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Work breakdown structure (WBS) development for underground construction

Elnaz Siami-Irdemoosa [a,*], Saeid R. Dindarloo [b], Mostafa Sharifzadeh [c]

[a] Department of Geosciences and Geological and Petroleum Engineering, Missouri University of Science and Technology, Rolla, MO 65401, USA
[b] Department of Mining and Nuclear Engineering, Missouri University of Science and Technology, Rolla, MO 65401, USA
[c] Dept. of Mining and Metallurgical engineering, Amirkabir University of Technology, 424 Hafez Ave., Tehran, Iran

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ABSTRACT

A work breakdown structure (WBS) can prove to be pivotal to successful project management planning. There are few published studies about the methodologies or tools to develop the appropriate WBS for a project, and those that are available are limited to the specific areas of construction such as apartment-building construction and boiler manufacturing. This research has an emphasis on developing a methodology with higher generalizability, which has the capability to be customized to complex underground projects. To address this issue, a new methodology that employs hierarchical neural networks to develop the WBS of complex underground projects is presented. This methodology has been applied to several tunnel case studies and it has been shown that for a real project, the model is able to generate the WBS and its activities that are comparable to those generated by a project planner. Consequently, it is concluded that these modeling methods have the capacity to significantly improve the WBSs for complex underground projects and improve key project tasks, such as workload planning, cost estimating and scheduling.

1. Introduction

A comprehensive efficient work breakdown structure (WBS) can prove pivotal within project management planning processes by partitioning projects into stages, deliverables and work packages. Consequently, it can positively impact other project management processes, such as activity definition, project schedule, risk analysis and response, control tools or project organization [1].

The planning of underground work and WBSs is different from other civil construction, when one considers the complexity, uncertainty and large number of activities involved [2]. An experienced complex underground project manager knows that despite detailed planning and execution, there is always the possibility of errors, mishaps and unexpected outcomes on the horizon. Developing the work breakdown structure of a complex underground project in a systematic, thorough, and methodological manner will decrease the potential for unwanted possibilities while providing a baseline for planning, estimating, scheduling and effective project management.

Despite such significance and repercussions, there is a dearth of research concerning methodologies or tools for the development of appropriate work breakdown structures (WBSs) for a project. The available research is mostly limited to a given range of construction projects, and therefore, the generalizability of the research remains limited to specific conditions. However, more recent research utilizing case-based reasoning (CBR) methods offers valuable material while providing a model for the acquisition and reuse of specific planning knowledge.

FASTRAK-APT, which was developed by Lee et al. [3], offers an important case- and constraint-based project planning tool for apartment construction. FASTRAK-APT relies on the fact that a human expert project planner uses previous cases for planning a new project. Despite the evident use of CBR methods for planning, the applicability of the system is limited; in contrast, the proposed methodology is applicable to domains that have available data and structured knowledge, such as apartment construction.

Dzeng and Tommelein [4] proposed a case-based expert system, CasePlan, based on a product model that describes and reuses the existing boiler erection project in power plant construction for planning a new project. The researchers believe that CasePlan will prove viable for projects with distinct components; thus, it may not be applicable for complex underground projects, which have no distinct component. Ryu et al. [5] developed CONPLA-CBR, a case-based reasoning planning tool with greater applicability. However, its applicability has not been evaluated for complex underground projects. More recently, some researchers have emphasized the use of neural networks in the development of planning systems [6,7]. Hashemi and Emamizadeh [8] proposed a decision tool that employs a modular neural network to plan the WBS of a limited project domain. The author cited the vast amount of knowledge required in generating a work breakdown structure as the primary reason why the use of neural networks is a

* Corresponding author.
E-mail address: esv23@mst.edu (E. Siami-Irdemoosa).

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preferable alternative; however, the proposed methodology is applicable to small-scale projects. For large-scale complex underground projects, the number of possible work breakdown structures and activities can expand rapidly and a bigger size of neural network should be employed. Therefore, designing and training of the neural network will be more complex and time consuming. Sharifzadeh et al. [9] formulated an approach for WBS development in tunnel projects using neural networks. Large-scale tunnel projects were tested by their proposed model; however, their model had the similar disadvantage, and hence the accuracy of the predicted WBS was decreased by increasing the number of WBS elements.

There is not a good process to objectively determine the WBS of complex underground projects and correlate them with the projects nature. With this in mind, this paper is going to introduce a process which helps a planer to make a more informed choice of WBS components and structure regarding project attributes. The outcome of the process is a hierarchical neural network, which has been implemented to develop the WBS of complex underground projects. First, the main concepts, including the work breakdown structure of a complex underground project and its attributes, are described, followed by detailed description of the proposed methodology. Finally, the results of applying the proposed methodology to several case studies are discussed.

2. Complex underground project attributes

Underground construction necessitates firm commitments and obligation to comprehensive and complicated procedures. Underground construction demands high management expertise to address complex and challenging eventualities. Lack of understanding of a number of significant factors, such as the unique contingent features and ensuing interrelated complexities, can increase the difficulties of underground construction endeavors [2]. Thus, complex underground construction projects are characterized by a large number of variables that can unfold in various quantities and combinations, including participating parties and individuals, a sundry of work packages at play, requirements, drawings, plans and reports, in addition to budget items and the time plan. Factors that affect project management may be enumerated as follow [2,10]:

1. Underground structures are a necessity of modern life, and such necessities cannot be disregarded.
2. Consideration of the needs of the general public as the major stakeholders is critical to the success of such projects.
3. Urban underground projects are constructed in dense, complex, and restrictive environments.
4. Public policy, public relations and the effective use of media can positively impact the construction of tunnel projects.
5. Underground construction is capital intensive and reliant on a high injection of initial capital expenditures.
6. Underground projects take considerable time to conclude.
7. Underground construction is carried out under conditions of geological uncertainty.
8. Underground construction is risky.

