Proceedings of the 2013 Federated Conference on
Computer Science and Information Systems pp. 1273–1278

Knowledge Acquisition for New Product Development with the Use of an ERP Database

Marcin Relich
University of Zielona Gora,
ul. Licealna 9, 65-216 Zielona Gora, Poland
Email: m.relich@wez.uz.zgora.pl

***Abstract*—Nowadays, a considerable number of enterprises develop new products using an Enterprise Resource Planning (ERP) system. One of the modules of a typical ERP system concerns project management. Functionalities of this module consist of defining resources, company calendars, sequence of project tasks, task duration etc. in order to obtain a project schedule. These parameters can be defined by the employees according to their knowledge, or they can be connected with data from previous completed projects. The paper investigates using an ERP database to identify critical factors, i.e. variables that significantly influence on new product development. Project duration and cost is estimated by a fuzzy neural system that uses data of completed projects stored in an ERP system.**

I. Introduction

THE present information and communication technologies have become one of the most important factors, conditions and chances of the firm development. These technologies enable the collection, presentation, transfer, access and using of enormous amount of data. The data are a potential source of information that in connection with manager skills and experience may influence on the choice of the correct decision. ERP systems help to collect, operate, and store data concerning daily activities of an enterprise (e.g. client orders), as well as the results of previous projects (development of products).

Project success or failure depends on many critical factors, such as the kind of project, access to resources, methods of project management, and environment [1], [2]. The reasons for project failure can be generally considered as a lack of accessibility of resources (e.g. human, financial, raw materials) and changeability of the external environment. Moreover, unstable requirements, lack of well-defined scope, quality of management, and skill of the employees can cause project failure. To reduce project overruns, there are two ways to approach the problem. The first way is to increase the accuracy of the estimates through a better estimation process and the second, to increase the project control.

It is unrealistic to expect very accurate estimates of project effort because of the inherent uncertainty in development projects, and the complex and dynamic interaction of factors that influence on its development. However, even small improvements will be valuable, especially by large-scale projects. More accurate forecasting supports the project managers in planning and monitoring the project, for instance, in project cost, resource allocation, and schedule arrangement.

New product development is connected with uncertainty that includes both internal (e.g. communication in project team, planning techniques, cash flow) and external environments (e.g. social, economic, political, technological conditions). Sources of uncertainty are wide ranging and have a fundamental effect on projects and project management [3]. Uncertainty is an important issue in the support of any decision-making in the process of new product development. Since most companies should estimate project parameters, there is a need to develop an approach that takes into account the imprecise character of data and copes with enormous amount of data. The description of project management and knowledge management in the context of an ERP system, as well as a fuzzy neural system combining the ability for learning and processing inaccurate data is presented in the next section.

II. Background

A. Project management in an ERP system

In recent years, the advancement of information technology in business management processes has placed ERP system as one of the most widely implemented business software in various enterprises. ERP software promises significant benefits to organizations. Some of these benefits include lowering costs, reducing inventories, increasing productivity [4], improving operational efficiency [5], [6], attaining competitive advantage [7], and bettering the reorganization of internal resources [8], [9].

The goal of an ERP based integrated information system is to make the system effective, efficient and user friendly. The performance of software depends on the interaction between the software and users. The primary task of an integrated system is to maintain the data flow of an organization and to reduce the redundancy [10]. ERP is a system for the seamless integration of all the information flowing through the company such as finances, accounting, human resources, supply chain, and customer information [11]. One of the functionalities of an ERP system also includes project management that company can use to develop new products.

The project management functionality comprises the definition of master files and obtaining a project schedule. The definition of master files includes resources that are use in a project, resource calendars, company calendars, time models (blocks), as well as project activities, estimates of activity duration, sequencing (order of activities), milestones. This

978-1-4673-4471-5/$25.00

data is the bases to obtain resource allocation, planned cost, network chart, and analyses concerning e.g. original and actual cost.

