CCC 2018

Proceedings of the Creative Construction Conference (2018)
Edited by: Miroslaw J. Skibniewski & Miklos Hajdu
DOI 10.3311/CCC2018-056

Creative Construction Conference 2018, CCC 2018, 30 June - 3 July 2018, Ljubljana, Slovenia

Design rules to improve efficiency in the steel construction industry

Mathieu Fokwa Soh [a], Daniel Barbeau [b], Sylvie Dore [a], Daniel Forgues [a]*

[a] *École de technologie supérieure, 1100 Rue Notre-Dame Ouest, Montréal, QC H3C 1K3 Quebec, Canada*
[b] *Groupe CANAM, 270, chemin Du Tremblay Boucherville, J4B 5X9 Québec, Canada*

Abstract

In steel construction projects, 88% of total decisions impacting cost are made during the design phase. These decisions are made by design professionals, who have neither the knowledge nor the experience of manufacturing operations. In manufacturing engineering, collaboration between designers and manufacturers is well established and formalized through different methods and design rules such as design for manufacturing and assembly (DFMA). These rules provide designers with essential knowledge to reduce the cost and time of manufacturing and assembly of parts during their design, while increasing customer satisfaction
Building Information Modeling (BIM) and TFV Theory (Transformation Flow and Value) provide to the construction industry, tools and processes to improve collaboration between design and manufacturing phases while reducing waste during projects. However, BIM and TFV theory do not formalize collaboration between designers and manufacturers of steel structures. Yet, the lack of collaboration between these two phases causes lot of rework, lot of waste of time and material during projects.
The aim this research is to develop design rules to overcome some of these issues. These rules use the information taken from the BIM model of 1000 steel structures from a steel manufacturer, to reduce the manufacturing time. These information are grouped and classified according to criteria evaluated using a neural network algorithm. In addition, the recent integration of artificial intelligence in construction projects provides industry with methods to draw from previous projects, essential knowledge for better decision-making. The research shows the strong dependence of the manufacturing time of the steel structures on the quantities of complete cuts and weld in full penetration and on the number of beams that do not come in right angles in the connections.

Keywords: Building-information-modelin; Design-rules; Neural-network-algorithm; Transformation-Flow-Value;

1. Introduction

Here 88% of total time and cost decisions for steel structures are made during the design phase [1]. However, in traditional processes (linear and fragmented) the manufacturer (third party of the subcontractors) is at the bottom of the supply chain: he has no opportunity for interactions with the design professionals to improve the design solutions considering the capabilities' of the manufacturer [2,3]. This situation causes a sub-optimal design that does not take into account the components and manufacturing constraints [4,5], resulting in increased cost and delays in steel construction projects [6]. In manufacturing engineering, collaboration between designers and manufacturers is well established and formalized through different methods and design rules such as design for manufacturing and assembly (DFMA) [7]. The DFMA acts directly on the cost and the time of realization of products by proposing up to 57% reduction of the time of manufacture and assembling, 68% of customers satisfaction and 51% reduction of the number of parts [8]. These rules provide designers with essential knowledge to reduce the cost and time of manufacturing and assembly of parts during their design, while increasing customer satisfaction [9]. We argue that, such design rules can be formulated and applied in steel construction projects, as a way to improve the efficiency and efficacy of the fabrication and installation of steel components. BIM brings to the construction industry, tools and processes that could

Fokwa Soh Mathieu: Mathieu.fokwa-soh.1@ens.etsmtl.ca

DOI 10.3311/CCC2018-056

facilitate collaboration between designers and manufacturers [10]. In steel construction, BIM is mostly used for constructability, and for quantitative estimation of structures [11]. BIM is not yet used to its high potential because it does not promote the integration of production practices with designers [12]. There is an opportunity to leverage BIM benefits by introducing new procurement approaches that permits this dialogue between designers and manufacturer, bringing the later at the front-end of the design process. However, this requires drastic changes in industry practices. The development of design rules is seen as a middle road to make available manufacturer knowledge to the design process. Design rules are closely related to the current production process [13]. In steel construction, the capability of production differ from one workshop to another. It is therefore necessary to identify the time indicators in production processes, which will inspire the establishment of design rules. Unfortunately, traditional estimation methods do not do enough, and artificial intelligence (AI) is increasingly being suggested to predict costs in construction industry and to describe the processes of production [14]. AI is increasingly used for predicting the manufacturing time of steel structures [14]. AI techniques make it possible to search and organize data from previous projects according to the variables that influence the time of realization of projects. The algorithms will be inspired by these data to predict with a good accuracy, the times of realization of future projects [15]. These data can be provided through BIM models. The research objective is to propose, design rules focusing on a particular production process that influence the time of realization of projects. To achieve this, the BIM models of 1000 steel structures will be analyzed and classified according to predefined variables. The weights of the variables will be established and design rules will be proposed according to the weight of the selected variables.

