Z_1 / X_1	class of building with regard to building's height[a] (low, medium-high, high)	one of n (1; 0; 0 or 0; 1; 0 or 0; 0; 1)
Z_2 / X_2	gross floor area	numerical (measured surface [m^2])
Z_3 / X_3	capacity of slabs, beams, landings, flights of stairs as construction members	numerical (measured cubic capacity [m^3])
$Z_4 / –$	capacity of walls and columns as construction members (without the division into reinforced concrete and masonry structures)	numerical (measured cubic capacity [m^3])
$– / X_4$	capacity of reinforced concrete walls and columns as construction members	numerical (measured cubic capacity [m^3])
$– / X_5$	capacity of masonry walls as construction members	numerical (measured cubic capacity [m^3])
Z_5 / X_6	location of building – voivodship of Poland	pseudofuzzy scaled descriptive values

[a]Classes of buildings were adopted according to legal regulation – Minister of Infrastructure (2002).

TABLE 2. Exemplary values of the model variants variables (own study)
TABELA 2. Przykładowe wartości zmiennych dla dwóch wariantów modelu (opracowanie własne)

Variables Zmienne	*p*-th sample index Indeks *p*-tej próbki			
	31	43	71	87
Y [thousand PLN]	75.82	205.77	220.32	173.74
Z_1 / X_1	low (1; 0; 0)	medium-high (0; 1; 0)	high (0; 0; 1)	medium-high (0; 1; 0)
Z_2 / X_2 [m^2]	206.4	331.9	349.3	274.5
Z_3 / X_3 [m^3]	32.2	75.5	75.4	59.3
$Z_4 / –$ [m^3]	38.5	84.8	160.3	124.6
$– / X_4$ [m^3]	1.5	39.7	33.9	29.7
$– / X_5$ [m^3]	37.0	45.1	126.4	94.9
Z_5 / X_6	Silesia (0.8)	Lesser Poland (1.4)	Mazovia (0.7)	Lower Silesia (0.9)

research training data have been collected and ordered. The database of the training data included 95 samples. Exemplary training data is presented in Table 2.

In reference to the equations (2) and (3) and assumptions made about the describing variables prediction of the variable Y can be given as $\hat{Y}$ as follows (respectively for variant 1 and variant 2):

$$\hat{Y} = F(Z_j) \quad (4)$$

$$\hat{Y} = G(X_j) \quad (5)$$

To find ANNs that implemented implicitly F and G functions number of neural simulations were made. The details about the neural networks omitted in this paper can be found easily in the lieterature – e.g. Tadeusiewicz (1993), Haykin (1994), Bishop (1995), Osowski (2013). Assumptions for neural simulations made with the use of Statistica software are presented as follows. Training data sets were divided randomly into: subset used in learning – L, testing subset – T, and validating subset – V, in relation L / T / V = 0.6 / 0.2 / 0.2. In the course of research multilayer perceptron type of ANNs were taken into account. Various network architectures, distinct activation functions and training algorithms were applied during the simulations. Architectures of the examined ANNs differed for variant 1 and variant 2:

– for variant 1: 7-h-1 (7 neurons in the input layer, h neurons in the hidden layer and 1 neuron in the output layer);
– for variant 2: 8-h-1 (8 neurons in the input layer, h neurons in the hidden layer and 1 neuron in the output layer).

Number of neurons in the hidden layer – h – for both variants ranged from od 2 do 6. The neurons in the hidden and output layers employed the following activation functions available in Statistica simulator: sigmoid (sigm), hyperbolic tangent (tanh), exponential (exp) and linear (lin) functions. The choice of training algorithms used in the course of neural simulations [Broyden–Fletcher–Goldfarb–Shanno (BFGS), conjugant gradients (CG), the steepest descent (SD)] also depended on their availability in Statistica software. In the course of neural simulations number of networks were examined. Below the results for best networks are reported. In Table 3 characteristics of three chosen networks for each variant are reported. In Table 4 values of RMSE and MAPE as the measures of errors for the chosen ANNs are presented.

In Figure 3 scatter plot of the training results for the chosen networks for both considered variants is shown. General remark after the neural modelling and numerous simulations is that the training quality expressed in the correlation of Y and $\hat{Y}$ was similar for most of the investigated ANNs. The ANNs presented in Table 3 were chosen due to the highest values of correlation reached for the testing (T). The points corresponding to the learning, testing and validating are decomposed mostly along a line of a perfect fit, however some deviations are present. Correlation coefficients are similar for both variants of regression models. RMSE errors are similar in both cases for networks teaching and validating. Correlation coefficients and RMSE errors of networks testing diverge from the values obtained in case of teaching and validating. One of the causes is the outlying case which can be seen in

TABLE 3. Characteristics of chosen ANNs (own study)
TABELA 3. Charakterystyki wybranych SSN (opracowanie własne)

Variant Wariant	Simulation ID ID symulacji	ANN's architecture Architektura SSN	Training algorithm Algorytm uczący	Activation functions Funkcje aktywacji		Training quality (correlation) Jakość trenowania (korelacja)		
				hidden layer warstwa ukryta	output layer warstwa wyjściowa	*L*	*T*	*V*
1	8	MLP 7-6-1	BFGS	exp	sigm	0.9548	0.8510	0.9611
	25	MLP 7-3-1	CG	sigm	lin	0.9544	0.8465	0.9583
	71	MLP 7-4-1	CG	sigm	lin	0.9544	0.8478	0.9581
2	6	MLP 8-5-1	CG	tanh	lin	0.9530	0.8516	0.9621
	18	MLP 8-6-1	CG	tanh	lin	0.9507	0.8509	0.9621
	38	MLP 8-4-1	BFGS	exp	lin	0.9520	0.8546	0.9632

