

A Multi-agent Framework for Cost Estimation of Product Design

Marcin Relich^{1(✉)} and Pawel Pawlewski²

¹ Faculty of Economics and Management, University of Zielona Gora, Zielona Gora, Poland
m.relich@wez.uz.zgora.pl

² Faculty of Engineering Management, Poznan University of Technology, Poznan, Poland
pawel.pawlewski@put.poznan.pl

Abstract. This paper presents the use of a multi-agent framework for evaluating parameters of new products and estimating cost of product design. Companies often develop many new product projects simultaneously. A limited budget of research and development imposes selection of the most promising projects. The evaluation of new product projects requires cost estimation and involves many agents that analyse the customer requirements and information acquired from an enterprise system, including the fields of sales and marketing, research and development, and manufacturing. The model of estimating product design cost is formulated in terms of a constraint satisfaction problem. The illustrative example presents the use of a fuzzy neural network to identify the relationships and estimate cost of product design.

Keywords: Multi-agent system · Fuzzy neural network · Constraint programming · New product development · Decision support system

1 Introduction

Decreasing product life cycles, increasing variety of products, and quick adjustment to market trends require the successful new product development (NPD) that is one of the most important factors in maintaining company's competitiveness. New product success depends on customer satisfaction that is related to utility, quality and price of a product [1–3]. Incorporating customer requirements in a new product incur expenditures during the NPD phases such as product design, prototype manufacturing and testing. The expenditure budget in research and development (R&D) is often limited, and company has to select the most promising NPD projects according to the criteria such as the expected profitability and R&D cost of a new product. Consequently, cost estimation for the NPD projects is needed.

The product design phase includes design reusability and engineering design, and it precedes phases such as product manufacturing and commercialisation. The poor product design raises many categories of cost relates to special equipment or modifications, inefficient assembly, excessive part proliferation, difficulties with part fabrication and product reliability, and finally, customer dissatisfaction [4, 5].

Today's enterprise information systems support the user in managing different phases of the NPD process, and also register and store the performance of the previous NPD projects (e.g. customer requirements, design parameters, product manufacturing). More and more companies are using solutions such as customer relationship management (CRM), computer-aided design (CAD), computer-aided engineering (CAE), computer-aided manufacturing (CAM), and enterprise resource planning (ERP) system. The data stored in an enterprise system can be used to identify the key factors influencing cost of a particular phase of the NPD process, and finally, improve the performance of the current NDP projects and the product success.

Product design involves many individuals and groups, including customers, analysts, project managers, R&D employees, chief marketing, production officers, etc. The product design process can be supported through an integrated business information system that combines the different agents and enables their communication. A multi-agent approach can replace the conventional centralized systems (for manufacturing, product design etc.) with a network of agents that are endowed with a local view of its environment and the ability to respond locally to that environment. As a result, the overall system performance is not globally planned, but emerges through the dynamic interactions between agents in real time [6].

Despite increasing popularity and applications of agent-based technology in the business domain, there is still a lack of unifying framework that would used the multi-agent paradigm to cost estimation of product design. This study aims to develop an agent-based framework for estimating cost of product design providing a foundation for conceptual analysis. The proposed multi-agent system includes client agent, marketing agent, research and development agent and data mining agent that identify variables suspected of significant impact on the cost of past products. Relationships between the cost of past products and variables influencing the cost are sought with the use of a fuzzy neural network that is able to discovered complex nonlinear relations and is suitable tool for estimating the cost.

The cost estimation model is formulated in term of a constraint satisfaction problem (CSP) as a set of variables, their domains, and constraints linking and limiting the variables. CSP can be treated as a knowledge base that includes the identified patterns and expert knowledge, and enables formulating routine questions such as what is the cost of product design, what is the most promising NPD project portfolio, or what values should have the parameters of a NPD project to fulfil the cost expectations. Knowledge base formulated as CSP can be effectively implemented in constraint programming environment that is an emergent software technology for a declarative CSP description and can serve as a pertinent framework to develop a decision support system [7, 8].