B. ERP systems from a knowledge perspective

A variety of knowledge management and knowledge integrated manufacturing models have emerged one after another in recent years [12]. These models can be considered in the context of manufacturing or knowledge aspect [13]. The role of manufacturing knowledge is a key strategic resource and it can be presented as the interactive process between manufacturing knowledge and cross-functional activities [14], [15], [16]. Knowledge management may be incorporated into ERP implementation with the use, for instance, a self-sufficient model [17]. In turn, a base to characterize product development and knowledge evolution process can be an integrated knowledge reference system [18].

In the implementation phase, ERP systems have an impact on organizational knowledge (stock of knowledge, distribution, learning processes) [19], as well as on efficiency and flexibility of a knowledge management system [20]. Moreover, business knowledge in the ERP software package to the adopting organization (types of knowledge transferred, resolution of conflicts with existing organizational knowledge, changed knowledge structure) is transferred and internalized from consultants to clients [21], [22]. Knowledge-related ERP systems research mainly concerns the knowledge issues encountered during the system implementation phase or the 'shake-out' period immediately following implementation [23]. The use of an ERP database in the post-implementation phase of ERP system lifecycle is usually obscured. This provides the motivation to develop the approach dedicated for knowledge acquisition in the context of new product development in an enterprise that uses an ERP system.

C. Description of fuzzy neural system

Knowledge acquisition requires some techniques that cope with the description of relationships among data and that solve the problems connected with e.g. classification, regression, and clustering. These techniques include neural networks, fuzzy sets, rough sets, time series analysis, Bayesian networks, decision trees, evolutionary programming and genetic algorithms, Markov modeling, etc.

Fuzzy logic and artificial neural networks are complementary technologies and powerful design techniques that have their strengths and weaknesses [24]. Table I shows a comparison of the properties of these two technologies.

The fuzzy neural system has the advantages of both neural networks (e.g. learning abilities, optimization abilities and connectionist structures) and fuzzy systems (simplicity of incorporating expert knowledge). As a result, it is possible to bring the low-level learning and computational power of neural networks into fuzzy systems and also high-level human like IF-THEN thinking and reasoning of fuzzy systems into neural networks. The fuzzy neural method is rather a way to create a fuzzy model from data by some kind of learning method that is motivated by learning procedures used in neural networks. This substantially reduces development time and cost while improving the accuracy of the resulting fuzzy model. Being able to utilize a neural learning algorithm implies that a fuzzy system with linguistic information in its rule base can be updated or adapted using numerical information to gain an even greater advantage over a neural network that cannot make use of linguistic information and behaves as a black box [25].

The behaviour of a fuzzy neural system can be represented by a set of humanly understandable rules or by a combination of localized basis functions associated with local models, making them an ideal framework to perform nonlinear predictive modelling. Nevertheless, one important consequence of this hybridization between the representational aspect of fuzzy models and the learning mechanism of neural networks is the contrast between readability and performance of the resulting model [25]. The combination of fuzzy systems and neural networks has recently become a popular approach in engineering fields for solving problems in control, identification, prediction, pattern recognition, etc [26], [27], [28]. One well-known structure is the adaptive neuro-fuzzy inference system (ANFIS). ANFIS model is a universal approximator which has the non-linear modelling and forecasting function.

III. METHOD FOR ESTIMATING PROJECT DURATION AND COST

The proposed method is dedicated for new product development in an enterprise that uses an ERP system. New product development is often connected with the superficial changes in design and/or functionality of past products. Thus, data of completed projects can be used to identify relationships between the parameters of past projects and their durations and costs. The method consists of the following stages:

1) extracting data (parameters of past projects) from an ERP system;
2) identification of critical factors that significantly influence on new product development;
3) learning ANFIS in order to obtain rule base;
4) estimating duration and cost of new product development;
5) loading data (estimate of project duration and cost) to an ERP system (module project management).

The presented methodology concerns the estimation of project duration and cost in the different phases of new product development (see Fig. 1). In each of these phases, the critical factors (parameters of an ERP database) that significantly influence on new product development are sought.