It is important to understand the key attributes of an underground project before the creation of the project WBS. Project stakeholders, for example, affect some of the main characteristics of the WBS such as the level of details. In larger projects such as subway tunnels, politicians, owners, nearby resident and public might be the stakeholders. On the contrary, smaller projects such as a diversion tunnel might have only one or two stakeholders including the members of the parliament and environmental organizations. It should be noted that these attributes vary in different underground projects in different countries. Other factors have more or less similar effects on WBS development. However, the complexity arises from the variation of these attributes in different underground projects. Geological conditions might be highly variable for a certain project while it is almost constant in another project. The expectation of an underground project client might be too high so that weekly reporting is required, whereas a client of another project needs monthly reports. A few millimeters settlement during the construction of an urban tunnel might be the concern of the nearby residents and hold the project for months, while larger settlements are acceptable in other projects [11]. All of these attributes affect the main characteristics of the work breakdown structure and they should be well understood before the development of the WBS.

3. Work breakdown structure (WBS) of complex underground projects

Work breakdown structure (WBS) is the process of dividing a project's overall work to several more manageable hierarchy structured tasks. The level of details should represent the overall scope of the project while keeping the tasks manageable [1,12]. The WBS is typically designed through a top-down procedure. The upper levels of the WBS are decomposed into logical groupings of work, followed by the next level down and so on. Thus, the lowest-level component of WBS can be scheduled, and its cost can be estimated, monitored, and controlled. Fig. 1 illustrates the work breakdown structure of a metro tunnel project as an example.

There are many different methods that can be employed to create a WBS. While there is general agreement that the WBS is the fundamental managerial component upon which many project management processes are based, there is surprisingly little agreement on the best method for creating the WBS [1]. One of the main questions in this regard is how the optimal WBS can be identified from all possible structures. The Project Management Institute [13] stipulated that “a quality WBS is a WBS constructed in such a way that it satisfies all of the requirements for its use in a project”. When applying this quality principle, the optimal WBS in a complex underground project is a high-quality work breakdown structure, wherein specific content and the type of WBS elements appropriately address the full set of needs of the project. Examples of a quality WBS characteristic in a complex underground project are as follow:

- Contains specific types of WBS components necessary for a complex underground project.
- Provides “sufficient” detail for communicating the scope of a complex underground project.
- Achieves a “sufficient” level of decomposition for effective complex underground project management.

Therefore the best method for creating the WBS of complex underground projects is a method that could find the optimal work breakdown structure with all necessary components, sufficient details and sufficient level of decomposition. One might ask what the exact definition of “sufficient” is in this context. Considering the varying attributes of a complex underground project, the real answer is that it depends. The attributes of a complex underground project entail the use of project-specific WBS characteristics. A specific WBS may prove highly appropriate for one project while failing completely for another. In fact, considering the variability and complexities of underground project management, it is not surprising that specific standards for WBS characteristics of complex underground projects are difficult to find.

4. Methodology

The overall process of the proposed methodology is presented in Fig. 2 under the headings ‘State Problem’, ‘System Design’, ‘Verification’ and ‘Validation’. The ‘State Problem’, ‘System Design’ and ‘Verification’ steps are presented in the following sections, while the ‘Validation’ step and results are discussed in Section 5.

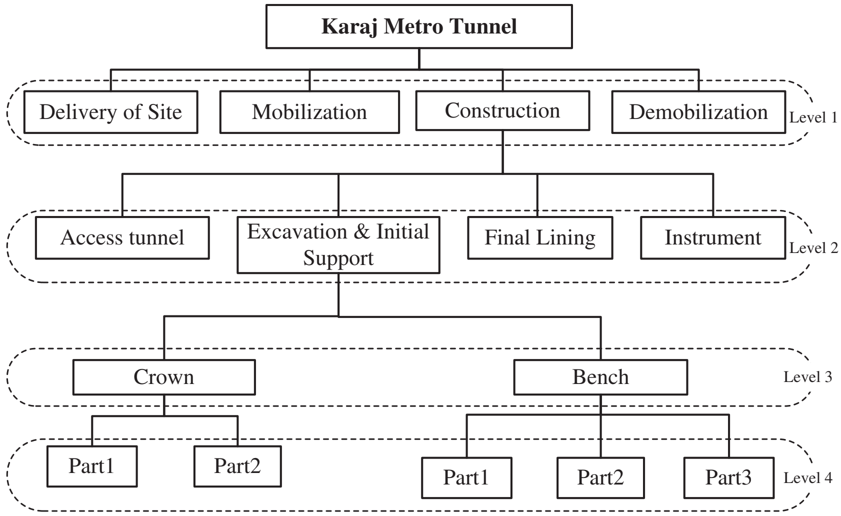

Fig. 1. A metro tunnel project WBS.

