Iranian Journal of Management Studies (IJMS) *http://ijms.ut.ac.ir/*
Vol. 13, No. 4, Autumn 2020 *Print ISSN: 2008-7055*
pp. 587-621 *Online ISSN: 2345-3745*
Document Type: Research Paper *DOI: 10.22059/ijms.2020.289483.673801*

A Multiple Adaptive Neuro-Fuzzy Inference System for Predicting ERP Implementation Success

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(Received: October 13, 2019 ;Revised: April 23, 2020; Accepted: May 13, 2020)

Abstract
The implementation of modern ERP solutions has introduced tremendous opportunities as well as challenges into the realm of intensely competent businesses. The ERP implementation phase is a very costly and time-consuming process. The failure of the implementation may result in the entire business to fail or to become incompetent. This fact along with the complexity of data streams has led the researchers to develop a hierarchical multi-level predictive solution to automatically predict the implementation success of ERP solution. This study exploits the strength and precision of the Adaptive Neuro-Fuzzy Inference System (ANFIS) for predicting the implementation success of ERP solutions before the initiation of the implementation phase. This capability is obtained by training the ANFIS system with a data set containing a large number of ERP implementation efforts that have led to success, failure, or a mid-range implementation. In the initial section of the paper, a brief review of the recent ERP solutions as well as ANFIS architecture and validation procedure is provided. After that, the major factors of ERP implementation success are deeply studied and extracted from the previous literature. The major influential implementation factors in the businesses are titled as Change Orchestration (CO), Implementation Guide (IG), and Requirements Coverage (RC). The factors represent the major elements that guide the implementation project to a final success or to a possible failure if mismanaged. Accordingly, three initial ANFIS models are designed, trained, and validated for the factors. The models are developed by gathering data from 414 SMEs located in the Islamic Republic of Iran during a three-year period. Each model is capable of identifying the weaknesses and predicting the successful implementation of major factors. After this step, a final ANFIS model is developed that integrates the outputs of three initial ANFIS models into a final fuzzy inference system, which predicts the overall success of the ERP implementation project before the initiation phase. This model provides the opportunity of embedding the previous precious experiences into a unified system that can reduce the heavy burden of implementation failure.

Keywords
ANFIS, ERP, Success, Sustainable Implementation, Prediction.

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1. Introduction

Enterprise resource planning (EPR) solutions are process-oriented systems that provide seamless integrated information flow among business units. ERP solution provides various business benefits and opportunities, including the standardization of processes across multiple business departments, integrated master data management, vertical harmony for multi-branch or multi-company organizations, the full coverage of financial management, human capital management, materials management, sales, and distribution channels, as well as the reduction of the overall cost of running the business (Blackwell, Esam, Kay John, 2006; Raeesi & Sohrabi, 2011; You, Lee, Chen, & Jiao, 2012). A sustainable approach to the implementation of ERP solutions requires a controlling mechanism that is always online, updated, and accurate to predict the shortcomings of the project in time in order to take corrective actions before major problems and obstacles occur in the process.

The cost and timetable of ERP implementation are always tough managerial challenges for firms. Predicting the status of the indicators is also a very challenging aspect of measurement since the input data streams are complicated and the real-time decision-making requirements makes it very difficult for managers to effectively make on-time decisions. SMEs cover a significant percentage of active businesses around the world and the ERP implementation failure imposes a deadly financial and even survival risk to such firms.

This might also pose a challenge to large enterprises, though with a lower risk of losing the entire business. The concepts of sustainable ERP implementation and assessment have been studied in the recent years (Chofreh, Goni, & Klemeš, 2017a, 2017b, 2017c). The authors of the current research have been long working on providing SMEs with ERP solutions for more than a decade. During this period, several major implementation challenges have shown predictable behaviors that can be analyzed and mitigated before the initiation of the project. For this reason, current research was conducted on more than 400 SMEs for which standard ERP solutions have been implemented. Gathering enough intelligence on the mentioned ERP implementations, the researchers started to develop a system that is capable of learning the previous experience and putting the learned experience into action for predicting the implementation success of future projects.

The continuous prediction and controlling of implementation measures are of significance for enterprise-level solutions. Sustainable ERP implementation has been a trend of attention in the past few years. The implementation success can be evaluated in each phase of implementation so the sustainability can be ensured during each phase of deployment. For this reason, the automatic neuro-fuzzy systems, a type of fuzzy expert systems, can be applied for measuring the progress of each key performance indicator of ERP solution. The justification behind the current research is that the successful and sustainable implementation of ERP solutions has not been well understood and applied in the Iranian enterprises. In our country, we still have problems with the reciprocal integration of modules into the processes, the quality of training, the orchestration of change, proper consultations for transition from legacy systems to new solutions, and the maintenance of the ERP solution with a cost-effective approach.

Researchers of the current study have a long-term experience of ERP implementation in Iranian firms across the country. There are still many problems with the successful implementation of ERP modules, and organizations are not well prepared to embrace the full potential of the solutions. One of the major drawbacks of current implementation designs lies in the mechanism with which the steps of implementation are monitored. There are still traditional approaches to implementation appraisal using questionnaires, interviews, and BI dashboards. The ERP implementation project is a long-term plan and the monitoring mechanisms should incorporate the embedded knowledge of implementation from previous successful and failed projects. That is the reason behind the selection of adaptive neuro-fuzzy expert systems in the current research to automatically extract the knowledge of previous implementations and to apply them effectively for the new projects with the purpose of continuous measurement in order to reach a final sustainable ERP solution.

Considering the abovementioned facts, the massive amounts of collected data as well as the data quality problems (Gunther, Colangelo, Wiendahl, & Bauer, 2019) have led to the development of intelligent systems that can be embedded with the enterprise solutions. The automatic integration and analysis of data streams can be a precious asset for managerial decision making as it dramatically reduces the burden of routine decision making in favor of concentrating on more sophisticated enterprise process and information system integrations. The balance between ERP implementation benefits against implementation problems has led the researchers to design and implement an intelligent system that aims at providing managers with an effective predictive analytical solution to the heavy burden of implementation obstacles. A predictive solution with multilayers will effectively enable the managers to monitor each step of implementation from a specific aspect and then to integrate them into a single integrated output for measuring the real-time partial and final success of the implementation project. The next section briefly reviews the ERP implementation and its measurement indicators of success.