Database of an ERP system comprises an enormous number of parameters that can be considered as potential variables to identify the duration and cost of project phases. The second stage in the above-presented procedure concerns the identification of critical factors that influence on the project duration and cost, and indirect on new product development. If the relationship between a variable and the project duration and cost is significant (greater than a level defined by the user), then the variable is considered as the critical factor. The

TABLE I
PROPERTIES OF NEURAL NETWORKS AND FUZZY SYSTEMS

Skills	Type	Fuzzy Systems	Neural Networks
Knowledge acquisition	Inputs	Human experts	Sample sets
	Tools	Interaction	Algorithms
Uncertainty	Information	Quantitative and qualitative	Quantitative
Reasoning	Cognition	Heuristic approach	Perception
	Mechanism	Low	Parallel Computation
	Speed	Low	High
Adaption	Fault-tolerance	Low	Very high
	Learning	Induction	Adjusting weights
Natural language	Implementation	Explicit	Implicit
	Flexibility	High	Low

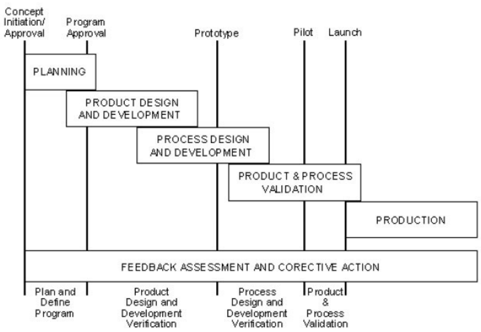


Fig. 1. New product planning phases
Source: [29]

variables are chosen according to the user's experience and can be as follows: a number of human resource (in person-hour), machine-hour, raw material, and activities in a project phase, as well as financial means, delay in client's payment and material delivery by suppliers, quality of material (number of complaints), time of machine inspection, absenteeism during project implementation, project team members, and project manager.

A large number of independent variables in a large data set can present two major problems. Firstly, too many variables result in long training times when the model is built. Secondly, large number of observations and variables tend to retain redundant information through multicollinearity leading to unreliable models. Some of the variables present in historical data are needed for some problems and some variables for others. Often, different variables may carry the same information [30].

A variable reduction method can be based on principal component analysis that is used as a dimension reduction technique for linearly mapping high dimensional data onto a lower dimension with minimal loss of information. The variable reduction is not the main issue in this research and it is not further considered.

The third stage in the proposed methodology concerns obtaining rule base with the use of ANFIS. The identification of rules and the initial parameters of membership function of fuzzy sets are obtained with the use of e.g. grid partition, fuzzy c-mean, or subtractive clustering. The learning stage requires the declaration of optimisation weights method (e.g. backpropagation algorithm) and stop criterion (e.g. error value or the number of iteration). After learning phase, the testing data are led to input of system to compare the results with target. Next section presents an example concerning the use of the above procedure.

IV. EXAMPLE OF PROJECT DURATION AND COST ASSESSMENT

The output variables contain the duration (d_i in months) and cost (c_i in monetary unit - m.u.) of the *j*-th phase in project *i*. In turn, the input variables include:

- h_{ji} - number of human resource in the *j*-th phase of project i (person-hour);
- a_{ji} - number of activities in the *j*-th phase of project *i*;
- s_{ji} - number of subcontractors in the *j*-th phase of project *i*;
- tm_{ji} - number of project team members in the *j*-th phase of project i.

Table II presents data of eight past projects (development of products) for product design phase that has been applied to the proposed approach.

Calculation has been generated with the use of ANFIS tool that is Matlab software. The application of fuzzy-neural system requires the declaration of input variables and parameters connected with ANFIS, e.g. defuzzification method. Figure 2 presents two ANFIS, for the duration and cost of project phase, respectively.

After the declaration of input variables in fuzzy neural system, the initial parameters of membership functions of fuzzy sets are estimated. As a result, the structure of fuzzy neural system is determined. In next stage, the fuzzy neural system is learnt according to e.g. backpropagation algorithm, and consequently, the shape of membership function is determined (Fig. 3).