The remaining sections of this paper are organised as follows: Sect. 2 presents the use of multi-agent approaches in new product development. Section 3 presents a model of cost estimation of product design in terms of constraint satisfaction problem. The proposed multi-agent framework for evaluating parameters of new products and estimating the cost of product design is shown in Sect. 3. An illustrative example of the proposed approach is presented in Sect. 4. Finally, some concluding remarks are contained in Sect. 5.

2 Multi-agent Systems in New Product Development

Multi-agent systems (MAS) are systems with multiple agents and are suitable for complex problems that have alternative problem solving techniques, involve reasoning with multiple models at different levels of abstraction and representations, and usually involve distributed knowledge sources [9]. MAS are intelligent distributed approach suited for applications that are modular, complex, and changeable, for example, in product design. These systems have capabilities such as autonomy, integration, reactivity and flexibility, and they are an emerging sub-field of artificial intelligence that is concerned with a society of agents interacting in order to solve a common problem [10]. The paradigm of MAS provides a very suitable architecture for a design and implementation of integrative business information systems. The complex information systems development can be supported with the use of agent-based technology in the context of natural decomposition, abstraction and flexibility of management for organisational structure changes [11].

Agent technology is a result of convergence of many technologies within computer science such as object-oriented programming, distributed computing and computational intelligence [12]. Recently, an increasing number of approaches related to computational intelligence, including neural networks and fuzzy logic has been used to multi-agent applications. For instance, the artificial neural networks have been used to the output regulation problem of the nonlinear multi-agent systems [13], create a machine agent who determines the appropriate machine in order to fulfil clients' requirements [14], form a classifier agent team [15], MAS that incorporates a case-based reasoning system and automates the business control process [16], or create a multi-agent identifier in order to identify the dynamics of the plant [17].

The use of fuzzy logic-based approaches in the context of MAS includes the fields such as modelling the controller that regulates the number of agents in MAS [18], designing fuzzy model for supply chain modelling based on agents [19], developing the agent-based negotiation process for e-commerce [20], or making decision rules [21]. There are also hybrid approaches based on fuzzy neural network structures that can be used to intelligent task planning and action selection in MAS [22] or modelling the controller in multi-agents [23].

Design is a complex knowledge discovery process in which information and knowledge derives from various sources. Complex design combines automated software components with human decision makers. Software agents provide the necessary support for keeping humans in the loop, and multi-agent framework combines various sources of information and reasoning [24]. The use of the MAS paradigm in the context of knowledge management includes tasks such as [25]: knowledge search, acquisition, analysis and classification from diverse data sources; information given to human and computing networks once usable knowledge is ready to be consulted; negotiation on knowledge integration or exclusion into the system; explanation of the quality and reliability which are related to the system integrated knowledge; and learning progressively all along the knowledge management process.

Product design strongly impact on assembly planning enabling reduction of manufacturing cost and enhancing production efficiency and product quality. Zha [26] presented

advantages of a multi-agent framework for developing the integrated design and assembly planning system. Chu et al. [27] considered the effectiveness of multi-agent technologies to implement a collaborative three-dimensional design system. A multi-agent system has also been used to identify the variables influencing the product success and select portfolio of new product development project [28].

Knowledge acquisition in the field of new product development is of significant importance for a contemporary organisation taking into account potential increment of technology and infrastructure. As in the knowledge discovery process is not possible to eliminate a human dimension, a multi-agents approach seems to be a suitable framework to model the problem of identifying a set of variables influencing the cost of product design and evaluating the parameters of a new product. This type of information and knowledge is needed to estimate the cost of product design, and support the project managers in selecting the most promising NPD project portfolio and conducting what-if analysis.

3 Model of Estimating Product Design Cost

Specifications of the past NPD projects, including design parameters, product portfolios, and customer requirements are registered and stored in an enterprise information system that includes e.g. CAD, CRM and ERP system. If new product development is related to slight modification of previous products, then enterprise database may be used to identify the factors influencing the cost of designing previous products, and estimating the cost of a new design. The presented model is formulated in terms of CSP and consists of a set of decision variables, their domains, and the constraints that refer to the company's resources and performance indicators. The model description encompasses the limitations of a company, parameters of new products and a set of routine queries formulated in the framework of CSP. The structure of the constraint satisfaction problem may be described in the following form [29]:

$$\text{CSP} = ((V, D), C)$$

where:

- V is a finite set of variables,
- D is a finite set of discrete domains of variables,
- C is a finite set of constraints.