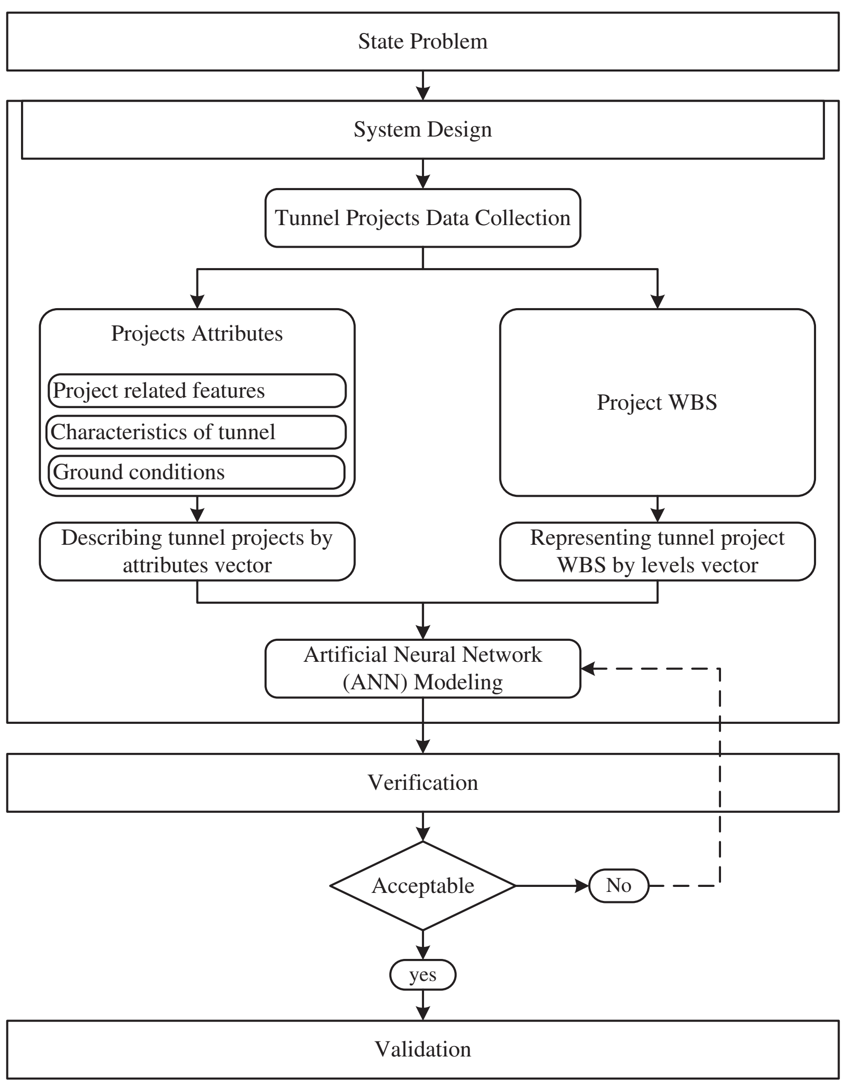

Fig. 2. The overall procedure of proposed methodology.

Table 1
The specification of attributes to describe the projects.

Project attributes	Type of quantity	Bit space	ID
Project related feature			
Client expectations	Lexical	2	A1
Contractor expectations	Lexical	2	A2
Project stakeholders	Lexical	9	A3
Location of the project	Lexical	2	A4
Land possession	Lexical	2	A5
Time	Numerical	8	A6
Cost	Numerical	17	A7
Characteristics of excavation			
Purpose	Lexical	2	A8
Shape	Lexical	3	A9
Diameter	Numerical	11	A10
Length	Numerical	15	A11
Depth	Numerical	10	A12
Construction method	Lexical	5	A13
Ground condition			
Surrounding rock/soil	Lexical	3	A14

Table 2
Structure of the proposed neural model with optimum networks parameters.

Networks parameters	WBSL1	WBSL2	WBSL3	WBSL4	WBSL5	WBSL6
No. of input layer neurons	90	195	832	905	678	664
No. of output layer neurons	105	742	815	597	574	882
No. of hidden layer neurons	49	73	57	52	35	62
No. of hidden layer	1	1	1	1	1	1
Training algorithm	BPN	BPN	BPN	BPN	BPN	BPN
Training mode	BT	BT	BT	BT	BT	BT
Stop criteria	CV	CV	CV	CV	CV	CV
Learning rate (η)	0.9	0.9	0.5	0.1	0.5	0.9
Momentum (μ)	0.5	0.1	0.5	0.9	0.9	0.5
No. of training epochs	107	109	107	113	113	111
MSE	0.00172	0.00234	0.00095	0.00723	0.00651	0.00096

BPN: Back-propagation.
BT: Batch training.
CV: Cross validation.

4.1. State problem

The main problems of developing WBSs for complex underground projects have been detailed in previous sections. The main purpose of this study is to propose a specific methodology to model the relationship between the attributes of projects and WBSs. This task relies on the premise that the optimal WBS of a complex underground project could be related to the attributes of the project. Previous studies have shown that this relation is very complex and cannot be represented by the classical methods of knowledge representation. However, a substantial number of case histories of previously constructed projects and their WBSs are available. Therefore, artificial neural networks (ANNs) were used to extract the unknown, complex and implicit knowledge of underground projects experts in WBS planning. A brief introduction of this method is provided below.

Artificial neural networks (ANNs) employ a massive interconnection of simple processing elements that are capable of performing a significant number of parallel computations for data processing and knowledge representation [14,15]. ANNs imitate some of the brain's creative processes, albeit in a simplistic way, that cannot be imitated by existing conventional problem-solving methods [16]. The attractiveness of neural networks comes from their ability to learn and generalize [14]. The artificial intelligence of neural networks is provided by combination of several simple computations at neurons level [17,18]. Each neuron receives inputs, and associated with every input is a weight that corresponds loosely to electrochemical impulses and synaptic connections in the brain [19]. The synaptic weights are determined as the ANN learns. The method used in this study, supervised learning, uses an actual output for each input pattern guiding the learning process. One of the most widely used supervised algorithms is the feed-forward back-propagation network (BPN) [20]. A BPN consists of an input layer, an output layer and one or more hidden layers. In this type of network, the data are fed forward into the network without feedback. The development of ANNs in this study constitutes a cycle of three phases that will be presented in the following sections.

4.2. System design

The main objective of system design is to determine the structure of ANN and learning rules. This phase also involves data collection and partitioning the data into three distinct subsets for use during the training, testing and validation processes. The performance of the neural networks strongly depends on the quality of the training data; thus the

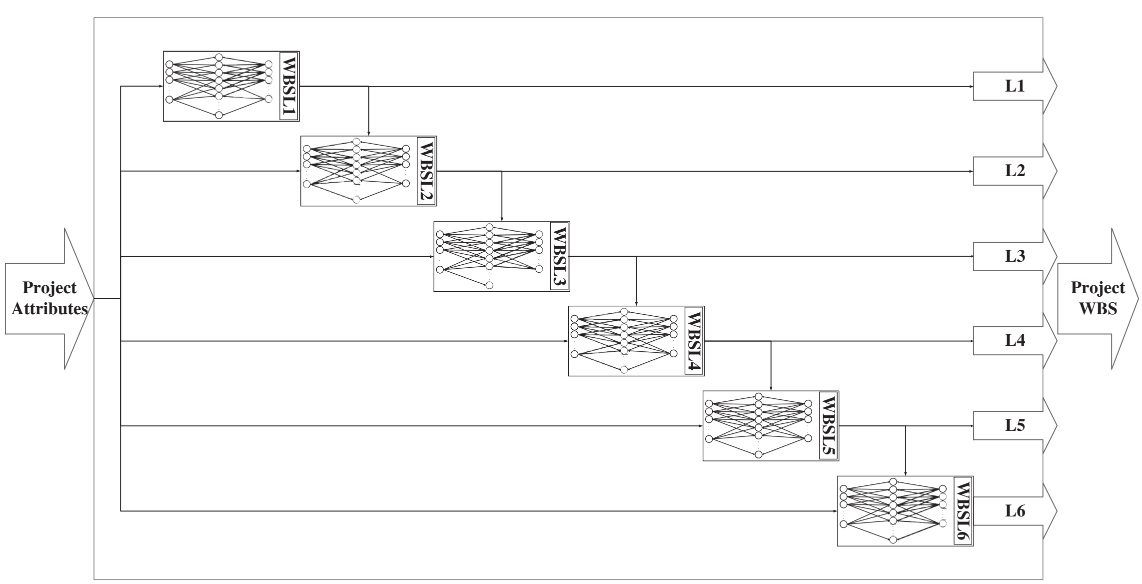

Fig. 3. Structure of the proposed neural network model.