2. A Concise Review of Literature

The efficient resource allocation and effective flow of information across business units have been the aim of ERP implementation. An ERP system can be defined and recognized according to its breadth, depth, modularity, and capabilities. A typical ERP solution is mostly defined through the following features (Huang & Dun, 2008; Kazemifard, Zaeri, Ghasem-Aghaee, Nematbakhsh, & Mardukhi, 2011; Oliveira, Braga, Lima, & Cornélio, 2010):

- ERP contains sub-systems that integrate financial accounting and controlling, manufacturing and material management, human capital management, sales and distribution, and business analytics.
- ERP has a modular design that allows software development firms to separately implement the system features across various functional departments without losing the overall integrity.
- ERP solution operates under a single integrated database that covers the information needs of all organizational processes. There is no duplication and re-entry of master data across ERP modules.
- ERP relies on the best practices of the industry upon which the system is best implemented.
- There is tremendous customization, personalization, form generation, and report generation facilities embedded in the software.

- The system is preferably web-based or web-enabled in order to efficiently and easily integrate the geographically distributed servers across business units.
- Modules of ERP solutions are very effective in reducing the time and cost of running the core business functions; however, they can pose threats to the integration of processes with ERP solution constraints and also the entire business when it comes to cost-effective decision making in the long-run.

The aforementioned typical characteristics of an ERP system make it a standard solution for most industries to implement it as a total integrative system. This will provide a wide range of benefits as well as numerous challenges to the entire business entity. A long-term plan is mostly required for a successful implementation of ERP solutions in combination with the rest of the technologies that shape the digital transformation of an enterprise. Master plans mostly consist of a roadmap of development and evaluation, a framework and implementation, and a set of guidelines that comprise the best practices in the industry (Gholamzadeh Chofreh, Ariani Goni, & Klemeš, 2018). Without a master plan, several problems might occur and the potential benefits may not be realized. Integrating the knowledge of best practices into a seamless repository of knowledge and expertise requires a tremendous effort and broad expertise in different industries (Sohrabi & Jafarzadeh, 2010, Akhgar, Rasouli, & Raeesi Vanani, 2012). Considering the trend of ERP solutions toward sustainable ERP implementations, governments have imposed industries to change their vision, mission, and strategies toward the sustainability approaches. Enterprises now prioritize sustainability in their policies and regulations (van Zanten, & Van Tulder, 2018). Sustainable approaches to enterprise information systems implementation have embraced sustainable business practices in the value chains. This has led to a number of important benefits such as increasing productivity and creativity (Bryson, 2017), evading fraud and mismanagement (Moosa & Ramiah, 2018), and improving employees' loyalty (Law, Hills, Hau, 2017). Tsai (2019) points out that the implementation of sustainable ERP solutions will assist the enterprises in achieving sustainability goals in the realm of Industry 4.0. In such an approach, all business processes can be connected through advanced digital technologies. The use of a predictive solution from the domain of machine learning can be an effective step onward for the materialization of automatic alternative extraction and selection in the process of managerial decision-making.

Predictive analytics and forecasting models are at the center of scientific attention as machine learning, data science, and meta-heuristics are gaining momentum in the current literature (Sohrabi, Raeesi Vanani, & Baranizadeh Shineh, 2017, Raeesi Vanani & Jalali, 2017). Predictive solutions tend to use machine learning algorithms to forecast future trends accurately and prescribe solutions upon reaching validated results (Sohrabi, Raeesi Vanani, Gooyavar, & Naderi; Sohrabi, Raeesi Vanani, & Abedin, 2018; Raeesi Vanani & Jalali, 2018).

Adaptive Neuro-Fuzzy Inference Systems (ANFIS) are considered as one of the most accurate and effective methods of predictive analytics (Chen, 2015, Dokić & Jović, 2017, Siminski, 2017, Svalina, Simunovi´c, Sari´c, & Luji´c, 2017, Tana, Shuaia, Jiaoc, & Shenb, 2017, Wan & Si, 2017) as it can predict the implementation success value with high RMSE and R^2 while designing and delivering a fuzzy inference system that can be directly put to use for analyzing the implementation process and discussing the shortcomings and weaknesses.

ERP projects are also getting integrated into new technologies like cryptocurrencies and blockchain, the Internet of things, Cloud Computing, Big Data Management, and machine learning. The Machine learning realm plays a central role in the above-mentioned technologies as most of the technologies constantly gather data and guarantee the smooth flow of data streams throughout the organizational processes, while machine learning and data science domains are the converging points where all data is pre-processed and transformed, and hidden patterns and analytical trends are discovered, learned, and discussed for the purpose of managerial decision making.

This study designs and implements an adaptive neuro-fuzzy inference system which resembles the inference and learning capabilities of ERP implementation experts in order to analyze and predict the ERP implementation success through a pervasive exploration of implementation indicators as well as the application of a learning mechanism on a large data set from a wide range of organizations that have already implemented ERP solutions and have also addressed a number of major problems in the implementation process.

ERP Implementation Success Indicators

In order to avoid costly implementation failures and taking more advantage of the system implementation, a great deal of effort has been made by researchers. There is a valuable insight into the process of ERP implementation (Mandal & Gunasekaran, 2002; Soja, 2008; Subramanianh & Hoffers, 2005; Yusuf, Gunasekaran, & Abthorpe, 2004). Major efforts have also been made to identify the critical factors and key indicators of successful implementation (Amid, Moalagh, & Zare Ravasan, 2012; Nah & Delgado, 2006). Understanding the nature of ERP implementation success has also been the focus of scholarly research interest in recent years (Wu & Wang, 2007).

Many of the success indicators of ERP implementation have not changed during the last decade. However, due to the maturity level of ERP solutions and the advent of new technologies like blockchain, the Internet of things, big data, cloud computing, and machine leaning, the transformation of enterprises has gained momentum toward new challenges and opportunities. Various indicators such as the business requirements, intellectual capitals, the capability of the vendors (Badawy, 2003), system performance and infrastructure (Hicks, Culley, McMahon, & Powell, 2010), and the adequacy of training and consultancy have been deeply studied (You et al., 2012). The most famous assessment model is the D&M or Delone and McLean model (Bernroider, 2008). Derived from a review of 180 empirical studies, this model consists of six major indicators, including “system quality”, “information quality”, “use”, “user satisfaction”, “individual impact,” and “organizational impact”. Later, Delone and McLean (2003) revised their model and replaced individual impact and organizational impact with net benefit.