The presented model of estimating product design cost contains the following variables:

- Number of interviewed clients to survey client's requirements
- Number of client's requirements for a new product
- Number of client's requirements translated into product specification
- Number of ideas for a new product
- Number of components in a new product
- Number of modified components in a new product
- Number of project team members

The constraints include the total number of team members directly involved in a NPD project $C_{1,t}$ and financial means $C_{2,t}$ in the t -th time unit ($t = 0, 1, \dots, T$). The decision criterion for product portfolio selection is minimisation of the cost of product design by the given constraints.

The constraint satisfaction problem can be considered in the context of a knowledge base that is a platform for query formulation and obtaining answers [7, 30]. The model formulation in terms of CSP integrates technical parameters, available resources, identified patterns (rules) and user requirements in the form of knowledge base, and facilitates the development of a decision support system. The problem solution is related to seeking the answer to the following questions:

- What is the product design cost and what products should be selected to the product portfolio to obtain the minimal cost of NPD projects by a fixed amount of resources?
- What values should have the parameters of NPD projects to fulfil the cost expectations?

Constraints satisfaction problems can be solved with the use of constraint programming that seems to suit very well for modelling decision problems [31]. Constraint programming techniques have embedded ways to solve CSP with greatly reduction of the amount of search needed [32]. This reduces the processing time of calculations, what is especially important for extensive search space, and it is sufficient to solve many practical problems such as supply chain problem [33–35] or scheduling problem [36, 37].

A multi-agent approach can be successfully used to solve constraint satisfaction problems, for example, n -queen problems and coloring problems. In solving a CSP with this approach, each agent can represent a variable and its position corresponds to a value assignment for the variable. The environment for the whole multi-agent system contains all the possible domain values for the problem. The conducted research shows that the performance of a multi-agent approach in solving CSPs for approximate solution is time-efficient [38].

4 The Proposed Multi-agent System for Estimating Product Design Cost

The design parameters of past products are routinely registered and stored in an enterprise information system. The big amount of data and easiness of data retrieval from an enterprise system increases an opportunity to acquire valuable information, and finally, improve cost estimation of product design. To automate the process of analyzing huge amount of data and discovering nontrivial and potentially useful patterns, data mining techniques are used. One of data mining techniques is a fuzzy neural network that can identify complex nonlinear relationships and is a suitable tool for modelling, simulating, and estimating [3].

In the case of product customization, cost estimation of product design can be based on information obtained from customers and the parameters of past products. The product design process can be divided into a few sub-processes, such as identification of the customer requirements, seeking the relationships between different variables suspected of

the impact on the cost of NPD projects, evaluation of NPD projects, and selection of the most promising NPD portfolio. To successful performance, these sub-processes require cooperation and communication between the agents involved. Figure 1 illustrates a multi-agent system for estimating cost of product design.

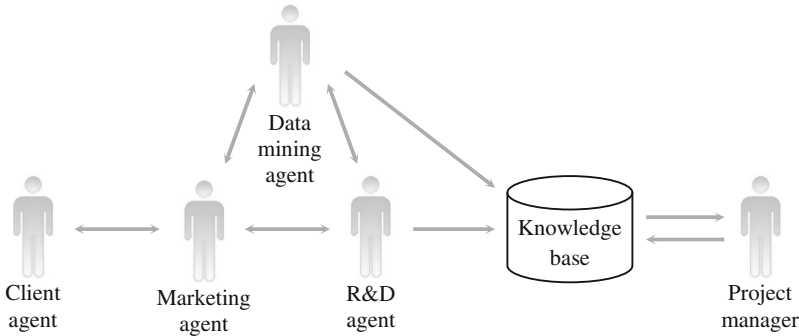


Fig. 1. Multi-agent system for estimating product design cost

In the phase of identification of the customer requirements, a marketing agent communicates with customers to investigate their needs for a new product. In the next phase, a marketing agent communicates with an R&D agent to specify the customer requirements for a new product. An R&D agent determines the expected time of new product development and the range of the customer requirements translated into product specification, and sends these parameters to a marketing agent who in turn investigates customer acceptance of a new product. A data mining (DM) agent identifies variables suspected of significant impact on the cost of past products and sends the requests of the expected values of these variables for a new product to a marketing agent and an R&D agent. Finally, an R&D agent and DM agent store the identified rules in knowledge base that is used to estimate the cost of new products, conduct what-if analysis on the basis of the parameters specified by the project manager, and select the most promising NPD portfolio. Apart from rules, knowledge base stores the facts related to the constraints such as the NPD project budget, a number of project team members, the expected time-to-market for a new product.