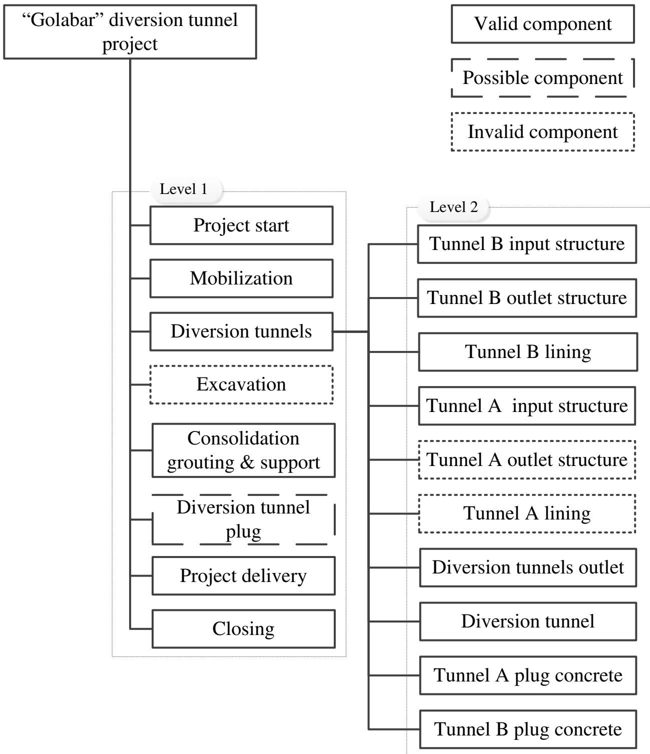

Fig. 4. Developed project WBS for project 1.

sufficient amount of data from previous successful complex underground projects with a quality WBS should be collected to train the neural networks. A dataset of 20 tunnel projects (including 3433 activities) was accumulated. The selected projects are the most successful underground projects constructed in Iran according to tunneling experts, and the project WBSs are high quality. The maximum number of levels in the WBSs of the selected projects is 6. Also the selected WBSs (developed by project contractor) contain 3433 activities in total. The data from 18 projects were used in the verification process, while data from 2 projects were used in the validation process.

The generalization of the ANN models to unseen data will be affected by the size of database. Training data should be sufficiently large to cover the possible variation in the problem domain. Database size can be expanded by obtaining new data. In this study data enrichment was not possible; hence, the leave-one-out method [21] was used for developing the neural networks. In this method, a network is trained on M-1 (i.e. 18-1) example, and is tested on the one hold-out example. The process is repeated M times. The solution of M network is then averaged to obtain a solution with higher generalizability.

The projects data contain values for project attributes and their work breakdown structures. Project attributes are a limited set of variables that should represent the general nature of a complex underground project. To this end, three major sets of project attributes were defined. The first is the project-related features, which include the total amount of time, total budget and location of the project. The second set is the characteristics of the underground excavation, such as the size and construction method. The third set is ground conditions.

The attributes of project set can be defined by $\boldsymbol{A} = \{A_i\}$, $(0 < i < 14)$. The members of **A** are arranged in a column vector. Then, the values of the project attributes are assigned to the related rows of the resulting vector. Therefore, there are 20 column vectors that will be considered as the inputs for the training, testing and validation patterns. Project attributes are assigned by a combination of lexical and numerical values. As the inputs and outputs of a neural network should be numerical, binary code is assigned to each assignable lexical value. Furthermore, the equivalent binary forms of the project attributes are used for distinct quantities. Table 1 shows the specifications of the complex underground project attributes.

A WBS consists of elements from different levels. Regarding the large number of WBS elements in complex underground projects, the collected WBSs were decomposed into vectors according to the component level to show WBS in the outputs. The vector of the WBS level can be represented by $\boldsymbol{L}_l = \{w_1, w_2, \ldots, w_{nl}\}$, where $\boldsymbol{L}_l$ is the level vector of the WBS at level l, l is the level ID, w_i is the component and n_l is the maximum number of components at level l. Therefore, 20 level vectors with the same size for each level of the WBS are created. These vectors will be considered as the outputs of the training, testing and validating examples.

This study employs feed-forward neural networks with back-propagation learning algorithms, also known as a back-propagation network (BPN). The proposed model is a hierarchical neural network consisting of six different BPNs, which are used to establish the relationships between project attributes and their work breakdown structure. Six BPNs are used due to the hierarchical structure of WBSs. Each BPN has a different configuration, which is used to infer the complex underground project WBS and activities from the project attributes. Fig. 3 shows the structure of the proposed neural model. As shown in Fig. 3, the inputs of WBSL1 only consist of project attributes. This BPN should establish which components should be implemented in the first level of the WBS with respect to the project attributes. Therefore, the output

Table 3
The project attributes for validation datasets.