2. Related work

This section presents these key points related to this study: the use of BIM models as data sources, the establishment of a prediction to find the weight of the variables that influence the manufacturing time and the development of design rules

2.1. BIM models as data sources

Monteiro (2013) and Shen (2010) propose to use BIM data as sources for prediction. BIM offers the possibility of adapting BIM models to extract data according to estimation criteria [16]. Integrating BIM models into project cost and time estimating processes produces better results than traditional methods [17]. BIM also offer the possibility of introducing information related to the manufacturing of steel structures in design process [18], in order to build a database, which will be used to estimate the cost and time of project. Data extraction can be done automatically from the model, in order to plan and control phases [19,20].

2.2. Prediction of manufacturing time for project steel components

- Choice of algorithm

Several authors suggest to use the neural network as prediction algorithm in steel construction [21-24]. The application of neural network has many advantages for prediction. Among its advantages: his speed of execution, its ability to generalize results and insensitivity to data noise and the capability to undertake into account complex prediction cases with several variables [25]. The use of neural network in the prediction of steel structures offers effective results with errors ranging from 4.63% to 16% [26]. However, neural networks require many resources to function and present results that are difficult or impossible to interpret [27]. This study will use the neuron network as the algorithm.

One of the most important steps in estimating project completion time is the selection of variables or estimation factors. The selection of these variables should be done in a way to avoid errors and over-processing. Table 1 proposes variables used by some authors, for estimating the cost of steel construction.

DOI 10.3311/CCC2018-056

Table 1. Variables proposed by the authors.

Authors	Variables	units
Mohsenijam & Lu (2016)	steel weight	ton
	the complete penetration weld	m
	the hex type bolt	number
	the I-beam	m
	the round hollow steel section	m
Sarma & Adeli (2000)	the geographic localisation	position
	the number of connections	number
	weight of rolled sections	kg
	different section types used in the structure	number
	the cost of rolled sections	$
Hu et al. (2014)	…	
	the length of the types of profiles used	m
	the length of complete fusion weld	m
	the length of partial fusion welds	m

According to these authors (table 1), the estimation variables are circumscribed by masses, length and quantities of the elements of the steel structures, which could be extracted from the BIM models database. However, criteria such as the volume of the structure, the number of cuts, the number of holes, and the length of preparation of the steel structures are not considered. Yet these criteria directly influence the duration and cost of manufacturing [28].

2.3. Development of design rules

In the manufacturing industry, DFMA is a method to help reduce the cost and duration of realization of the products by reducing the quantities of elements, the complex operations, the manual operations, and by simplifying the structure of the products [29]. Construction activities are like a manufacturing process [30], especially in steel construction. However, variables related to transport, maintenance, technical assistance, use of standard tools and materials can also influence the cost of the product [9]. Variables related to product structure and machining operations are therefore essential to the development of design rules.

 DOI 10.3311/CCC2018-056

3. Research method

The method for this research to develop design rules is divided in 3 (three) steps (figure 1). These steps are: harvesting and data mining, predicting manufacturing time and determination of variable weights, designing rules for steel structures.