Reviewing the broad literature, many factors and indicators of ERP implementation success were identified. Table 1 illustrates the findings on implementation factors and indicators. There are 3 major factors, 9 sub-factors, and 82 indicators extracted from the broad and rich literature. Some of the high-impact references of each factor and its sub-factors are also provided. Due to the limited room for providing the findings, the list of detailed indicators is not provided. Each major factor is also short-named according to the sub-factors and indicators pertaining to it.

Table 1. Major factors and sub-factors of ERP implementation success assessment

Major Factors	Sub-Factors	References
Environmental And Organizational Change Orchestration (*CO*)	Change Management	Ifinedo et al., 2010; Basoglu, Daim, & Kerimoglu, 2007; Law, Chen, & Wuc, 2010; Wu, 2011; Gholamzadeh Chofreh et al., 2018; Shen, Chenb, & Wanga, 2016; Costa, Ferreira, Bento, & Aparicio, 2016;
	Business User Involvement	Doom & Milis, 2009; Wang, Lina, Jiang, & Klein, 2007; Andersson & Wilson, 2011; Chuen, 2010; Shen et al., 2016; Costa et al., 2016;
	Environmental Factors	Hakim & Hakim, 2010; Sheu, Chae, & Yang, 2004; Sen, Baraçlı, Sen, & Basligil, 2009; Sen & Baracli, 2010; Gholamzadeh Chofreh et al., 2018; Costa et al., 2016;
Project Implementation Guide (*IG*)	Project Management	Salmeron & Lopez, 2010; Moohebat, Asemi, & Jazi, 2010; Poon & Yu, 2010; Shen et al., 2016; Gholamzadeh Chofreh et al., 2018;
	Implementation Organization	Moohebat et al., 2010; Hakim & Hakim, 2010; Nicolaou, 2004; Momoh, Roy, & Shehab, 2010; Gholamzadeh Chofreh et al., 2018;
	Vendor Qualifications	Sohrabi & Jafarzadeh, 2010; Wei & Wang, 2004; Sen et al., 2009; Sen & Baracli, 2010; Nikookar, Safavi, Hakim, & Homayoun, 2010; Gholamzadeh Chofreh et al., 2018; Shen et al., 2016;
Software Requirements Coverage (*RC*)	Requirements Management	Sommer, 2009; Rose & Kraemmergaard, 2006; Sawah, Tharwat, & Rasmy, 2008; Poon & Yu, 2010; Shen et al., 2016;
	Functional Coverage	Wagner, Moll, & Newell, 2011; Wu, Shin, & Heng, 2007; Cao, Calderon, Chandra, & Wang, 2010; Wu, Ong, & Hsu, 2008; Shen et al., 2016; Costa et al., 2016;
	Non-Functional Coverage	Sen et al., 2009; Sen & Baracli, 2010; Lin, Chen, & Ting, 2011; Sankar & Rau, 2006; Andersson & Wilson, 2011; Shen et al., 2016; Costa et al., 2016;

The factors provided in Table 1 have been extracted through pervasive content analysis and coding of various measurement factors and indicators in the literature according to the frequency of usage in top-level journals and highly referenced papers. These factors should be actively monitored and updated in any phase of implementation.

In addition to the various factors and indicators explored and discussed in the literature, ERP implementation projects require efficient, continuous control mechanisms to schedule and manage the project details. For addressing the continuous challenge, there are many predictive estimation approaches like Regression Analysis, Case-Based Reasoning, Artificial Neural Networks, Support Vector Machine, Genetic Algorithms, Activity-Based Costing, and Function Point Analysis. These methods have mostly used as single techniques rather than hybrid intelligence mechanisms for taking the most advantage of an efficient hybrid architecture (Sohrabi, Raeesi Vanani, & Mahmoudian, 2012a, 2012b). In this study, a multiple Adaptive Neuro-Fuzzy Inference System has been designed and validated against real-world data in order to provide the scholars and practitioners with an adaptive mechanism that is based on accurate measurement data from various enterprises. The developed system comprises a learning algorithm as well as inference and reasoning mechanisms that make it capable of predicting the implementation success through learning from past projects.

3. Research Methodology

It seems complicated to control all of the implementation project phases by developing a precise mathematical model that rarely changes. Due to the complexity and imprecise nature of large-scale implementations, a model that has a classification, adaptation, and forecasting capabilities is required. This makes the Adaptive Neuro-Fuzzy Inference System (ANFIS) an appropriate technique to apply for assessing the ERP implementation success, as it is commonly used in the literature for different measurement efforts (Ata & Kocyigit, 2010; Buia, Pradhanc, Lofmana, Revhauga, & Dicka, 2012; Hosoza, Ertuncb, & Bulgurcuc, 2011; Tahmasebi & Hezarkhani, 2010; Ubeyli, Cvetkovic, Holland, & Cosic, 2010; Venugopal, Devi, & Rao, 2010).

The sequence of input-output-input variable selection makes the simple ANFIS architecture incapable of calculating the results unless a new method is devised for receiving the outputs of the previous layer as inputs for the next layer. In the current study, the researchers encountered a similar challenge that needs to be addressed. To address the problem, a solution has been provided and validated in the form of a multiple-ANFIS architecture. As shown in Figure 1, a separate ANFIS for each major factor is developed. Each ANFIS separately receives the measurement of indicators before and after the implementation.

As a research instrument, a questionnaire was developed containing 82 questions concerning the factors of ERP implementation. The accessible 414 surveyed organizations were requested to answer the questions, based on the ERP implementation success criteria listed in Table 1. In other words, the questionnaire requested opinions about the organizational status before project initiation and the perceived success of the ERP system after implementation. Responses were evaluated on a 5-point Likert scale. To conduct a questionnaire content validity analysis, the authors asked forty ERP implementation experts to participate in the study. Each question was reviewed and revised according to the comments provided by experts.