Attribute ID	Project 1		Project 2	
	Attribute value	Input neuron value	Attribute value	Input neuron value
A1	High	00	Low	01
A2	High	00	High	00
A3	Members of the parliament Environmental organizations	100000010	Members of the parliament Politicians Owners Nearby residents Public	110111000
A4	Neutral	10	Positive	00
A5	Difficult	0	Difficult	0
A6	42	01010100	11	01000000
A7	18820	001000011001001000	22500	110000010100100000
A8	Diversion tunnel	11	Metro	00
A9	Horseshoe	010	Horseshoe	010
A10	830	01111100110	830	01111100110
A11	870	011001101100000	3070	011111111101000
A12	200	000100110	15	001100000
A13	Drilling & Blasting	0000	NATM	10100
A14	Rock-Moderate	100	Soil-Cohesive	001

of WBSL1 is a row vector whose columns are linked to the individual elements of the first level of the project's WBS. If any columns take a value of 1, the related element can be employed in the first level of the project's WBS. Next, the ***L1***-vector and the vector of the complex underground project attributes are considered as the inputs of WBSL2. This network establishes which components should be implemented in the second level with respect to the project attributes and the upper level of the WBS. Therefore, the output of WBSL2 is represented in the second level of the project WBS. Similarly, WBSL3 establishes the third level, WBSL4 establishes the fourth level and so on. As shown in Fig. 3, a six-level complex underground project WBS can be realized through the learning process. Six networks are used for the identification of the six levels because the maximum level number for the collected WBSs is 6.

4.3. Verification

Verification involves training of the proposed neural model using the training and test subsets and simultaneously assessing the network performance by analyzing the mean squared error. The leave-one-out method [21], which is an extreme form of multifold cross-validation, was used to minimize the impact of data dependency on the result.

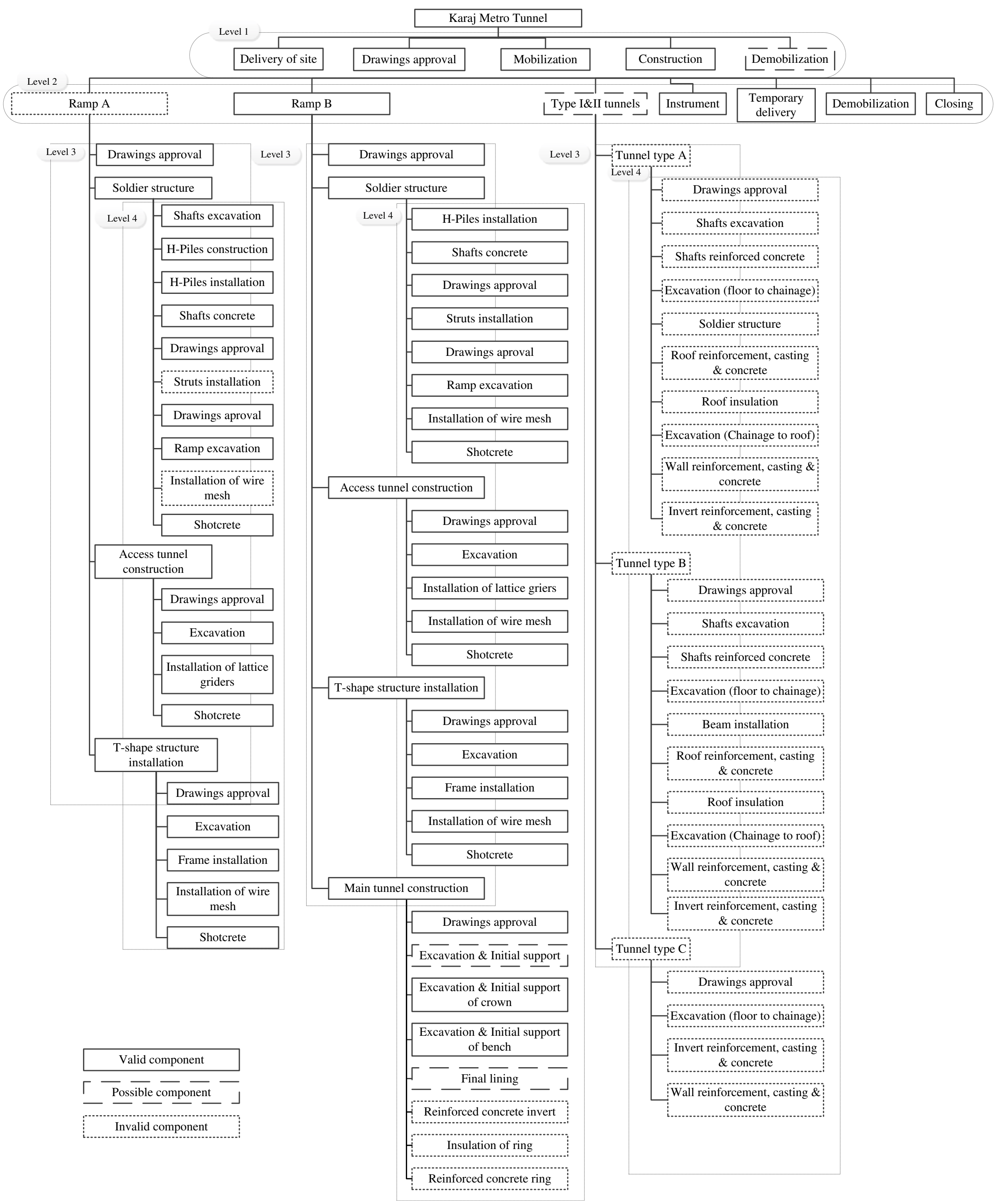

Fig. 5. Developed WBS for project 2 — Levels 1 to 4.

Accordingly, the data from 17 projects (i.e., 18-1) were used to train a model to establish the model parameters, while the hold-out example was used to test the generalization capability of the model. This process was repeated 18 times, with a different example being left out for verification during each run. The squared errors were then averaged over the 18 rounds of training.