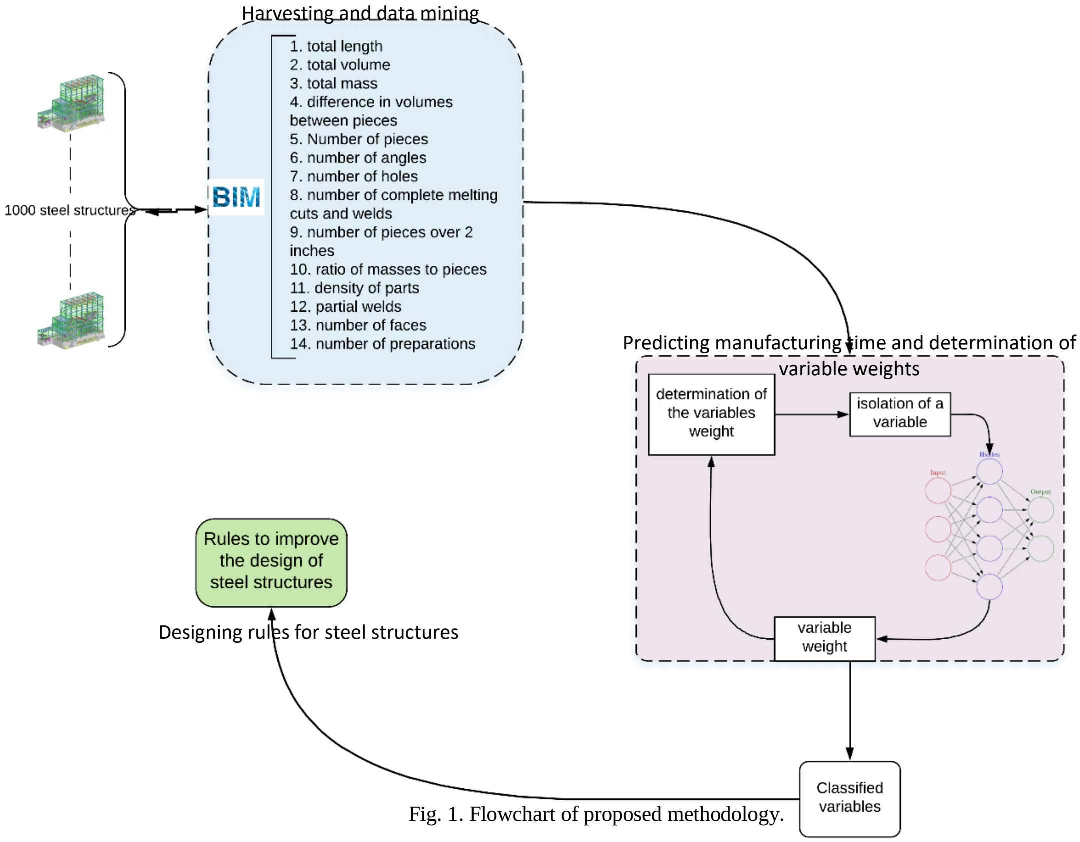

Fig. 1. Flowchart of proposed methodology.

3.1. Harvesting and data mining

In this step, the data come from BIM models (Tekla structure 21.0), organized according to the selected criteria, which take into account the factors that influence the duration of the fabrication of steel structural elements. For better results in prediction using neural networks, normalized variables data is required [27]. Normalized variable data means: reduce the variable to values ranging from 0 to 1. To do this, Equation (1) is used.

$$function(x) = ((x - \min(x)))/((\max(x) - \min(x))) \qquad (1)$$

3.2. Predict manufacturing time and determination of variable weights

To better compare the results of a prediction with the real data, Lantz (2015) proposes to calculate the following values: The correlation (Cor), the Mean absolute error (MAE) and the relative absolute error (RAE).

Correlation
$$Cor = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{(n-1)\, S_x S_y} \qquad (2)$$

Mean absolute error
$$MAE = \frac{1}{N}\sum_{i=1}^{N} |\bar{x}_i - x_i| \qquad (3)$$

Relative absolute error
$$RAE = \frac{\sum_{i=1}^{N}|\bar{x}_i - x_i|}{\sum_{i=1}^{N}|\bar{x} - x_i|} \qquad (4)$$

Where $\overline{x_i}$ is a mean value of x_i and $\overline{y_i}$ is a mean value of y_i

The algorithm will perform several predictions with each time, a variable less, to find the weight of the variables involved in the prediction.

3.3. Design rules for steel structures.

Through predictions, variables now have weight. Based on these weights, the study will propose instructions to be considered during the design phase of the steel structures, to reduce the manufacturing time of the elements. These instructions will define our design rules.

4. Results and interpretations

Table 2 presents the results of the prediction.