The rules can be presented for decision maker in descriptive form. The example of fuzzy rules for the duration and cost is presented in Fig. 4.

To eliminate too strictly function adjustment to data and to increase the estimation quality, the data set is divided into

TABLE II
PROJECT VARIABLES FOR PRODUCT DESIGN PHASE

Variable	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8
Human resource	500	400	350	450	600	400	650	500
Number of activities	25	22	20	25	28	22	25	20
Number of subcontractors	3	4	4	5	6	4	5	5
Number of team members	8	7	6	8	12	10	12	10
Duration	14	12	10	15	16	15	15	15
Cost	380	320	320	400	500	420	650	600

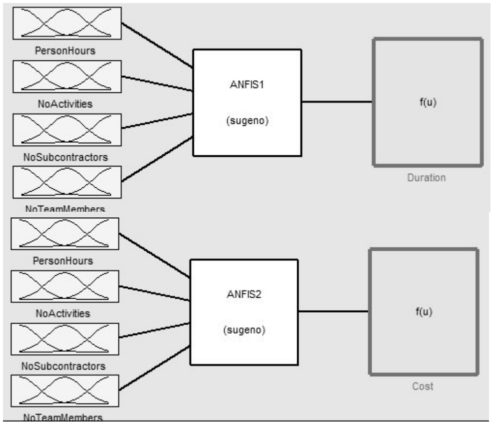


Fig. 2. Specification of fuzzy neural system

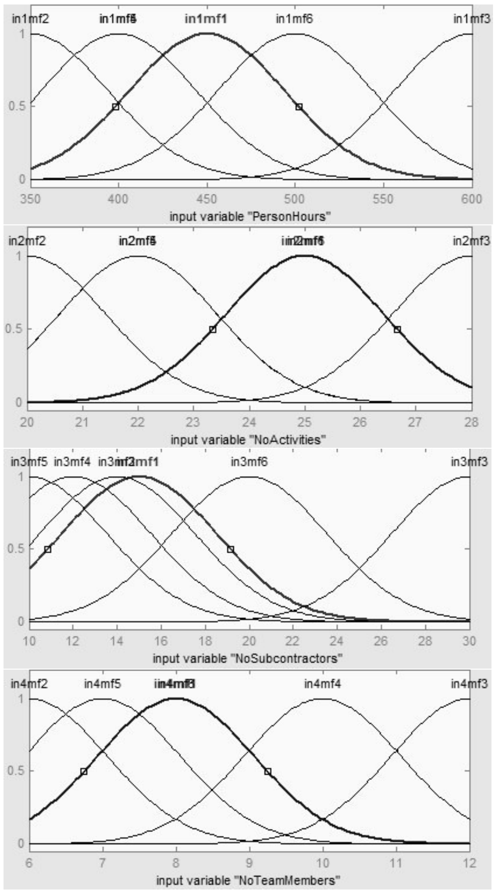


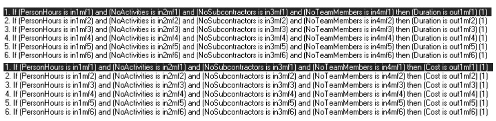
Fig. 3. Membership function for input variables

learning (P_1-P_6) and testing set (P_7-P_8). The learning phase requires the declaration of method of weights optimisation, and stop criterion (e.g. error value or the number of iteration). After learning phase, the testing data are led to input of system to compare the error between different models. Mean square error (MSE) for various models are presented in Table III. It is noteworthy that the least error in testing set for the duration has been generated with the use of average. It can be connected with a low level of variance for the duration of project design phase. In turn, the least error for the cost has been generated with the use of ANFIS with subtractive clustering method.

The membership functions and rules are a basis to evaluate the duration and cost of an actual project. Let us assume that for the actual project are considered the following values: number of person hours equal 475, number of activities equal 24, number of subcontractors equal 11, and number of team members equal 9. Thus, the duration equals 16.4 months and cost of project phase equals 440 m.u. (see Fig. 5).