BPN training requires the selection of proper values for network parameters. In this study, the optimal values of the network parameters were determined through three stages. In the first stage of simulation, 16 different combinations of learning rate (η) and momentum (μ) within [0, 1] are investigated. Each combination is trained with the same set of initial weights. At the end of stage 1, the model with the

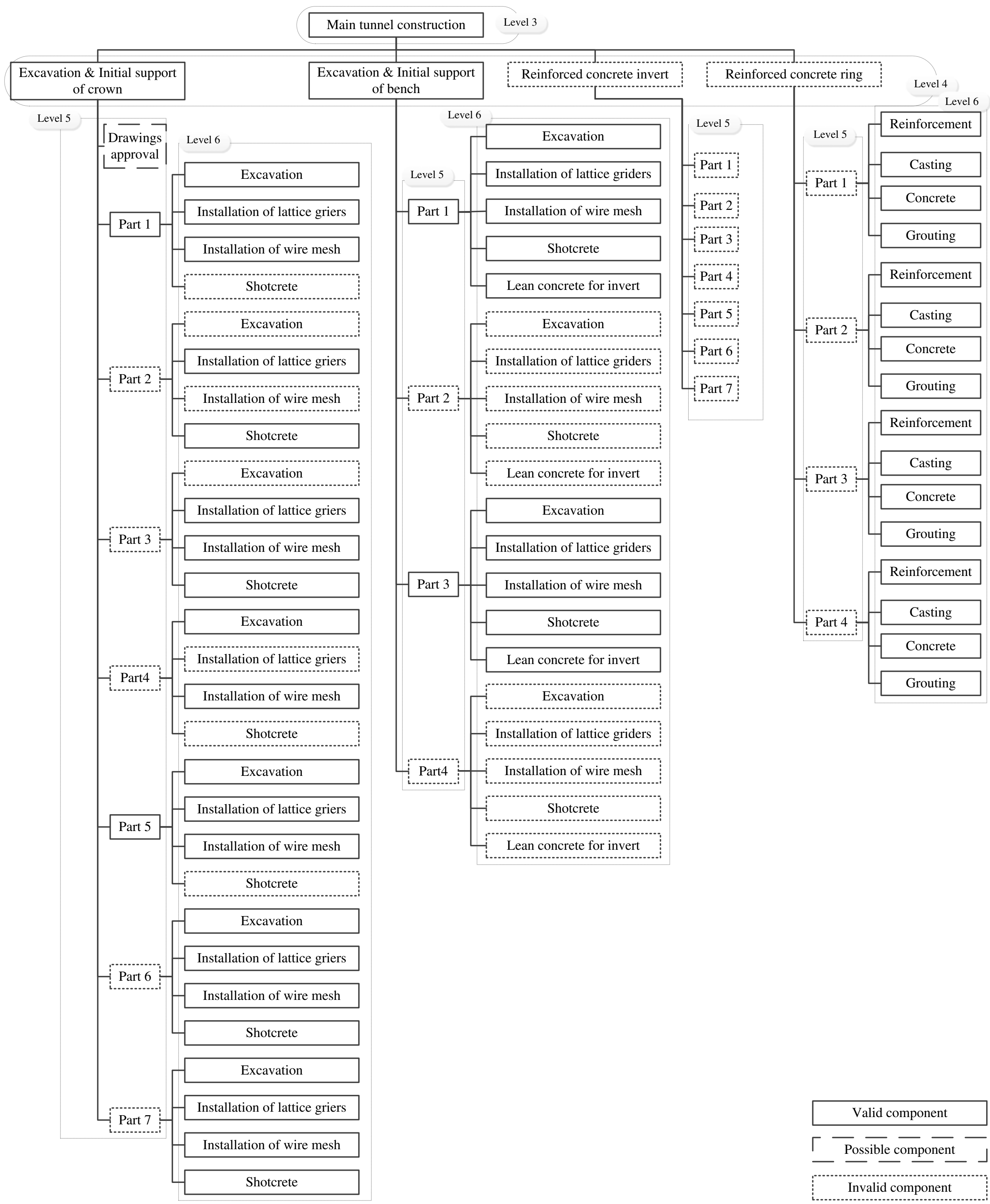

Fig. 6. Developed WBS for project 2 — Levels 5 to 6.

minimum error is selected for use in the following stages. In the second stage of simulation, 10 independent models with different initial random weights are trained with the optimal learning parameters found in the previous stage. Finally, the optimal size of the hidden layer is determined by a search of the possible structures. This search begins with a certain number of nodes, which are the minimum value of a calculated hidden node number based on several rules of thumb that are available in the literature [22–24]; in this manner, the model is trained and analyzed. Each time, the number of hidden nodes is increased by one. Again, cross-validation was used to determine the proper size of the hidden layers. Table 2 illustrates the structure of the proposed neural model with the optimum network parameter values.

5. Validation and results

In verification, the proposed model was tested against the test data during the training process. Furthermore, for the purpose of enhanced rationale, the proposed model was validated for its generalization capability. In this phase, the capability of the proposed model to respond accurately to projects that have not been used in network development is confirmed. Two tunnel projects were considered in the validation subset. Their attributes and WBSs demonstrated that both projects were substantially different from those used in the training and testing subsets.

Fig. 4 shows the calculated WBS for project 1 (Golabar diversion tunnel, with attributes per Table 3). The attributes of project 1 were entered into the model. The ***L1*** vector from WBSL1 was calculated with respect to the project attributes. First level of the WBS in Fig. 4 represents the ***L1*** vector. The attributes of the project and the ***L1*** vector were then entered to the WBSL2, and the L2 vector was calculated. Second level of the WBS in Fig. 4 represents the L2 vector. Subsequently, the outputs of WBSL3, the L3 vector, were calculated, and a similar process was conducted for L4, L5 and L6. In this case, the outputs for L3 to L6 vectors were zero. Thus, the calculated WBS has only two levels.

The same procedure was used to calculate the WBS of the project 2 (Karaj Metro Tunnel). The attributes of the project (Table 3) were entered into the model. The ***L1*** vector from WBSL1 was calculated with respect to the project attributes. The attributes of the project and the ***L1*** vector were then entered to the WBSL2, and the L2 vector was calculated. Subsequently, the outputs of WBSL3, the L3 vector, were calculated, and a similar process was conducted for L4, L5 and L6. Figs. 5 and 6 show the calculated WBS for project 2. Developed WBS is illustrated in two individual Figures (Figs. 5 and 6) due to the large number of the WBS elements. Fig. 5 depicts levels 1 to 4 of the WBS, and levels 5 to 6 are presented in Fig. 6. Furthermore, in order to make a better representation of the whole WBS, several elements of the level 3 and 4 also are illustrated in Fig. 6.

Three types of element outlines can be recognized in Figs. 4 to 6. Each line dash type represents the validity of WBS element which will be discussed further in the following.