Table 2. fabrication time prediction results.

results	*variables*	*correlation*	*MAE*	*RAE*
R all	all variables	0,9841005410	0,0083005274	0,1725046537
R1	1. total length	0,9214258619	0,0847322012	1,2711706370
R2	2. total volume	0,5068106424	0,2392389322	1,3994818300
R3	3. total mass	0,9668307042	0,0516198343	0,7267404529
R4	4. difference in volumes between pieces	0,9685086988	0,0466218118	0,6623405512
R5	5. number of pieces	0,4423277468	0,2552932616	2,4596952140
R6	6. number of angles	0,4423277468	0,2552932616	2,4596952140
R7	7. number of holes	0,9659978485	0,0202921947	0,3692790984
R8	8. number of complete melting cuts and welds	-0,1787795600	0,4941618021	2,4027818090
R9	9. number of pieces over 2 inches	0,8678071094	0,1150959974	2,8127183850
R10	10. ratio of masses to pieces	0,9739915642	0,0251589375	0,4168327297
R11	11. density of parts	0,9608203939	0,0141813740	0,2597240733
R12	12. partial welds	0,9518767118	0,0118450157	0,2220511256
R13	13. number of faces	0,9816932789	0,0096399970	0,1925543997
R14	14. number of preparations	0,9849647839	0,0090870625	0,1870279812

In (R all) are the results that imply all the variables: "R all" corresponds to: 98.4% correlation coefficient, and 17% Relative absolute error with 0.8% of Mean absolute error. The predictions made with variable substitution give us the results from R1 (results without variable 1) to R14 (results without variables 14).

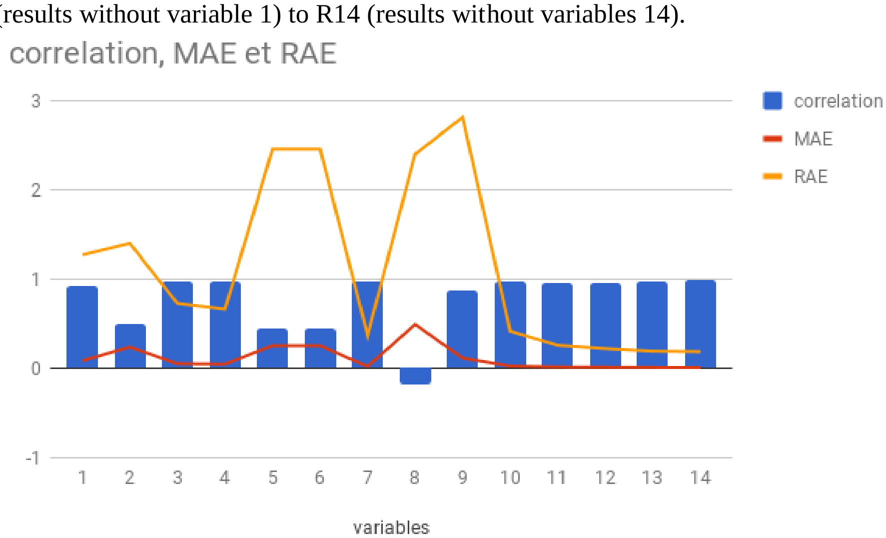

Fig. 2. summary of correlation calculations and errors.

 DOI 10.3311/CCC2018-056

Through these predictions, the variables are classified according to the influence that their absence causes in the accuracy of the algorithm on the Cor, the MAE and the RAE

results	variables	correlation
R14	14. number of preparations	0,9849647839
R13	13. number of faces	0,9816932789
R10	10. ratio of masses to pieces	0,9739915642
R4	4. difference in volumes between pieces	0,9685086988
R3	3. total mass	0,9668307042
R7	7. number of holes	0,9659978485
R11	11. density of parts	0,9608203939
R12	12. partial welds	0,9518767118
R1	1. total length	0,9214258619
R9	9. number of pieces over 2 inches	0,8678071094
R2	2. total volume	0,5068106424
R5	5. number of pieces	0,4423277468
R6	6. number of angles	0,4423277468
R8	8. number of complete melting cuts and welds	-0,1787795600

Fig. 3. impact of the variables on the correlation coefficient.

results	variables	MAE
R14	14. number of preparations	0,0090870625
R13	13. number of faces	0,0096399970
R12	12. partial welds	0,0118450157
R11	11. density of parts	0,0141813740
R7	7. number of holes	0,0202921947
R10	10. ratio of masses to pieces	0,0251589375
R4	4. difference in volumes between pieces	0,0466218118
R3	3. total mass	0,0516198343
R1	1. total length	0,0847322012
R9	9. number of pieces over 2 inches	0,1150959974
R2	2. total volume	0,2392389322
R5	5. number of pieces	0,2552932616
R6	6. number of angles	0,2552932616
R8	8. number of complete melting cuts and welds	0,4941618021