There is also possibility to conduct what-if analysis. For instance, if a number of subcontractors will be increased to 20, then the project will be decrease to 13.7 months (see Fig. 6).

The above-presented analysis is conducted for each phase of project and the obtained estimates can be used to evaluate cash flow, working capital, financial reserves, product launch, and other critical factors of an enterprise activity.


1. If (PersonHours is in1mf1) and (NoActivities is in2mf1) and (NoSubcontractors is in3mf1) and (NoTeamMembers is in4mf1) then (Duration is out1mf1) (1)
2. If (PersonHours is in1mf2) and (NoActivities is in2mf2) and (NoSubcontractors is in3mf2) and (NoTeamMembers is in4mf2) then (Duration is out1mf2) (1)
3. If (PersonHours is in1mf3) and (NoActivities is in2mf3) and (NoSubcontractors is in3mf3) and (NoTeamMembers is in4mf3) then (Duration is out1mf3) (1)
4. If (PersonHours is in1mf4) and (NoActivities is in2mf4) and (NoSubcontractors is in3mf4) and (NoTeamMembers is in4mf4) then (Duration is out1mf4) (1)
5. If (PersonHours is in1mf5) and (NoActivities is in2mf5) and (NoSubcontractors is in3mf5) and (NoTeamMembers is in4mf5) then (Duration is out1mf5) (1)
6. If (PersonHours is in1mf6) and (NoActivities is in2mf6) and (NoSubcontractors is in3mf6) and (NoTeamMembers is in4mf6) then (Duration is out1mf6) (1)

1. If (PersonHours is in1mf1) and (NoActivities is in2mf1) and (NoSubcontractors is in3mf1) and (NoTeamMembers is in4mf1) then (Cost is out1mf1) (1)
2. If (PersonHours is in1mf2) and (NoActivities is in2mf2) and (NoSubcontractors is in3mf2) and (NoTeamMembers is in4mf2) then (Cost is out1mf2) (1)
3. If (PersonHours is in1mf3) and (NoActivities is in2mf3) and (NoSubcontractors is in3mf3) and (NoTeamMembers is in4mf3) then (Cost is out1mf3) (1)
4. If (PersonHours is in1mf4) and (NoActivities is in2mf4) and (NoSubcontractors is in3mf4) and (NoTeamMembers is in4mf4) then (Cost is out1mf4) (1)
5. If (PersonHours is in1mf5) and (NoActivities is in2mf5) and (NoSubcontractors is in3mf5) and (NoTeamMembers is in4mf5) then (Cost is out1mf5) (1)
6. If (PersonHours is in1mf6) and (NoActivities is in2mf6) and (NoSubcontractors is in3mf6) and (NoTeamMembers is in4mf6) then (Cost is out1mf6) (1)

Fig. 4. Fuzzy rules generated by fuzzy neural system

TABLE III
COMPARISON OF MSE FOR DIFFERENT MODELS

Model	Duration	Cost
Average	1.78	236.32
Linear model	4.16	309.85
ANFIS - grid partition	12.87	564.63
ANFIS - subtractive clustering	2.99	96.10