One of the important aspects of designing an ANFIS is the data collection and preparation phase; therefore, the cases for training and validating have to be representative of all the possibilities related to the implementation process. The research respondents were IT managers and ERP project managers of Iranian firms that have implemented and utilized an ERP solution for a period of one year or more. The results of some studies have shown that the full effects of ERP adoption do not surface until after concluding a fiscal year or more (Hunton, McEwen, & Wier, 2002; Poston & Grabski, 2001).

The data set was gathered from firms that had already implemented ERP solutions and also measured their implementation success using a questionnaire containing all major factors and the related indicators as questions. The collected data was used for training the three initial ANFIS models. Figure 1 provides the overall architecture of the designed ANFIS model in the current research. The system is a multi-level ANFIS design that consists of the initial measurements and calculations for providing the second layer of ANFIS with inputs. The inputs are then used to predict the ultimate implementation success.

The first section of the measurement questionnaire evaluates the Change Orchestration indicators as input and a final score for this factor as output. The second section evaluates the Implementation Guide and the third section assesses the Requirements Coverage in the same way. Finally, the fourth section evaluates the Implementation Success.

Three initial ANFIS architectures predict the status of Change Orchestration (CO), Implementation Guide (IG), and Requirements Coverage (RC) after the implementation according to the real data collected after the project finalization. The outputs of initial ANFIS models are then provided to the final ANFIS model as input. The final ANFIS gets the score of the initial three major factors of implementation as inputs and is then trained to predict the project success. In short, the final ANFIS is trained by a data set that contains the mean score of major factors as inputs and the final implementation success or failure score as output, which is measured in the fourth section of the questionnaire. The final score of success or failure has been assessed by gathering the scores of a team of customer experts and calculating the mean of scores for each customer as the final output.

As mentioned, in the data collection phase, a questionnaire consisting of the factors and indicators was developed and distributed among more than 600 Iranian organizations at which the ERP solution was implemented. In response, 500 filled questionnaires were returned. After a full assessment of answers, 414 questionnaires were deemed viable for the development of ANFIS models. The results were then put in a file and used as an input for the MATLAB programming of the multiple hierarchical ANFIS solution.

The questionnaires were distributed and gathered by a team of 12 experts who held meetings with the IT departments of all accessible ERP implementers. After collecting the data from selected organizations, the resulted Cronbach's alpha was estimated to be 0.818 (greater than 0.7), which indicates the high reliability of the instrument (Nunnally, 1978).

The organizations were assessed in a two-year period. The pre-post implementation results from the questionnaire provided the inputs and outputs for designing, training, and validating the

ANFIS model. The organizations that had not implemented the system at the time of assessment only filled the pre-implementation status. After the completion of implementation, another round of data collection was conducted and the post-implementation data was also gathered. This process took a three-year period of 2011-2014 to accomplish.

The research steps are summarized in Figure 2.

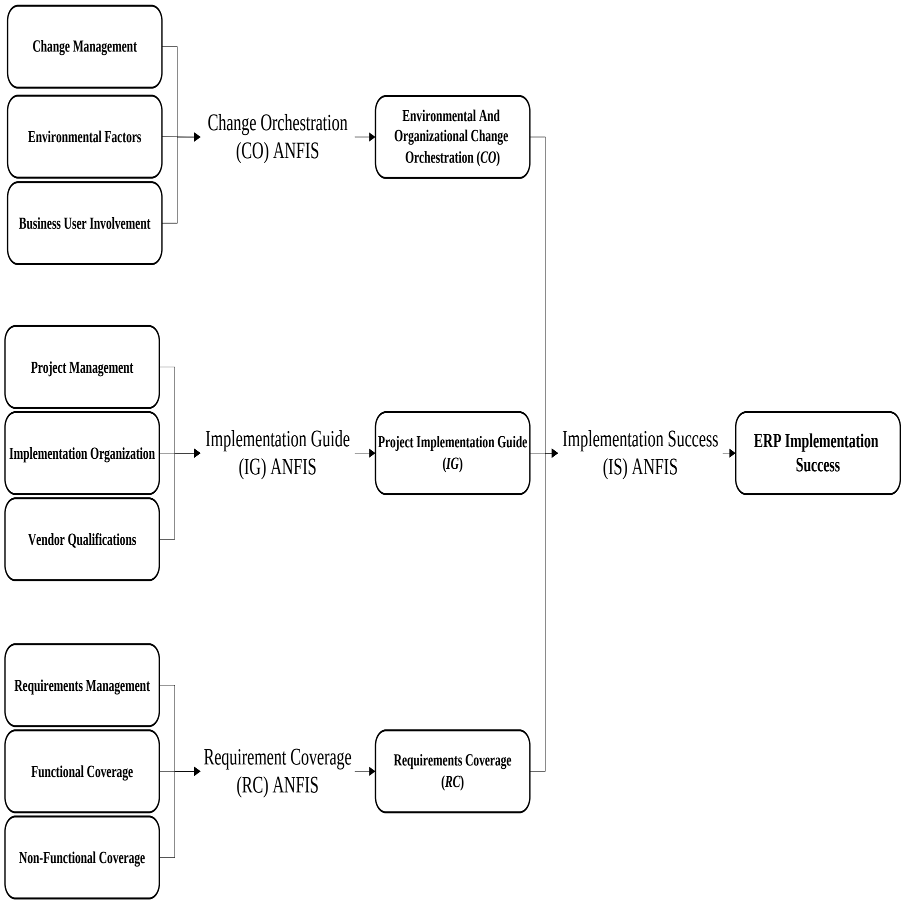

Fig. 1. Multiple ANFIS architecture

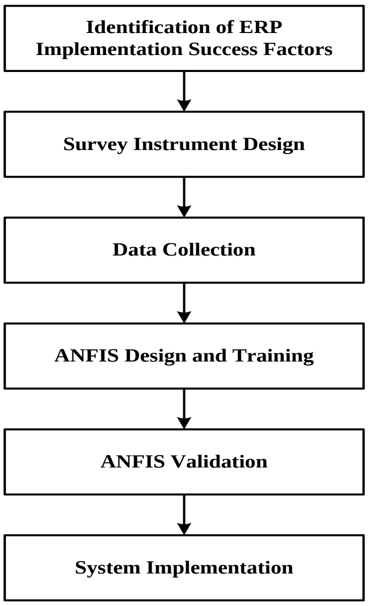

Fig. 2. Research steps

4. Results and Analysis

Given the available knowledge of the problem, the employed neural network–based learning procedure can be either 'supervised' or 'unsupervised'. The supervised learning method is performed with pairs of known input-output training data, whereas in unsupervised learning, training examples are presented to the network input while the network learns and organizes itself to reach maximal separation between the naturally occurring classes of cases (Liao & Wen, 2007).

