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# Evaluation of Concrete Plants Readiness to Produce High Quality Concrete for Municipal Constructions Using Past Information

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**ABSTRACT:** The only way to test the ability of concrete plants to produce high quality concrete is to test their final products. Also, the process of testing and controlling concrete quality is time consuming and expensive. In this regard, having a quick, cheap and efficient way to predict the readiness of concrete plants to produce high quality concrete is very valuable. In this paper, a probabilistic multi-attribute algorithm has been developed to address this problem. In this algorithm, the goal is to evaluate readiness of concrete plants to produce high quality concrete based on the error rate of concrete compressive strength. Using past information and data mining techniques, this algorithm predicts the readiness level of concrete plants by similarity of their production factors to past information. Readiness alternatives for plants are ranked using data mining techniques for order preference based on their production factors (PF) and by evaluating the similarity/difference of each PF to past information. A case study of 20 concrete plants is used to illustrate the capability of the new algorithm; with results showing that the algorithm generated nondominated solutions can assist plant managers to set efficient production plan, a task both difficult, cost and time-consuming using current methods. In the case study, lab test totally confirm the algorithm outcomes thus it has been successfully verified.

**Keywords**: Algorithm, Concrete Plant, Data Mining, Error Rate of Concrete Compressive Strength.

## INTRODUCTION

Concrete is one of the most popular building materials owing to its ability to customize its properties for different applications (Anderson, et al., 2003). As important structural constituent in civic construction, concrete finds wide use nowadays (Yu, et al., 2014). The development of the construction industry has greatly influenced the concrete industry in some developing countries, especially in Iran, where the demand for concrete has grown at an increasing rate in recent years (Shekarchizadeh et al., 2014). Although quality has had an important role to play in improving the industry in developed countries, producing high quality concrete for municipal usage is becoming a challenge to the producer in developing countries (Sarkar et al., 2010), concrete is a product which also

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should satisfy the requirements of the customer or consumer (Sarkar et al., 2017). There are several factors for this including incomplete infrastructure, defective equipment, low quality material, and lack of skilled workers (Defeo et al., 2010; Kazaz et al., 2004). These factors can be categorized into two groups of structured and unstructured factors. The structured factors (such as the quality and consumption of raw materials, mix design of concrete) have been well studied (e.g. Lee et al., 2009) and the relationship between the influencing factors and the analysis indicators has been described by fixed rules. Many errors can occur throughout the production of concrete and aggregate during material ordering, shipping, receiving, stockpiling, storage, handling, batching, and concrete delivery that can lower strength (Richardson et al., 2014). For the unstructured factors (like the stuff skill, control precision and production condition), there is no clear relationship between the influencing factors and the analysis indicators. However, the unstructured factors could also lead to quality fluctuation.

In this paper, in order to compensate the drawbacks of traditional models, a probabilistic multi-attribute algorithm has been developed. In this algorithm, the goal is to evaluate the readiness of concrete plants to produce high quality concrete based on the error rate of concrete compressive strength. Using past information and data mining techniques, this algorithm predicts the readiness level of concrete plants by similarity of their production factors to past information.

## METHODOLOGY

Because of the fact that there are considerable large sets of data about concrete plants available from past research and surveys, using past experiences as a base to predict the quality of future products is a very effective and efficient way. This paper uses data mining techniques to explore collected data.

Data mining is the process of discovering actionable information from large sets of data (Rajagopalan et al., 2002). Data mining uses mathematical analysis to derive patterns and trends that exist in data. Typically, these patterns cannot be discovered by traditional data exploration because the relationships are too complex or because there is too much data. These patterns and trends can be collected and defined as a data mining model (Fayyad et al., 1996). The objective of data mining is to identify valid novel, potentially useful, and understandable correlations and patterns in existing data (Chung et al., 1999). Mining models can be applied to specific scenarios such as: forecasting, risk and probability, recommendations and finding sequences. Building a mining model is part of a larger process that includes everything from asking questions about the data and creating a model to answer those questions and to deploying the model into a working environment (Han et al., 2011).

The first step in the data mining process is to clearly define the problem and consider ways that data can be utilized to provide an answer to the problem. This step includes analyzing requirements, defining the scope of the problem, defining the metrics by which the model will be evaluated and defining specific objectives for the data mining project. The next step is to unite the data that was identified in the defining the problem step. The third step in the data mining process is to explore the prepared data. By exploring the data in light of your own understanding of the problem, it can be decided whether the dataset contains flawed data or not, and then a strategy for fixing the problems can be devised. The fourth step is to build the mining model or models. The knowledge that is gained in the exploring data step will be used to help define and create the models. Test of the model performance should be performed before deploying the model into a production environment. Thus, the last step in the data mining process is to explore the mining models that have been built and validat the model. If the model fails, the process might have been returned to a previous step and redefine the problem or reinvestigate the data in the original dataset (Jackson, 2002).