The agents have the various objectives and constraints that concern the specific area of the product design process. Consequently, the cooperation between the agents is needed to adjust their local tasks and improve the estimating quality of product design cost. Table 1 presents an example of information that is specified in the messages between the agents.

The negotiation algorithm between a marketing agent and R&D agent is executed until the specification of a new product meets the customer requirements in the agreed range. The customer requirements are verified in the context of available technology and the cost that the company can incur to obtain the required materials, components and technology.

Table 1. An example of message description

Item	Description
Sender	Marketing agent
Receiver	R&D agent
Message type	Product design specification
Message task	Specifying customer requirements
Deadline	Time by which the R&D agent has to respond
Content	The description of the customer needs and requirements for a new product

Relationships between the cost of previous products and variables influencing the cost are sought with the use of a fuzzy neural network that includes advantages of both neural networks (e.g. learning abilities, optimization abilities and connectionist structures) and fuzzy systems (e.g. if-then reasoning, simplicity of incorporating expert knowledge). A fuzzy neural network identifies if-then rules that are further used to cost estimation of product design. In this study, the adaptive neuro-fuzzy inference system (ANFIS) has been used. The parameters of a new product (values of input variables) are specified by a marketing agent and R&D agent and led to the ANFIS that estimates the cost of product design. As the NPD cost is criterion of product portfolio selection, the most promising set of the NPD projects can be determined.

In this study, the knowledge base is formulated as a constraint satisfaction problem that can be effectively implemented in constraint programming (CP). CP is an emergent software technology for a declarative CSP description and can serve as a pertinent framework to develop a decision support system [7, 8]. The next section illustrates the use of a fuzzy neural network to identify relationships among data, develop knowledge base and estimate the cost, and the use of CP to seek the admissible solutions according to a user request.

5 Example

An illustrative example consists of two parts. The first part concerns the use of the ANFIS to identify relationships and estimate the NPD cost. In turn, the second part illustrates the use of constraint programming to seek the possible solutions (if there are any) for the constraints specified by the user.

5.1 Cost Estimation with the Use of ANFIS

Cost of product design (CD) has been estimated on the basis of the following variables: number of interviewed clients (CS), number of client's requirements for a new product (CR), number of client's requirements translated into product specification (CRT), number of ideas for a new product (INP), number of components in a new product (CNP), number of changed components in a new product (CCP), and number of project team members (PTM). The ANFIS uses data of previous projects and identifies the relationships (in the form of if-then rules) between input variables and the cost of past product.

In studies, the ANFIS has been learnt according to subtractive clustering method implemented in the Matlab® software, with the following parameters: range of influence – 0.3, squash factor – 1.25, accept ratio – 0.5, reject ratio – 0.15. The membership functions are specified for each input variables and the identified if-then rules that are further used to estimate the cost of product design. Figure 2 illustrates the membership functions of 10 rules identified by the ANFIS.