The outputs were validated by comparing the calculated vectors and equivalent level vectors of the actual WBS of the project. The vectors of the WBSs were compared by the values of their elements. For this purpose, three validity indices were defined. Each element of the calculated vectors (w_i) was assigned to one of the following validity indices:

(1) Valid: the related component is a part of the actual WBS of the project.
(2) Possible: the related component is not a part of the actual WBS of the project (or the component that should be a part of the project WBS, while it is not been produced by the model), but it could be valid with respect to the judgment of experts.
(3) Invalid: the related component cannot be a part of the actual WBS of the project (or the component that should be a part of the project WBS, while it is not been produced by the model).

The second level of the calculated WBS and actual WBS of project 2 are illustrated in Fig. 7. "Ramp B" in Fig. 7.b. is a valid component, because it is a part of the real WBS of the project. "Ramp A" takes a value of 0 in ***L2*** vector (Fig. 7. b); hence, it is not a component of the calculated WBS. However, the real WBS includes the "Ramp A" component in the second level. "Ramp A" is therefore an invalid component.

"Possible" index were assigned to the project's WBS elements according to the tunneling project management experts. "Type I&II tunnels" component in Fig. 7a, for example, was not calculated by the model. However, this project specific component can be excluded from a tunnel project WBS according to the project manager's decision. "Valid", "Possible", and "Invalid" components of the calculated WBS of projects 1 and 2 are presented in Figs. 4 to 6. In Figs. 4 to 6, rectangular shapes with solid line represent the "Valid" elements, with dashed line "Possible" elements, and with dot line the "Invalid" elements.

The entire model and its networks were validated by calculating the statistics of the validity indices that were assigned to the validation process outputs. The outputs of the networks were validated by dividing the total number of calculated vector elements (wi) that were validated

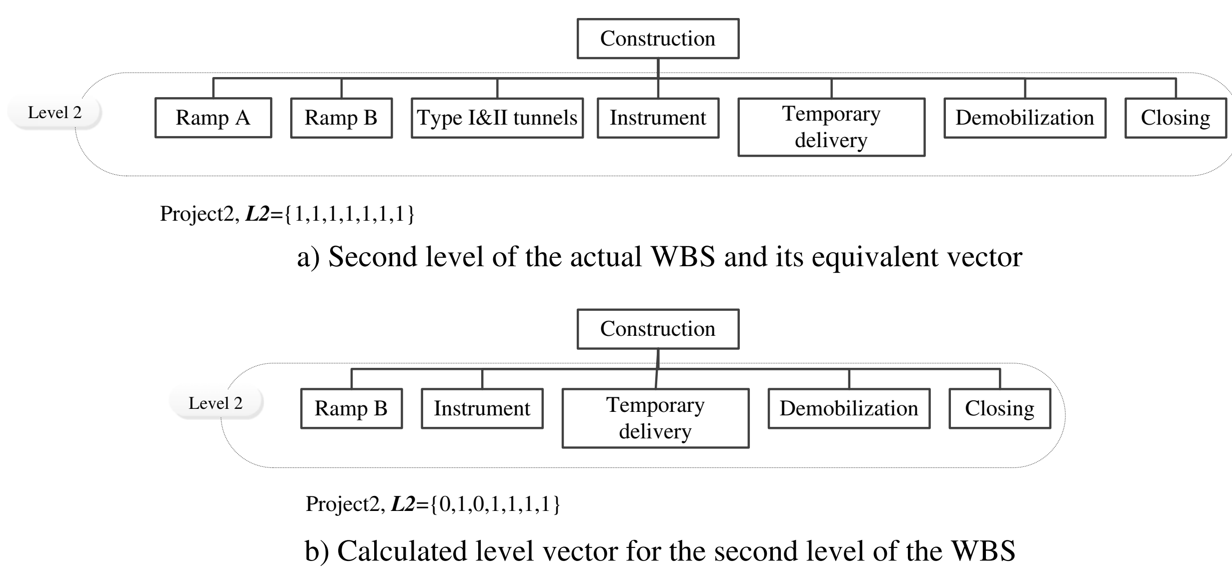

Fig. 7. Second level of the calculated WBS and actual WBS of project 2.

Table 4
Validity of proposed model and its networks.

Network ID	Validation projects	Total number of elements	Number of elements in validity index:			Percentage of elements in validity index:		
			Valid	Possible	Invalid	Valid	Possible	Invalid
WBSL1	Project 1	8	6	1	1	75	12.5	12.5
	Project 2	5	4	1	–	80	20	–
WBSL2	Project 1	10	8	–	2	80	–	20
	Project 2	7	5	–	2	71.43	–	28.57
WBSL3	Project 1	0	–	–	–	–	–	–
	Project 2	12	9	–	3	75	–	25
WBSL4	Project 1	0	–	–	–	–	–	–
	Project 2	71	40	3	28	56.33	4.22	39.44
WBSL5	Project 1	0	–	–	–	–	–	–
	Project 2	28	4	17	7	14.29	60.71	25
WBSL6	Project 1	0	–	–	–	–	–	–
	Project 2	64	47	11	6	73.43	17.19	9.38
Overall model		205	123	33	49	60	16.1	23.9

by a particular index to the total number of elements of the calculated vector (n_l) for each project. Then, the average of the three validity percentages within all projects was calculated to obtain the overall validity of each network. Table 4 shows the results of the average validity percentages of the model and its networks.

The validity of the model was estimated with respect to the quantities in Table 4. The valid and possible components of the calculated WBS percentages were found to be 60% and 16.1%, respectively. Therefore, after entering the attributes of a tunneling project, it is expected that 76.1% of the WBS and resultant activities are certainly or possibly valid.

In addition to the relatively accurate recognition of the project WBS elements, several important characteristics of the project WBS were determined by the model. The correct number of WBS levels was identified (for example, two for project 1, and six for project 2). A combination of process-oriented and deliverable-oriented structure was produced for both projects by the model. Project 1, for instance, was decomposed to the processes in levele1, while the second level was a deliverable-oriented decomposition. The level of details for project 1 was two, and levels were decomposed to 8–10 elements. Moreover, the model produced 6 levels for project 2, and several levels were composed of more than 60 elements. Furthermore, in the proposed methodology, different management approaches can be employed to develop the WBS of the project. For instance, the developed WBS by the model for project 2 subdivides the tunnel bench and crown to several parts in level 6, then decomposes the parts into the processes in level 6 such as “Excavation” and “Shotcrete”. Alternatively, another management approach might subdivide the processes to parts in level 6. Therefore, the proposed model was able to recognize the structure of the projects WBSs.