In this study, an algorithm has been developed in order to: first, build usable database from past information of concrete plants and the final product; and second, evaluating and predicting the readiness level of concrete plants based on similarity of their production factors to the data base. The step-by-step description about the preparation of the usable data matrix and development of the algorithm is explained in the following section of the paper.

## ALGORITHM STEPS

Probabilistic multi-attribute algorithm for predicting the readiness of concrete plants to produce high quality concrete consists of following Parts.

### Step 1: Determining the Readiness Alternatives (Level) of Concrete Plants (RL)

Compressive strength has been generally considered to be one of the most essential qualities of concrete (Yuan et al., 2014). Therefore, there are many studies devoted to develop models to predict and evaluate concrete compressive strength (e.g. Chen et al., 2010; Pham et al., 2015).

Study of Yeh (1998) aimed to demonstrate the possibilities of adapting artificial neural networks (ANN) to predict the compressive strength of high-performance concrete. This study led to the conclusion that a strength model based on ANN is more accurate than a model based on regression analysis (Yeh, 1998). Multi-layer feed-forward neural networks (MFNNs) was proposed to predict 28-day compressive strength of concrete based on the inadequacy of present methods dealing with multiple variable and nonlinear problems (Hong-Guang et al., 2000). Different forms of artificial neural networks have been developed and used to predict compressive strength of concrete in the past. Lee (2003) purposed an artificial neural networks (ANN) model that can learn cylinder test results as training patterns. The purpose of this model is to provide in-place strength information of the concrete to facilitate concrete form removal and scheduling for construction (Lee, 2003). Beside ANN models, fuzzy logic models have been used to predict compressive strength of concrete. In a study, fuzzy logic models for predicting the 7, 28 and 90 days' compressive strength of concretes containing high-lime and low-lime fly ashes have been developed. The data used in this models were arranged in a format of nine input parameters that cover the day, portland cement, water, sand, crushed stone I (4-8 mm), crushed stone II (8-16 mm), high range water reducing agent replacement ratio, fly ash replacement ratio and CaO, and an output parameter which was compressive strength of concrete (Topçu et al., 2008).

Although these models have many cost and time saving advantageous, but having a compressive strength prediction neither is a reliable measurement of concrete quality nor test the ability of concrete plants to produce high quality concrete. Therefore, the error rate of concrete compressive strength has been identified as the most important quality indicator in concrete industry (Yuan et al., 2014).

Based on the error rate of concrete compressive strength, readiness levels of concrete plants are divided into six groups (Table 1).

**Step 2: Determining Production Factors ($PF_i$)**

There are many factors which have an effect on concrete plants. Although, there is no scientific way to precisely determine all the effective factors in production of concrete, but literature has introduced some factor more effective than others (Yuan et al., 2014, Arıöz et al., 2007). Using past literatures in the field, 7 factors have been chosen as effective to the ability of concrete plants to increase the quality of their products. Table 2 shows production factors which have been used in the algorithm. The PFs chosen to be used in the algorithm have no correlation to each other so each factor is related to the readiness level of concrete plant disregard to other factors.

**Step 3: Determining the Quality Level of Production Factors ($LPF_i$)**

Each factor has a level of quality exclusively that has a direct effect on the readiness level of the concrete plant. To determine the readiness of the concrete plant all of the PFs should be rated. For this purpose, a linguistic scale has been defined and set as a reference (Table 3). According to this scale the factor with the highest level of quality is scored 9, while the factor with the lowest level of quality score is 1. Other factors in this extreme are scored subsequently from 1 to 9.

**Step 4: Collecting Past Information and Forming Database ($PI_j$)**

Information collection for data matrix is the next step. In this step a database is built based on information collected from past productions of concrete plants. For each $PI_j$ in the database, the readiness level of concrete plant and level of every factor should be collected.

Table 4 demonstrates a sample database for the algorithm. In such table the rows are past information of concrete plants ($PI_j$) and the columns demonstrate scores for each PF. The last column shows the readiness level of concrete plant, which were calculated based on testing the error rate of concrete compressive strength in a certified lab.

**Step 5: Determining the Weights of Production Factors ($WPF_i$)**

The importance of factors in evaluating the readiness level of concrete plants is not the same. The weights of production factors are the reflection their importance. These weights should be determined based on judgment of professionals in the field of concrete production. The scale for the weighting process is listed in Table 5.