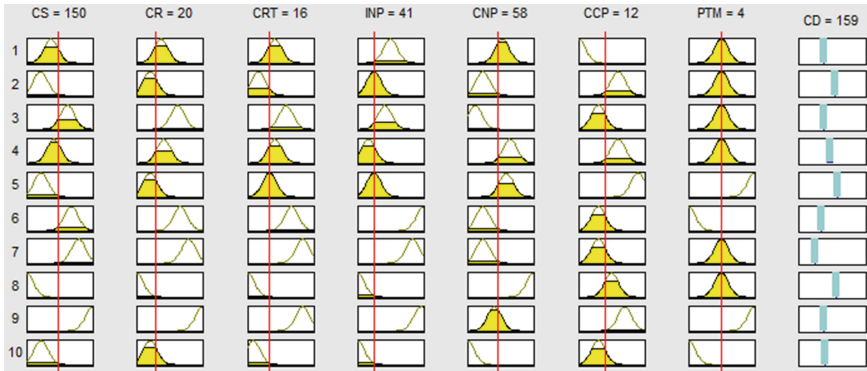


Fig. 2. The use of ANFIS to cost estimation of product design

The forecast of product design cost is calculated after inputting the expected parameters of a new product to the learnt ANFIS. The values of two input variables (number of interviewed clients and number of client’s requirements for a new product) are specified by the marketing agent. In turn, the values of five input variables (number of client’s requirements translated into product specification, number of ideas for a new product, number of components in a new product, number of changed components in a new product, and number of project team members) are specified by the R&D agent. In the presented example, the forecast of product design cost (CD) equals 159 monetary units (m.u.) for the following input variables: CS – 150, CR – 20, CRT – 16, INP – 41, CNP – 58, CCP – 12, and PTM – 4. The identified rules are stored in knowledge base and can be further used to feasibility study of the NPD projects and selecting the most promising projects for development.

5.2 Fulfilling Cost Expectations with the Use of CP

If the NPD cost exceeds the project budget, the project manager can need information about the conditions to fulfil cost expectations. In this case, such values of input variables are sought that fulfil the project budget. Let us assume that the budget of product development is limited to 100 m.u., and the range of the selected variables is as follows: CNP from 45 to 75, CCP from 8 to 18, and PTM from 3 to 6. A large number of admissible solutions imposes the use of techniques that enable the reduction of the amount of search needed, such as constraint programming. The considered problem has been implemented in the Oz Mozart programming environment that includes constraint programming

paradigms. The number of admissible solutions equals 10 instances by the minimal cost of product design reaches 93 m.u. Figure 3 presents the explored search tree for the considered case.

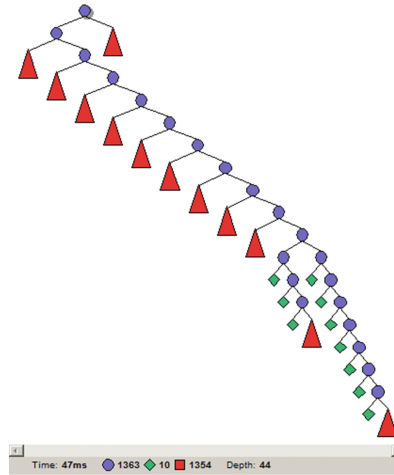


Fig. 3. The use of CP to seek admissible solutions

The search tree illustrates choice nodes as purple circles and solution nodes as green diamonds. The fully explored subtrees, which do not contain solution nodes, are presented as a single red triangle.

6 Conclusion

The new product development process involves many agents in the field of customers, marketing, research and development, manufacturing, etc. As in new product development is required knowledge acquisition from the different local areas and communication between these areas, the use of a multi-agent framework seems to be a pertinent framework to evaluate the parameters of product design, and finally, estimate its cost. The proposed approach takes a global perspective concerning product design and presents a mechanism of interaction between agents. As an enterprise information system stores the data related to the various areas of business, including customer requirements for a new product and specification of the past NPD projects, enterprise database can be used to seek the relationships between the cost and variables suspected of influencing cost. In this study, a fuzzy neural network has been used to identify potential relationships that can also be used to feasibility study and selecting the most promising NPD project portfolio.

The characteristics of the presented approach includes the use of expert domain knowledge to select variables used in the knowledge discovery process, fuzzy neural network to seek the relationships and their description in the form of if-then rules, and framework of constraint satisfaction problem to specify a knowledge base. This knowledge base includes the facts

(e.g. R&D budget), rules identified by fuzzy neural network or/and an data mining agent, and it allows the project managers to obtain an answer to the routine questions such as what is the cost of product design, what is the most promising set of NPD projects or what values should have the parameters of NPD projects to fulfil the cost expectations. The use of constraint programming environment solves CSP in an effective way and enables creating an interactive task-oriented decision support tool.