6. Conclusions

A new methodology was proposed to plan the WBS of complex underground projects, which assists a planer to make a more informed choice of WBS components and structure regarding project attributes. A hierarchical neural model with 6 BPN networks was developed; each with a different configuration. The outputs of first 5 networks were connected to the inputs of the others, to enable the inference of project structure with respect to the hierarchical structure of the WBS. The proposed methodology focused on two important requirements of generating the WBS of a complex underground project: First, modeling the relationship between the attributes of a project and WBS; and second, to minimize the complexity of the model. This was due to the large number of components of WBS in complex underground projects and various possible structures.

Validation of the results revealed that the proposed neural network model presents a powerful tool for modeling the complex relationship between the attributes of complex underground projects and their work breakdown structures. The approach was demonstrated to be capable of recognizing the components and structure of the WBS with a sufficient degree of validity that are comparable to those generated by a project planner. Neural networks learn from examples; thus, the performance of the proposed neural model strongly depends on the size and quality of the training data. Due the vast amount of knowledge required for WBS planning in a complex underground project, the proposed model can foster effectiveness in WBS development. In other words, the greater the number of different underground projects that are used to train the networks, the more extensive the data, and the higher the quality of the data used to train the networks, the higher the quality of the resultant overall WBS will be.

Although the neural models herein were developed for the purpose of planning the WBS of a complex underground project during the construction stage, the neural model concept can be extended, particularly to preconstruction stages. The proposed methods for representing the values of project attributes and the WBS can also be modified. Examination of different neural networks structures, other than BPNs, is also a potential topic of future research.

References

[1] E.S. Norman, S.H.A. Bortherton, R.T. Fried, Work Breakdown Structures: The Foundation for Project Management Excellence, 1st ed. Jhon Wiley & Sons, Canada, 2008 1–25.
[2] A.M. Wood, Tunnelling: Management by Design, 1st ed. Taylor & Francis, USA, 2000.
[3] K.J. Lee, H.W. Kim, J.K. Lee, T.H. Kim, Case- and constraint-based project planning for apartment construction, AI Mag. 19 (1) (1998) 13–24.
[4] R.J. Dzeng, I.D. Tommelein, Product modeling to support case-based construction planning and scheduling, Autom. Constr. 13 (3) (2004) 341–360.
[5] H.G. Ryu, H.S. Lee, M. Park, Construction planning method using case-based reasoning (CONPLA-CBR), J. Comput. Civ. Eng. 21 (6) (2007) 410–422.
[6] M. Chambers, C.A. Mount-Campbell, Process optimization via neural network meta-modeling, Int. J. Prod. Econ. 79 (2) (2002) 93–100.
[7] Hsu-Pin (Ben) Wang, Richard A. Wysk, Intelligent reasoning for process planning, Comput. Ind. 8 (4) (1987) 293–309.
[8] S.A. Hashemi, B. Emamaizadeh, Designing work breakdown structures using modular neural network, Decis. Support. Syst. 44 (1) (2007) 202–222.
[9] M. Sharifzadeh, M. Ataeepour, E. Siami, Designing work breakdown structure (WBS) in tunneling projects using neural networks, Proc., 45th US. Symp. on rock mechanics/Geomechanic, ARMA, San Francisco, CA, 2011.
[10] J.J. Reilly, The management process for complex underground and tunnelling projects, Tunn. Undergr. Space Technol. 15 (1) (2000) 31–44.
[11] S.R. Dindarloo, E. Siami-Irdemoosa, Maximum surface settlement based classification of shallow tunnels in soft ground, Tunn. Undergr. Space Technol. 45 (2015) 320–327, http://dx.doi.org/10.1016/j.tust.2015.04.021.
[12] Project management institute, A Guide to Project Management Body of Knowledge, 4th ed. PMI Standards Committee, USA, 2008.
[13] Project management institute, Practice Standard for Work Breakdown Structures, 2nd ed. PMI Standards Committee, USA, 2006.
[14] S. Haykin, Neural Networks: A Comprehensive Foundation, Macmillan, New York, 1994.
[15] R.J. Schalkoff, Artificial Neural Networks, McGraw-Hill, New York, 1997.
[16] S. Samarasinghe, Neural network for applied sciences and engineering: From fundamentals to complex pattern recognition, *Auerbach publications*, New York, Taylor and Francis group, 2006.
[17] B.K. Bose, Expert system, Fuzzy logic and Neural networks in Power Electronics and Drives, Proc. Power Electronics and Variable Frequency Drives: Technology and

Applications. IEEE Press, Standard Publishers Distributors, New Delhi, India, 2000 602–605.
[18] D.E. Rumelhart, J.L. McClelland, Parallel Distributed Processing, Vol. 1: Foundations, MIT Press, Cambridge, MA, 1986.
[19] E. Turban, J.E. Aronson, Decision Support Systems and Intelligent Systems, 6th ed. Prentice International Hall, Hong Kong, 2001.
[20] D.E. Rumelhart, G.E. Hinton, R.J. Williams, Learning internal representation by error propagation, in: D.E. Rumelhart, J.L. McClleland (Eds.), Proc. Parallel Distributed Processing: Exploration in the Microstructure of Cognition, vol. 1, MIT Press, Cambridge, MA, 1986 (Chapter 8).
[21] S. Haykin, Neural Networks: A Comprehensive Foundation, 2nd ed. Prentice Hall, N.J. London, Upper Saddle River, 1999.
[22] G. Lachtermacher, J.D. Fuller, Backpropagation in time series forecasting, J. Forecast. 14 (4) (1995) 381–393.
[23] T. Masters, Practical Neural Network Recipes in C11, Academic Press, MA. Boston, 1994.
[24] B. Upadhaya, E. Eryureka, Application of neural network for sensory validation and plant monitoring, Neural Technol. 97 (1992) 170–176.