TABLE 4. RMSE and MAPE errors for chosen ANNs (own study)
TABELA 4. Błędy RMSE i MAPE wybranych SSN (opracowanie własne)

Variant Wariant	Simulation ID ID symulacji	ANN architecture Architektura SSN	RMSE			MAPE		
			L	*T*	*V*	*L*	*T*	*V*
1	8	MLP 7-6-1	26.55	33.75	24.19	9.04%	8.85%	9.30%
	25	MLP 7-3-1	25.96	33.89	23.79	9.23%	9.10%	9.63%
	71	MLP 7-4-1	25.90	33.97	23.34	9.32%	8.69%	9.03%
2	6	MLP 8-5-1	25.49	34.99	22.56	9.39%	9.69%	8.34%
	18	MLP 8-6-1	26.20	34.35	22.25	9.60%	8.75%	7.92%
	38	MLP 8-4-1	28.63	38.82	31.61	13.56%	8.60%	13.12%

Figure 3 for both variants. MAPE errors for all of the chosen ANNs except MLP 8-4-1 fall within similar ranges.

Conclusions

In the light of the presented discussion and results of initial research ANNs may be considered as a supportive artificial intelligence tool applicable in macro BIM cost analyzes. The case study presented in this paper allows for assumption that implementation of ANNs in such analyzes will bring costs estimates with a reasonable accuracy. Especially MAPE errors calculated for chosen networks legitimate previous conclusion. Most of cost predictions made by the chosen networks (with the use of data collected so far) fall within a reasonable range of errors. Few large errors of the estimations can be found in the case study results. This deficiency can be over-

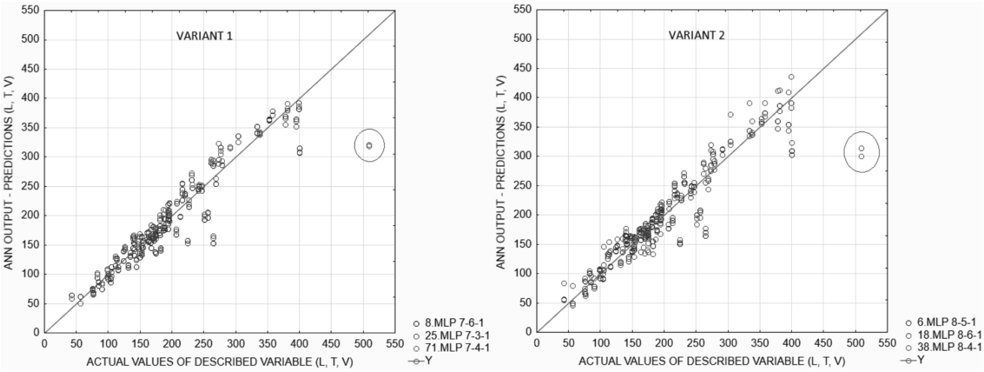

FIGURE 3. Scatter plot of chosen ANNs training results for variant 1and variant 2 (own study)
RYSUNEK 3. Wykres rozrzutu wyników trenowania wybranych SSN dla wariantu 1 i wariantu 2 (opracowanie własne)

come by collecting, preparation and use of larger sets of training data. Proposed selection of the parameters for the purpose of ANN-based macro BIM cost estimation of the floor structural frames of buildings initially confirmed to be correct. However, further studies on the general assumptions for the macro BIM analyzes both in terms of definition of higher level elements and their parameters is necessary.

What is also worth mentioning, a collection of BIM models assembled of elements with assigned cost attributes may serve as a source of knowledge about the costs of buildings. Such collection can be used as a repository and database from which the data used in the ANNs training could be derived.

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Summary

Studies on the ANN implementation in the macro BIM cost analyzes. The paper presents an approach which combines the concept of macro-level BIM-based cost analyzes and application of artificial intelligence tools – namely artificial neural networks. Discussion and foundations of the proposed approach are introduced in the paper to clarify the problem's core. An exemplary case study reports the results of initial studies on the application of neural networks for the purposes of BIM-based cost analysis of a buildings' floor structural frame. The results obtained justify the proposal of application of neural networks as a supportive mathematical tool in the problem presented in the paper.

Streszczenie

O możliwościach zastosowania SSN w analizach kosztowych „macro BIM". Artykuł przedstawia podejście, w którym połączono koncepcję analiz kosztowych macro BIM z zastosowaniem narzędzi sztucznej inteligencji – sztucznych sieci neuronowych. W artykule zaprezentowano dyskusję i podstawowe założenia proponowanego podejścia stanowiące wyjaśnienie istoty problemu. Studium przypadku przedstawia wyniki wstępnych badań dotyczących różnego zastosowania sieci neuronowych w analizach kosztów z zastosowaniem BIM na przykładzie oszacowań kosztów konstrukcji nośnej kondygnacji budynku. Uzyskane wyniki uzasadniają propozycję wykorzystania sieci neuronowych jako narzędzia matematycznego rozwiązywania problemu przedstawionego w artykule.

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