In this study, the pair of input-output data gathered by the questionnaire is provided to the net, and the supervised learning approach is considered since data set feeds the pre-implementation and post-implementation results to the neural network so the system will learn and resemble the implementation success according to the real project outcomes in various organizations.

Techniques such as Fuzzy Inference Systems (FIS) and Adaptive Neuro-Fuzzy Inference System (ANFIS) have been recently used as efficient alternative tools for the modeling of complex systems. They have been widely used for prediction. A simple FIS is a rule-based system consisting of three conceptual components, including (Ata & Kocyigit, 2010; Buia et al., 2012; Hosoza et al., 2011; Tahmasebi, & Hezarkhani, 2010; Ubeyli et al., 2010; Venugopal et al., 2010):

(1) a Rule-Base, containing a selection of fuzzy if-then rules;

(2) a Data-Base, defining the membership functions used in the fuzzy rules;

(3) an Inference Engine, performing the inference procedure upon the rules to derive an output

ANFIS is a multilayer feed-forward network. Five layers are used to construct the inference system. Each layer contains several nodes described by the node function. Adaptive nodes, denoted by squares (Fig. 3), represent the parameter sets that are adjustable in the nodes, whereas fixed nodes, denoted by circles, represent the parameter sets that are fixed in the system (Yan, & Wang, 2010). The output data from the nodes in the previous layers will be input in the next layer. There are two types of FIS output design described in the literature (Mamdani & Assilian, 1975; Takagi & Sugeno, 1985). The most crucial difference between the two systems is the definition of the consequence or output parameter. The consequence parameter used for designing an ANFIS is of Sugeno type, which is either a linear equation, called “first-order Sugeno FIS”, or a constant coefficient, called “zero-order Sugeno FIS” (Jang, Sun, & Mizutani, 1997). Figure 3 illustrates the ANFIS architecture.

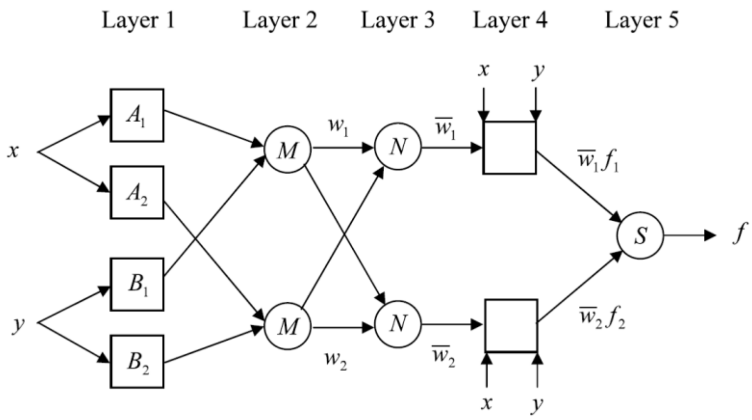

Fig. 3. ANFIS architecture

In the next section, the training and validation of the ANFIS model are provided.

ANFIS Training

The designed ANFIS model is trained using a hybrid learning algorithm, which consists of the combination of "Gradient Descent" and "Least-Squares" methods. Each epoch of this hybrid learning procedure is composed of a forward pass and a backward pass. In the forward pass of the hybrid learning procedure, the node output goes forward until layer 4 and the consequent parameters are identified by the least-squares method. In the backward pass, the error signal propagates backward and the premise parameters are updated by gradient descent (Jang et al., 1997; Yan et al., 2010). The task of a learning algorithm for this architecture is to tune all the modifiable parameters, namely {ai , bi , ci} and {pi , qi , ri}, to make the ANFIS output match the training data. When the premise parameters are fixed, the output of the ANFIS model can be written as (Ubeyli et al., 2010):

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2.$$

The equation can be restated as:

$$f = \bar{w}_1 f_1 + \bar{w}_2 f_2.$$

Substituting the fuzzy if–then rules into equation, it becomes:

$$f = \bar{w}_1 (p_1 x + q_1 y + r_1) + \bar{w}_2 (p_2 x + q_2 y + r_2).$$

After rearrangement, the output can be expressed as

$$f = (\bar{w}_1 x) p_1 + (\bar{w}_1 y) q_1 + (\bar{w}_1) r_1 + (\bar{w}_2 x) p_2 + (\bar{w}_2 y) q_2 + (\bar{w}_2) r_2$$

which is a linear combination of the modifiable consequent parameters. When the premise parameters are not fixed, the search space becomes larger and the convergence of the training becomes slower. It has been proven that the hybrid algorithm is highly efficient in training the ANFIS.

ANFIS Validation

Model validation is the process by which the input vectors from input/output data sets. The validation data pairs are not used for training the ANFIS. They are presented to the trained model to see how well the model works. Some statistical methods, such as the Root Mean Square (RMS) error or RMSE, and the coefficient of multiple determinations (R^2) might be used to compare the predicted and actual values for model validation. The RMS and R^2 are defined as follows (Boyacioglu & Avci, 2010):

$$\mathrm{RMS} = \sqrt{\frac{\sum_{m=1}^{n}(y_{\mathrm{pre,m}} - t_{\mathrm{mea,m}})^2}{n}},$$

$$R^2 = 1 - \frac{\sum_{m=1}^{n}(y_{\mathrm{pre,m}} - t_{\mathrm{mea,m}})^2}{\sum_{m=1}^{n}(t_{\mathrm{mea,m}})^2}$$

Where n is the number of data patterns in the independent data set, while $y_{pre,m}$ indicates the predicted and the $t_{mea,m}$ is the measured value of one data point m. The RMS statistic indicates a model's ability to predict a value away from the mean. There are also several other statistical measures used for validating the model. The extra validation measures are SSE[1], Adjusted-R^2, MSE[2], MAE[3] (Boyacioglu & Avci, 2010).