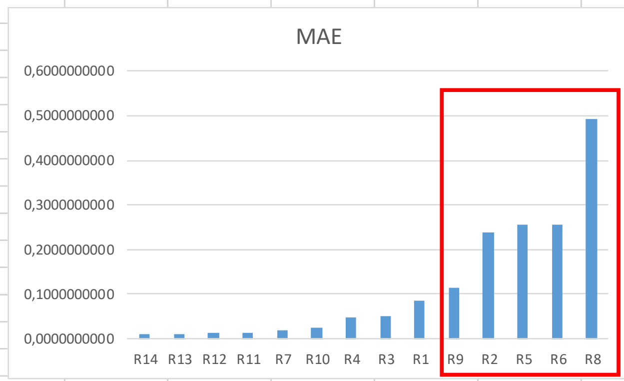

Fig. 4. impact of the variables on the Mean absolute error.

results	variables	RAE
R14	14. number of preparations	0,1870279812
R13	13. number of faces	0,1925543997
R12	12. partial welds	0,2220511256
R11	11. density of parts	0,2597240733
R7	7. number of holes	0,3692790984
R10	10. ratio of masses to pieces	0,4168327297
R4	4. difference in volumes between pieces	0,6623405512
R3	3. total mass	0,7267404529
R1	1. total length	1,2711706370
R2	2. total volume	1,3994818300
R8	8. number of complete melting cuts and welds	2,4027818090
R5	5. number of pieces	2,4596952140
R6	6. number of angles	2,4596952140
R9	9. number of pieces over 2 inches	2,8127183850

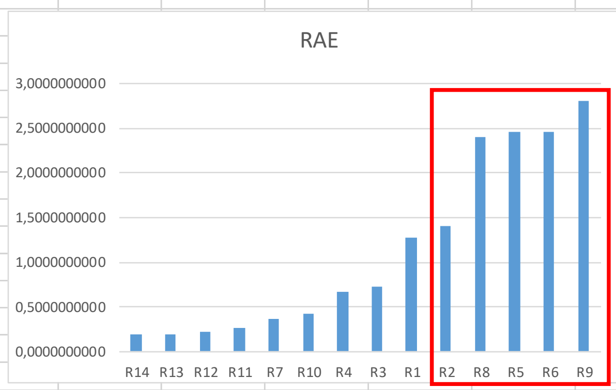

Fig. 5. impact of the variables on the Relative absolute error.

These data present the most influential variables that are:
R8: the number of complete melting cuts and welds,
R6: number of pieces that come in angles.

 DOI 10.3311/CCC2018-056

R5: number of pieces,
R2: total volume,
R9: number of pieces over 2 inches

5. Development of design rules

From the analysis of these results, the following major design lines are proposed:

- Avoid designing structures having many full fusion welds.
- Avoid designing structures with a very large number of parts.
- favor the connection in right angles.
- Avoid designing assemblies with large volume,
- Avoid designing works with thick pieces.

6. Conclusion

This work proposes design rules to reduce the machining time of steel structures. To achieve this, this study collected and organized information from 1000 BIM models of steel structures. An algorithm based on the neuron network made it possible to make predictions of manufacturing time of the structures. This algorithm allowed the classification of the variables according to their impact on the time of realization of projects. The study has formulated design rules to reduce the manufacturing time of steel structures. A working perspective for this study will be to apply these design rules to the design of new projects to be realized in these same workshops, in order to appreciate the impact of these rules on the manufacturing time of the structures.