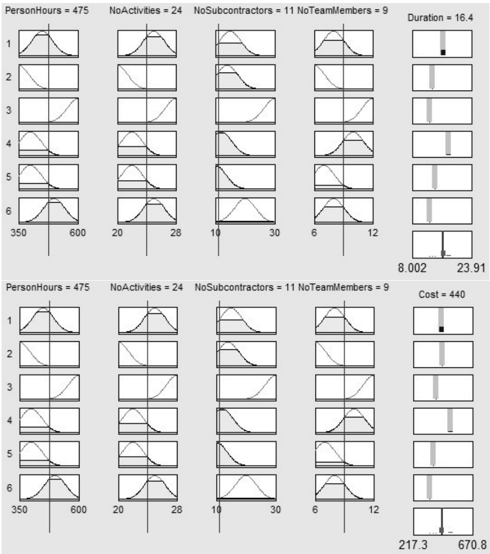


Fig. 5. Estimation of project duration and cost

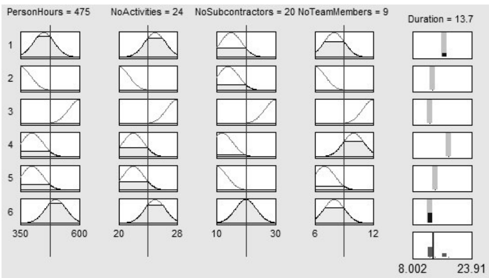


Fig. 6. Project duration for additional subcontractors

V. CONCLUSION

The capabilities of an enterprise to create, share and utilize knowledge effectively are today regarded as one of the key drivers of competitive advantage for industrial enterprises. Competition in quality, design, cost of new products, and time their launching into the market has increased with new competitors having established segments and, in some cases, with change in competitive tools. This forces more frequent and larger-scale changes in contemporary companies, also changes in the use of new information technologies. One of the technologies concerns a fuzzy neural system that is used in this paper to evaluate the project duration and cost.

More exact identification of project duration and cost enables more precision of cash flow planning and finally, decreases the risk of lack of liquidity. If in the enterprise is a database of past projects, then there is the possibility to gather additional information in the form of conditional rules. The application of the proposed approach encounters some difficulties, among other things, by the collecting enough amounts of data of the past similar projects. Moreover, the lack of uniform rules that concern the development of fuzzy neural systems may cause an acceptance problem for the decision-makers. However, the presented approach seems to have the promising properties for acquiring information from an ERP system.

Further research focuses on the development of the presented approach towards searching a set of key performance indicators according to their influence on the success of completed projects. Moreover, future research will be aimed at verifying the proposed approach in a real world to test its practicality.

REFERENCES

[1] P. Nitithamyong and M. J. Skibniewski, "Success/failure factors and performance measures of web-based construction project management systems: professionals' viewpoint," *Journal of Construction Engineering and Management,* vol. 132, 2006, pp. 80–87.

[2] S. Robertson and T. Williams, "Understanding project failure: using cognitive mapping in an insurance project," *Project Management Journal,* vol. 37, 2006, pp. 55–71.

[3] R. Atkinson, L. Crawford, and S. Ward, "Fundamental uncertainties in projects and the scope of project management," *International Journal of Project Management,* vol. 24, 2006, pp. 687–698.

[4] D. Olson, *Managerial Issues of Enterprise Resource Planning Systems,* McGrawHill/Irwin, Boston, 2004.

[5] J. Benders, R. Batenburg, and H. Van der Blonk, "Sticking to standards; technical and other isomorphic pressures in deploying ERP systems," *Information & Management*, vol. 43, 2006, pp. 194–203.

[6] L. Häkkinen and O. Hilmola, "ERP evaluation during the shakedown phase: lessons from an after-sales division," *Information Systems Journal,* vol. 18(1), 2008, pp. 73–100.

[7] J. Beard and M. Summer, "Seeking strategic advantage in the post-net era: viewing ERP systems from resource-based perspective," *Journal of Strategic Information Systems,* vol. 13, 2004, pp. 129–150.

[8] J. Stratman, "Realizing benefits from enterprise resource planning: does strategic focus matter?" *Production and Operations Management,* vol. 16(2), 2007, pp. 203–216.

[9] J. May, G. Dhillon, and M. Caldeira, "Defining value-based objectives for ERP systems planning," *Decision Support Systems,* vol. 55, 2013, pp. 98–109.

[10] A. Imtiaz and M. G. Kibria, "Modules to optimize the performance of an ERP based integrated information system," IEEE International Conference on Informatics, Electronics & Vision, 2012, pp. 598–601.

[11] T. Davenport, "Putting the enterprise into the enterprise system," *Harvard Business Review,* July-August, 1998, pp. 121–131.