ANFIS Development

MATLAB is used to design, train, and validate the ANFIS architecture. Researchers used the programming capabilities of MATLAB for developing the final system. A user interface has also been developed for ANFIS models that facilitates the utilization of the final system. After the data-gathering phase, the programming was started. Using the code, a user interface for designing the ANFIS model was developed (Fig.4). In the current research, all three methods were used and the validation results were compared for the generation of the most optimal FIS.

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1. Sum of Squares due to Errors
2. Mean Squared Error
3. Mean Absolute Error

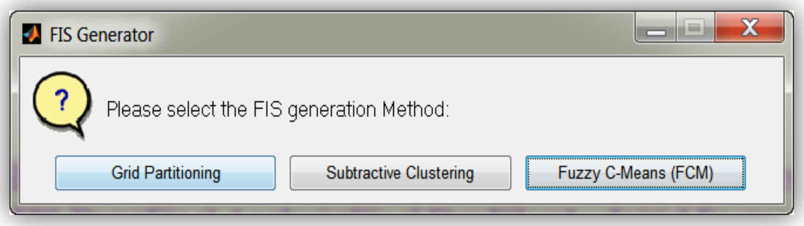

Fig. 4. FIS generation method selection

After selecting the FIS generation method, another user interface was developed for the selection of the training algorithm (Fig. 5). There are two significant algorithms available, Back Propagation and Hybrid Algorithm. Both algorithms were used and compared in order to find the best validation result for ANFIS models.

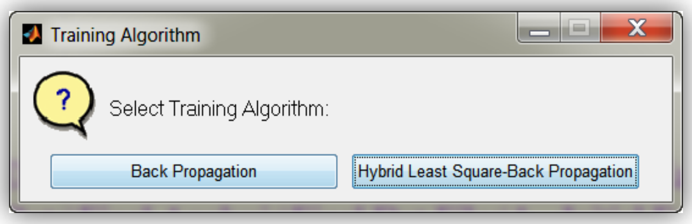

Fig. 5. Training algorithm selection

After the selection of the FIS generation method and the training algorithm (which are six available methods and algorithms in combination), the training and validation process was started. The results of the training and validation process are shown in Figure 6.

About 70% of data pairs were used for training the model. The separate percentage of data dedicated to validation and test has been 15%. Test data was used for validating the model after the finalization of training and within-training validation. Other combinations of design-train-validation were also all tested and evaluated. However, the structure shown in Fig. 6 is the best result obtained after the completion of training and validation steps.

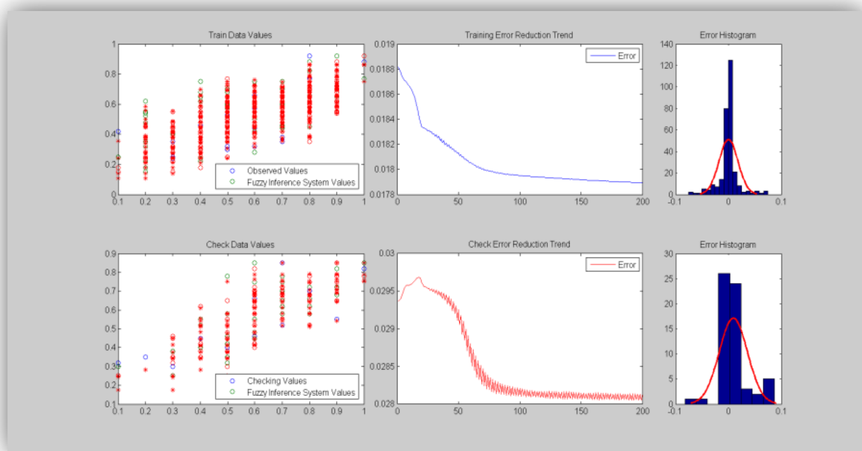

Fig. 6. Training and validation results

The error reduction trend for validation data proves that the system has been well trained and validated, and no significant over-fitting of training has occurred. There have been many attempts to find the most optimal combination of FIS generation, training, and validation algorithms for finding the best ANFIS model. The repetition of this process proved that the Subtractive Clustering and Fuzzy C-Means for FIS generation combined with a Hybrid training algorithm would provide the most viable ANFIS model that can effectively predict the output of ERP implementation success.

For the Change Orchestration ANFIS and Implementation Guide ANFIS, the Subtractive Clustering method for FIS generation and the Hybrid Algorithm for training proved to be the best design and training approaches. Also, for the Requirements Coverage ANFIS and Implementation Success ANFIS, the Fuzzy C-Means and Hybrid Algorithm proved to have the best performance. Table 2 illustrates the validation measures for the final ANFIS model that is used for predicting the Implementation Success of ERP solutions. The validation results of other ANFIS models were also viable and similar to the results provided in Table 2.

Table 2. Validation results

Training Algorithm / FIS Design Method	Hybrid (Back Propagation + Least Square)		
	Validation Measure	**Training Data**	**Validation Data**
FCM (Fuzzy C-Means)	SSE	0.05	0.0135
	RMSE	0.0138	0.0150
	R^2	0.9849	0.9614
	A-R^2	0.9848	0.9608
	MSE	0.0029	0.0045
	MAE	0.0418	0.0535

The values of RMSE and R^2 as well as the other validation measures show a high level of validity for the developed system. The RMSE is lower than 0.1 and R^2 provides a strong coefficient for model outputs and the ANFIS predictive estimates.

For validating ANFIS models after the completion of training and within-training validation, the data gathered from 62 organizations were used as the test data (15% of total data). Figure 7 provides the results of final test data validation which shows a near-zero error for predicting the outcome of ERP implementation as illustrated in error histogram.

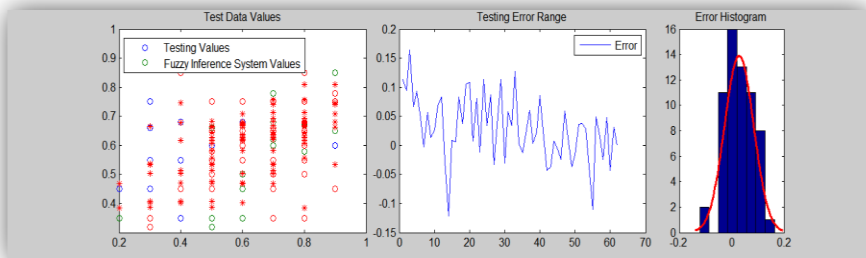

Fig. 7. Model validation with test data

The 62 error values for the test data fluctuate between -0.15 and 0.2, which provides an accurate system performance. Test data validation results are provided in Table 3.