Advantages of the presented approach can be considered in the context of placing product design in a global perspective that involves the external (customers) and internal (employees) actors of the NPD process, the low effort of data retrieval to analysis because the data are stored in an enterprise system, the possibility of sensitivity and what-if analysis, as well as the selection of the most promising product portfolio according to the project manager's preferences. Drawbacks of using the proposed approach are connected with constructing the stop criterion in the negotiation algorithm between client and marketing agent, collecting enough amounts of data of the past similar NPD projects, and specifying several parameters to build and learn a fuzzy neural network.

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References

1. Cooper, R., Edgett, S.: Maximizing productivity in product innovation. *Res. Technol. Manag.* **51**(2), 47–58 (2008)
2. Spalek, S.: Improving industrial engineering performance through a successful project management office. *Eng. Econ.* **24**(2), 88–98 (2013)
3. Relich, M., Bzdyra, K.: Knowledge discovery in enterprise databases for forecasting new product success. In: Jackowski, K., et al. (eds.) *IDEAL 2015. LNCS*, vol. 9375, pp. 121–129. Springer, Heidelberg (2015). doi:[10.1007/978-3-319-24834-9_15](https://doi.org/10.1007/978-3-319-24834-9_15)
4. Ulrich, K.T., Eppinger, S.D.: *Product Design and Development*. McGraw-Hill, Boston (2011)
5. Anderson, D.M.: *Design for Manufacturability: Optimizing Cost, Quality and Time-to-Market*. CIM Press, Cambria (2001)
6. Yan, Y., Kuphal, T., Bode, J.: Application of multiagent systems in project management. *Int. J. Prod. Econ.* **68**, 185–197 (2000)
7. Bocewicz, G., Nielsen, I., Banaszak, Z.: Iterative multimodal processes scheduling. *Annu. Rev. Control* **38**(1), 113–122 (2014)
8. Relich, M., Swic, A., Gola, A.: A knowledge-based approach to product concept screening. In: Omatu, S., et al. (eds.) *Distributed Computing and Artificial Intelligence. AISC*, vol. 373, pp. 341–348. Springer, Heidelberg (2016)
9. Madhusudan, T.: An agent-based approach for coordinating product design workflows. *Comput. Ind.* **56**, 235–259 (2005)
10. Fazel Zarandi, M.H., Ahmadpour, P.: Fuzzy agent-based expert system for steel making process. *Expert Syst. Appl.* **36**, 9539–9547 (2009)
11. Kishore, R., Zhang, H., Ramesh, R.: Enterprise integration using the agent paradigm: foundations of multi-agent-based integrative business information systems. *Decis. Support Syst.* **42**(1), 48–78 (2006)