References

1. Evers HGA, Maatje IRF. Cost based engineering and production of steel constructions. In: Steel Design Codes—Fourth International Workshop on Connections in Steel Structures. 2000. p. 14–22.
2. Forgues D, Iordanova I. An IDP-BIM framework for reshaping professional design practices. In: Construction Research Congress 2010: Innovation for Reshaping Construction Practice. 2010. p. 172–82.
3. Forgues D, Koskela L. The influence of a collaborative procurement approach using integrated design in construction on project team performance. Int J Manag Proj Bus [Internet]. 2009;2(3):370–85. Available from: https://www.scopus.com/inward/record.url?eid=2-s2.0-77956273236&partnerID=40&md5=efb21cffc0ad706031202f4cc40d1270%5Cnhttp://www.emeraldinsight.com/doi/pdfplus/10.1108/17538370910971036%5Cnhttp://dx.doi.org/10.1108/17538370910971036
4. Latham Sir M. Constructing the team: Final report of the government/industry review of procurement and contractual arrangements in the UK construction industry. London: HMSO; 1994.
5. Egan J. The Egan report-rethinking construction. Rep Constr Ind task force to deputy prime Minist London. 1998;
6. Jeong W, Chang S, Son J, Yi J-S. BIM-integrated construction operation simulation for just-in-time production management. Sustainability. 2016;8(11):1106.
7. Boothroyd G. Product design for manufacture and assembly. Comput Des. 1994;26(7):505–20.
8. Ashley S. Cutting costs and time with DFMA. Mech Eng. 1995;117(3):74.
9. Da Silva CES, Salgado EG, Mello CHP, Da Silva Oliveira E, Leal F. Integration of computer simulation in design for manufacturing and assembly. Int J Prod Res. 2014;52(10):2851–66.
10. Eastman CM, Eastman C, Teicholz P, Sacks R. BIM handbook: A guide to building information modeling for owners, managers, designers, engineers and contractors. John Wiley & Sons; 2011.
11. Mohsenijam A, Lu M. Achieving sustainable structural steel design by estimating fabrication labor cost based on BIM data. Procedia Eng. 2016;145:654–61.
12. Oti AH, Tizani W. BIM extension for the sustainability appraisal of conceptual steel design. Adv Eng Informatics. 2015;29(1):28–46.
13. Holt R, Barnes C. Towards an integrated approach to "design for X": An agenda for decision-based DFX research. Res Eng Des. 2010;21(2):123–36.
14. Sarma KC, Adeli H. Cost optimization of steel structures. Eng Optim A35. 2000;32(6):777–802.
15. Adeli H. Neural networks in civil engineering: 1989–2000. Comput Civ Infrastruct Eng. 2001;16(2):126–42.
16. Monteiro A, Martins JP. A survey on modeling guidelines for quantity takeoff-oriented BIM-based design. Autom Constr. 2013;35:238–53.
17. Shen Z, Issa RRA. Quantitative evaluation of the BIM-assisted construction detailed cost estimates. 2010;
18. Heinisuo M, Laasonen M, Haapio J. BIM based manufacturing cost estimation of build-ing products. eWork Ebus Archit Eng Constr ECPPM. 2010;53–9.
19. Plebankiewicz E, Zima K, Skibniewski M. Analysis of the first polish BIM-based cost estimation application. Procedia Eng. 2015;123:405–14.

20. Hu X, Lu M, AbouRizk S. BIM-based data mining approach to estimating job man-hour requirements in structural steel fabrication. In: Proceedings of the 2014 Winter Simulation Conference. IEEE Press; 2014. p. 3399–410.
21. Kaveh A, Fahimi-Farzam M, Kalateh-Ahani M. Performance-based multi-objective optimal design of steel frame structures: Nonlinear dynamic procedure. 2015;22(2):373–87.
22. Kaveh A, Shojaei I, Gholipour Y, Rahami H. Seismic design of steel frames using multi-objective optimization. Struct Eng Mech [Internet]. 2013 Jan 25 [cited 2018 Mar 30];45(2):211–32. Available from: http://koreascience.or.kr/journal/view.jsp?kj=KJKHB9&py=2013&vnc=v45n2&sp=211
23. El Dsoki C, Hanselka H, Kaufmann H, Röbig A. Das ANSLC programm zur abschä tzung zyklischer werkstoffkennwerte. Materwiss Werksttech [Internet]. 2009 Aug [cited 2018 Mar 30];40(8):612–7. Available from: http://doi.wiley.com/10.1002/mawe.200800363
24. Song L, Allouche M, Abourizk S. Measuring and Estimating Steel Drafting Productivity. In 2003. p. 67–75.
25. Siqueira I. Neural network-based cost estimating. Concordia University; 1999.
26. El-Sawah H, Moselhi O. Comparative study in the use of neural networks for order of magnitude cost estimating in construction. J Inf Technol Constr. 2014;19(27):462–73.
27. Lantz B. Machine learning with R. Packt Publishing Ltd; 2015.
28. Ali NBH, Sellami M, Cutting-Decelle A-F, Mangin J-C. Multi-stage production cost optimization of semi-rigid steel frames using genetic algorithms. Eng Struct. 2009;31(11):2766–78.
29. Dalgleish GF, Jared GEM, Swift KG. Design for assembly: influencing the design process. J Eng Des. 2000;11(1):17–29.
30. Anumba C, Kamara JM, Cutting-Decelle A-F. Concurrent engineering in construction projects. Routledge; 2006.