Table 3. Model test results

Validation Measure	Change Orchestration (CO)	Implementation Guide (IG)	Requirements Coverage (RC)	Implementation Success (IS)
SSE	0.0318	0.0215	0.1399	0.0464
RMSE	0.0230	0.0189	0.0483	0.0278
R^2	0.9653	0.9807	0.8688	0.8942
A-R^2	0.9647	0.9804	0.8666	0.8924
MSE	0.0005	0.0003	0.0023	0.0039
MAE	0.0127	0.0150	0.0267	0.0490

The test data evaluation illustrates a strong predictive behavior for ANFIS models. In other words, the system is capable of predicting the Implementation Success based on the initial status of organizations before the project initiation with an acceptable precision on project final outputs.

The ANFIS model validity can also be assessed using a regression diagram. If ANFIS outputs correspond well to real observed outputs, then the regression equation will nearly equal y=x since both models and observed values are the same. The final model predicts the implementation success on a spectrum of 0 to 10. The observed data has also been collected using the same spectrum. The regression diagram is shown in Figure 8. It can be summarized that ANFIS has nearly predicted the observed values with a high level of precision.

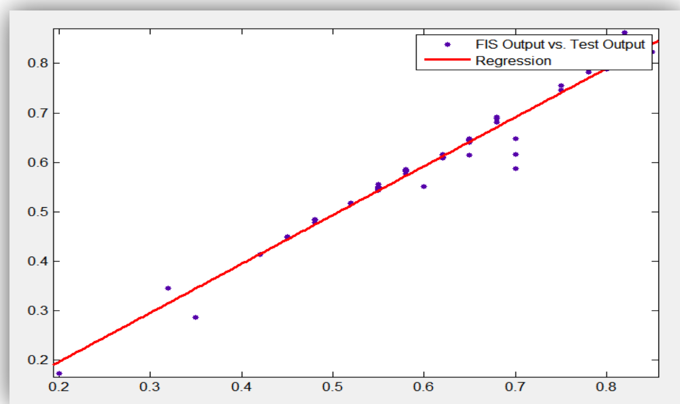

Fig. 8. Regression equation for FIS output versus observed output

Figure 9 illustrates the multiple ANFIS model in an integrated view. The inputs for the three initial ANFIS models are the sub-factors assessed through the questionnaire of 82 indicators. The outputs of these ANFIS models are then considered as inputs for the final IS ANFIS. Finally, the IS model predicts the project implementation success score:

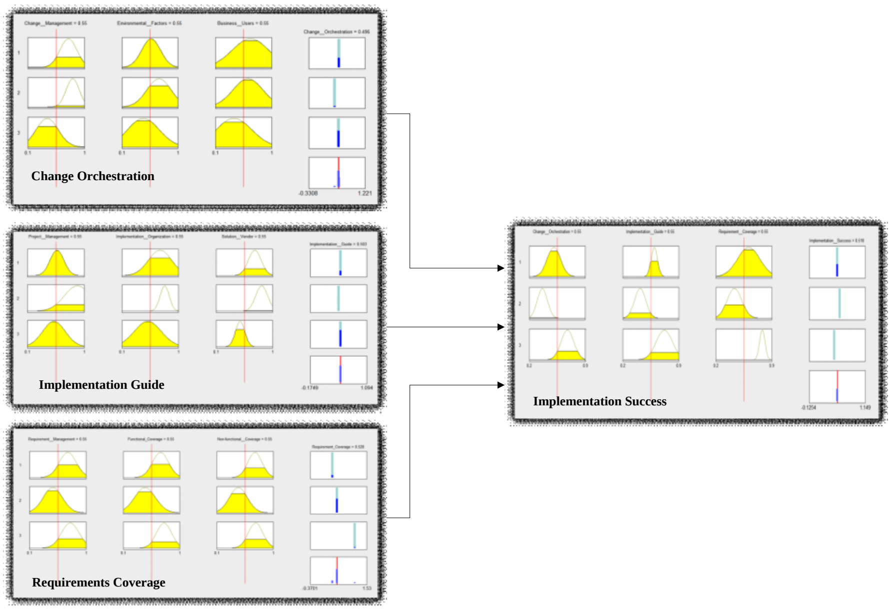

Fig. 9. Final Multiple ANFIS model

5. Discussion

The orchestration of modern changes and the management of resistances against new moves, a well-directed implementation process, and a near-optimum coverage of ERP solution features can be concluded as the preliminary requisites for a successful implementation through a pervasive deep review of the literature. After designing, training, and validating the final system, a sensitivity analysis of inputs parameters against final implementation success was conducted. Figures 9 to 11 provide a 3-D view of all possible combinations of inputs versus implementation success. The diagrams effectively illustrate the intensity and direction of impact for each factor on the final success.

Figure 10 highlights the role of the Implementation Guide in achieving a successful implementation. Effective investment in the Implementation Guide returns a much higher impact on Implementation Success than for Change Orchestration. This finding indicates the fact that having a proper plan for guiding the implementation process, the orchestration of changes will be more effective in advancing the project.

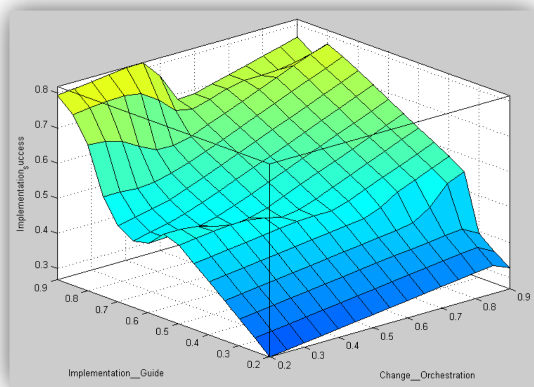

Fig. 10. Effect of Implementation Guide and Change Orchestration on Implementation Success

Figure 11 illustrates the great importance of Requirements Coverage over Change Orchestration. Without sufficient coverage on functional and non-functional software requirements, the orchestration of organizational and environmental changes will be less effective. This also provides a clue for investing in more accurate and precise meeting of the requirements before project initiation. Failure in covering organizational requirements can lead to a full failure of the project, while the inefficient orchestration of environmental changes will have a moderate effect on the ultimate success.