12. Tweedale, J., Ichalkaranje, N., Sioutis, C., Jarvis, B., Consoli, A., Phillips-Wren, G.: Innovations in multi-agent systems. *J. Netw. Comput. Appl.* **30**, 1089–1115 (2007)
13. Liu, J., Chen, Z., Zhang, X., Liu, Z.: Neural-networks-based distributed output regulation of multi-agent systems with nonlinear dynamics. *Neurocomputing* **125**, 81–87 (2014)
14. Lopez-Ortega, O., Villar-Medina, I.: A multi-agent system to construct production orders by employing an expert system and a neural network. *Expert Syst. Appl.* **36**, 2937–2946 (2009)
15. Quteishat, A., Lim, C., Tweedale, J., Jain, L.: A neural network-based multi-agent classifier system. *Neurocomputing* **72**, 1639–1647 (2009)
16. Borrajo, L., Corchado, J., Corchado, E., Pellicer, M., Bajo, J.: Multi-agent neural business control system. *Inf. Sci.* **180**, 911–927 (2010)
17. Lopez-Franco, M., Sanchez, E., Alanis, A., Lopez-Franco, C., Arana-Daniel, N.: Decentralized control for stabilization of nonlinear multi-agent systems using neural inverse optimal control. *Neurocomputing* **168**, 81–91 (2015)
18. Olajubu, E., Ajayi, O., Aderounmu, G.: A fuzzy logic based multi-agents controller. *Expert Syst. Appl.* **38**, 4860–4865 (2011)
19. Hanafizadeh, P., Sherkat, M.: Designing fuzzy-genetic learner model based on multi-agent systems in supply chain management. *Expert Syst. Appl.* **36**, 10120–10134 (2009)
20. Huang, C., Liang, W., Lai, Y., Lin, Y.: The agent-based negotiation process for B2C e-commerce. *Expert Syst. Appl.* **37**, 348–359 (2010)
21. Daskocil, R., Doubravsky, K.: Decision-making rules based on rough set theory: creditworthiness case study. In: *Proceedings of the 24th International Business Information Management Association Conference*, pp. 321–327, Milan (2014)
22. Jolly, K., Kumar, R., Vijayakumar, R.: Intelligent task planning and action selection of a mobile robot in a multi-agent system through a fuzzy neural network approach. *Eng. Appl. Artif. Intell.* **23**, 923–933 (2010)
23. Vatankhah, R., Etemadi, S., Alasty, A., Vossoughi, G.: Adaptive critic-based neuro-fuzzy controller in multi-agents: distributed behavioural control and path tracking. *Neurocomputing* **88**, 24–35 (2012)
24. Liu, H., Tang, M.: Evolutionary design in a multi-agent design environment. *Appl. Soft Comput.* **6**, 207–220 (2006)
25. Monticolo, D., Miaita, S., Darwich, H., Hilaire, V.: An agent-based system to build project memories during engineering projects. *Knowl.-Based Syst.* **68**, 88–102 (2014)
26. Zha, X.F.: A knowledge intensive multi-agent framework for cooperative/collaborative design modelling and decision support for assemblies. *Knowl. Based Syst.* **15**, 493–506 (2002)
27. Chu, C., Wu, P., Hsu, Y.: Multi-agent collaborative 3D design with geometric model at different levels of detail. *Robot. Comput.-Integr. Manuf.* **25**, 334–347 (2009)
28. Relich, M., Pawlewski, P.: A multi-agent system for selecting portfolio of new product development projects. In: Bajo, J., Hallenborg, K., Pawlewski, P., Botti, V., Sánchez-Pi, N., Duque Méndez, N.D., Lopes, F., Vicente, J. (eds.) *PAAMS 2015 Workshops. CCIS*, vol. 524, pp. 102–114. Springer, Heidelberg (2015)
29. Rossi, F., van Beek, P., Walsh, T.: *Handbook of Constraint Programming*. Elsevier Science, Philadelphia (2006)
30. Relich, M.: A knowledge-based system for new product portfolio selection. In: Rozewski, P., et al. (eds.) *New Frontiers in Information and Production Systems Modelling and Analysis. ISRL*, vol. 98, pp. 169–187. Springer, Heidelberg (2016)
31. Sitek, P., Wikarek, J.: A hybrid approach to the optimization of multiechelon systems. *Mathematical Problems in Engineering* **2015**, Article ID 925675 (2015). doi: [10.1155/2015/925675](https://doi.org/10.1155/2015/925675)

32. Van Roy, P., Haridi, S.: *Concepts, Techniques and Models of Computer Programming*. Massachusetts Institute of Technology, Cambridge (2004)
33. Sitek, P.: A hybrid CP/MP approach to supply chain modelling, optimization and analysis. In: *Federated Conference on Computer Science and Information Systems (FedCSIS)*, pp. 1345–1352 (2014)
34. Grzybowska, K.: Selected activity coordination mechanisms in complex systems. In: Bajo, J., Hallenborg, K., Pawlewski, P., Botti, V., Sánchez-Pi, N., Duque Méndez, N.D., Lopes, F., Vicente, J. (eds.) *PAAMS 2015 Workshops. CCIS*, vol. 524, pp. 69–79. Springer, Heidelberg (2015)
35. Grzybowska, K.: Application of an electronic bulletin board, as a mechanism of coordination of actions in complex systems – reference model. *LogForum* **11**(2), 151–158 (2015)
36. Bocewicz, G., Nielsen, I., Banaszak, Z.: Automated guided vehicles fleet match-up scheduling with production flow constraints. *Eng. Appl. Artif. Intell.* **30**, 49–62 (2014)
37. Baptiste, P., Le Pape, C., Nuijten, W.: *Constraint-Based Scheduling: Applying Constraint Programming to Scheduling Problems*. Kluwer Academic Publishers, Norwell (2001)
38. Liu, J., Jing, H., Tang, Y.Y.: Multi-agent oriented constraint satisfaction. *Artif. Intell.* **136**, 101–144 (2002)