[12] A. Bernard and S. Tichkiewitch, *Methods and tools for effective knowledge life-cycle-management,* Springer, Berlin, 2008.

[13] Y. Xu and A. Bernard, "Quantifying the value of knowledge within the context of product development," *Knowledge-Based Systems,* vol. 24, 2011, pp. 166–175.

[14] E. L. Paiva, A. V. Roth, and J. E. Fensterseifer, "Organizational knowledge and the manufacturing strategy process: a resource-based view analysis," *Journal of Operations Management,* vol. 26(1), 2008, pp. 115–132.
[15] M. Cambal, D. Caganova, and J. Sujanova, "The industrial enterprise performance increase through the competency model application," Proceedings of the 4th European Conferences on Intellectual Capital, Helsinki, Finland, 2012, pp. 118–126.
[16] J. Sujanova, P. Gabris, M. Licko, P. Pavlenda, and R. Stasiak-Betlejewska, "Aspects of Knowledge Management in Slovak Industrial Enterprises," Proceedings of the 13th European Conference on Knowledge Management, Cartagena, Spain, 2012, pp. 1135–1144.
[17] T. C. McGinnis and Z. Huang, "Rethinking ERP success: a new perspective from knowledge management and continuous improvement," *Information & Management,* vol. 44(7), 2007, pp. 626–634.
[18] A. Bernard and Y. Xu, "An integrated knowledge reference system for product development," *CIRP Annals,*, vol. 58(1), 2009, pp. 119–122.
[19] R. Baskerville, S. Pawlowski, and E. McLean, "Enterprise resource planning and organizational knowledge: patterns of convergence and divergence," Proceedings of the 21st International Conference on Information Systems, Brisbane, Australia, 2000, pp. 396–406.
[20] J. C. Huang, S. Newell, R. D. Galliers, and S. L. Pan, "ERP and knowledge management systems: managerial panaceas or synergetic solutions?" Proceedings of the Seventh Americas Conference on Information Systems, 2001, pp. 1136–1141.
[21] D. G. Ko, L. J. Kirsch, and W. R. King, "Antecedents of knowledge transfer from consultants to clients in enterprise system implementation," *MIS Quarterly,* vol. 9(1), 2005, pp. 59–85.
[22] Z. Lee and J. Lee "An ERP implementation case study from a knowledge transfer perspective," *Journal of Information Technology,* vol. 15(4), 2000, pp. 281–288.
[23] T. Srivardhana and S. D. Pawlowski, "ERP systems as an enabler of sustained business process innovation: a knowledge-based view," *Journal of Strategic Information Systems,* vol. 16, 2007, pp. 51–69
[24] R. Fuller, "Introduction to neuro-fuzzy systems," Advances in Soft Computing Series, Springer-Verlag, Berlin/Heildelberg, 2000.
[25] A. T. Azar, *Adaptive neuro-fuzzy systems,* In: Fuzzy systems. InTech, 2010.
[26] J. Zeng, M. An, and N. J. Smith, "Application of a fuzzy based decision making methodology to construction project risk assessment," *International Journal of Project Management,* vol. 25, 2007, pp. 589–600.
[27] M. Y. Cheng , H. C. Tsai, and E. Sudjono, "Evolutionary fuzzy hybrid neural network for project cash flow control," *Engineering Applications of Artificial Intelligence,* vol. 23, 2010, pp. 604–613.
[28] S. C. Chien , T. Y. Wang, and S. L. Lin, "Application of neuro-fuzzy networks to forecast innovation performance," *Expert Systems with Applications,* vol. 37, 2010, pp. 1086–1095.
[29] K. Sanongpong, "Automotive process-based new product development: A review of key performance metrics," Proceedings of the World Congress on Engineering, London, U.K., 2009.
[30] G. L. Colmenares and R. Perez, "A data reduction method to train, test, and validate neural networks," Proceedings of IEEE, Southeastcon, 1998, pp. 277–280.