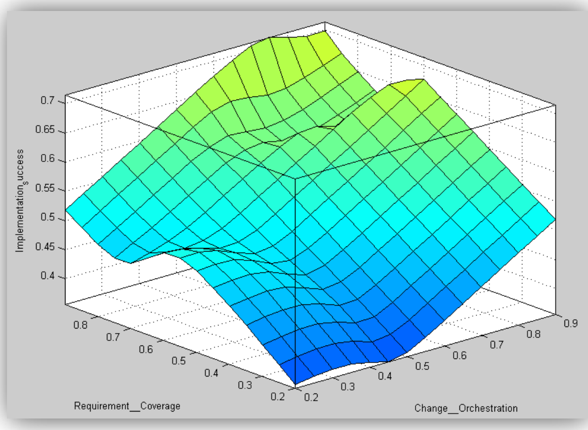

Fig. 11. Effect of Requirements Coverage and Change Orchestration on Implementation Success

Figure 12 shows the effect of Implementation Guide and Requirements Coverage on implementation success. It can be concluded from Figure 11 that the Implementation Guide has a more effective role in Implementation Success than Requirements Coverage, although the role of Requirement Coverage is also of significance.

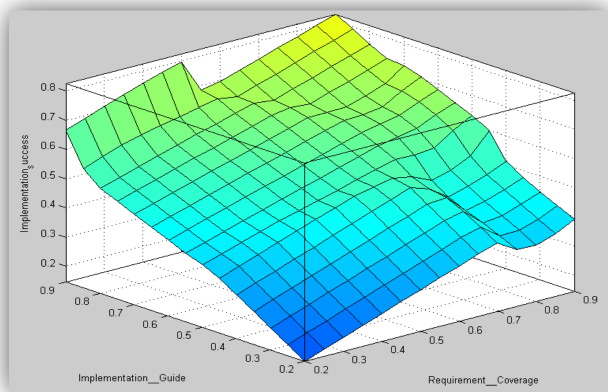

Fig. 12. Effect of Implementation Guide and Requirements Coverage on Implementation Success

Considering all sensitivity diagrams, it can be concluded that the most important factors in ERP projects are Implementation Guide, Requirements Coverage, and Change Orchestration. Another point to notice is that none of the major factors have a deterministic role in the implementation success as they all need to be deployed together to provide an effective synergy to the process.

The new trends of implementing the enterprise solutions suggest that there are many more factors to consider if a system is going to be effectively assessed and controlled. The effective management of ERP implementation projects requires an integrative view of ERP implementation embedded into the structure of digital transformation of enterprises. The development of enterprise solutions combined with blockchain, the Internet of things, data science and machine learning, and big data analytics requires a sustainable and long-term planning. The sustainable ERP implementation with a strong design thinking approach can provide new insights on how to utilize the most recent capabilities of enterprise solutions.

6. Conclusion and Future Research Directions

The results extracted from the analysis of the developed ANFIS model have shown interesting points and ideas. Worthwhile outputs that are driven from the 3-D sensitivity diagram rely on real data that are extracted from implemented projects. Through an analysis of the Implementation Guide factor, it can be found out that execution organization is one of the most prominent prerequisites of ERP project success in Iran, while it remains a weak point in many implemented projects. Surveying the literature, researchers have found that the lack of the presence of well-established international ERP vendors in Iran and insufficient capabilities of Iranian ERP developers have led to excessive scope creeps, feature creeps, over-budgeting, and less integrated modular implementations. This is due to a lack of well-documented best practices of different Iranian industries in ERP development firms as well as weak knowledge management and knowledge sharing mechanisms that can relay and insert the previous experiences into new projects.

Another point to notice is that Iranian ERP solutions are rarely designed for multi-branched distributed firms. Most ERP systems are web-based or web-enabled but few of them have real capabilities for supporting millions of transactions per day for a countrywide holding company. This has resulted in a managerial back-off in Iranian enterprises from purchasing domestic solutions and paying more attention to international possibilities since they can better focus on non-functional and performance-based priorities in ERP implementations.

The successful implementation guide and the well-managed requirements coverage are complementary prerequisites of a satisfactory implementation while a concentration on change management and environmental factors are in place. During an ERP implementation, many functional and process changes will be applied to the organizational structure that will in turn create organizational resistances as well. This requires a smooth and on-going management of changes in a manner that gains the support of all system users and managers. In Iranian companies, change management is considered a secondary priority since the shortcomings of the implementation process and lack of sufficient requirements coverage have led the projects into a slowly moving giant for which the management of changes is the last priority.

It is also important to consider the trend of sustainable Enterprise Resource Planning as a pervasive approach to the combination of enterprise solutions to the digital transformation strategy of organizations. The sustainable ERP solutions are noted in the literature as well (Chofreh, Goni, Shaharoun, Ismail, & Klemeš, 2014). The utilization of automatic models of prediction like ANFIS models can directly help the managers to control the successful implementation and integration of ERP solutions to the other high-tech innovations such as big data management, data science and machine learning, the Internet of things, and blockchain initiatives. It is recommended to consider the combination of inter-related technologies while assessing the strategic implementation success of ERP solutions for a sustainable digital enterprise. It is also recommended to make use of the most recent algorithms like deep learning, text analytics, and machine learning initiatives to update and improve the architecture and training effectives of algorithms. The integration with evolutionary algorithms also helps with optimizing the measurement results.

Emphasizing the above major factors helps intelligent managers invest in those project indicators that have the most impact on a successful implementation. The developed multiple ANFIS model helps the managers recognize the pitfalls and organizational weaknesses before initiating the project and also paves the way for future attempts that can continuously monitor the implementation process in real-time, considering the factors researched in the current study. Due to the limitations of data collection procedure that was only conducted in the Iranian companies, it is suggested to expand the research domain to consider some of the international enterprises that have managed to develop new models of sustainable ERP implementation within the digital transformation initiatives. This will also help in creating a more generalizable model of implementation success prediction.

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