**Table 1.** Readiness alternatives of concrete plants

| RL | Error Rate of Concrete Compressive Strength |
|---|---|
| A | Less than 10 percent |
| B | Between 20-10 percent |
| C | Between 30-20 percent |
| D | Between 40-30 percent |
| E | Between 50-40 percent |
| F | More than 50 percent |

**Table 2.** Concrete plant production factors

| Factor Number | Factor Statement |
|---|---|
| 1 | Raw materials |
| 2 | Mix-design process |
| 3 | QC and testing |
| 4 | Tools and equipment |
| 5 | Equipment calibration |
| 6 | Workmanship |
| 7 | Staff skills |

**Table 3.** Levels and scores of production factors

| Score | Quality Level |
|---|---|
| 1 | Poor |
| 2 | Very low |
| 3 | Low |
| 4 | Not Good |
| 5 | Median |
| 6 | Good |
| 7 | High |
| 8 | Very High |
| 9 | Perfect |

**Table 4.** Sample database for the algorithm

| Past Information | $PF_1$ | $PF_2$ | $PF_3$ | $PF_4$ | $PF_5$ | $PF_6$ | $PF_7$ | Readiness Level |
|---|---|---|---|---|---|---|---|---|
| 1 | 8 | 4 | 2 | 7 | 9 | 6 | 7 | A |
| 2 | 3 | 2 | 2 | 4 | 6 | 4 | 9 | B |
| 3 | 3 | 3 | 1 | 8 | 9 | 5 | 9 | B |
| 4 | 4 | 3 | 1 | 8 | 9 | 2 | 4 | E |
| 5 | 4 | 2 | 1 | 6 | 5 | 3 | 7 | D |
| 6 | 5 | 3 | 9 | 8 | 7 | 2 | 4 | C |
| 7 | 5 | 3 | 6 | 7 | 8 | 3 | 2 | F |
| 8 | 6 | 4 | 2 | 8 | 7 | 7 | 3 | C |

**Table 5.** Production factors weighs

| Weight | Description (Importance) |
|---|---|
| 1 | Very Low |
| 2 | Low |
| 3 | Moderate |
| 4 | High |
| 5 | Very High |

**Step 6: Determining the Effectiveness of Production Factors ($EPF_{i-j}$)**

Each Production factor in each concrete plant has its individual effect on the final readiness level of the plant. The difference in readiness levels of plants should be investigated in the quality level of their production factors. For instance, if two plants reach different readiness levels and have only two PFs with different quality levels, it is logical to assume that those factors are effective in differentiation of readiness levels of the plants.

In order to determine the effectiveness of each PF in each $PI_j$ in database, the quality level of that factor should be compared to the quality level of the same factor in another plant with different readiness level.

The difference between quality levels of the production factors means that they can be effective on difference of the readiness levels of the concrete plants (Eq. (1)). Table 6 depicts how effective the factors of past information in the sample database are.

$$\text{For } \forall j, k \quad \text{if } \; RL_j \neq RL_k \rightarrow \begin{cases} LPF_{i-j} \neq LPF_{i-k} \Rightarrow EPF_{i-jk} = EPF_{i-kj} = \text{Effective} \\ LPF_{i-j} = LPF_{i-k} \Rightarrow EPF_{i-jk} = EPF_{i-kj} = \text{None Effective} \end{cases}$$

$$RL_j \text{ means} \rightarrow RL \text{ of } PI_j \qquad (1)$$

$$LPF_{i-j} \text{ means} \rightarrow LPF_i \text{ of } PI_j$$

$$EPF_{i-jk} \text{ means} \rightarrow \text{Effectiveness of } PF_{i-j} \text{ compering to } PF_{i-k}$$

**Table 6.** Qualitative effectiveness evaluation of the sample data matrix

| | | $PI_k$ | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **$PI_j$** | **$PF_i$** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** |
| | 1 | - | E | E | E | E | E | E | E |
| | 2 | - | E | E | E | E | E | E | NE |
| | 3 | - | NE | E | E | E | E | E | NE |
| 1 | 4 | - | E | E | E | E | E | NE | E |
| | 5 | - | E | NE | NE | E | E | E | E |
| | 6 | - | E | E | E | E | E | E | E |
| | 7 | - | E | E | E | NE | E | E | E |
| | 1 | E | - | - | E | E | E | E | E |
| | 2 | E | - | - | E | NE | E | E | E |
| | 3 | NE | - | - | E | E | E | E | NE |
| 2 | 4 | E | - | - | E | E | E | E | E |
| | 5 | E | - | - | E | E | E | E | E |
| | 6 | E | - | - | E | E | E | E | E |
| | 7 | E | - | - | E | E | E | E | E |
| | 1 | E | - | - | E | E | E | E | E |
| | 2 | E | - | - | NE | E | NE | NE | E |
| | 3 | E | - | - | NE | NE | E | E | E |
| 3 | 4 | E | - | - | NE | E | NE | E | NE |
| | 5 | NE | - | - | NE | E | E | E | E |
| | 6 | E | - | - | E | E | E | E | E |
| | 7 | E | - | - | E | E | E | E | E |
| | 1 | E | E | E | - | NE | E | E | E |
| | 2 | E | E | NE | - | E | NE | NE | E |
| | 3 | E | E | NE | - | NE | E | E | E |
| 4 | 4 | E | E | NE | - | E | NE | E | NE |
| | 5 | NE | E | NE | - | E | E | E | E |
| | 6 | E | E | E | - | E | NE | E | E |
| | 7 | E | E | E | - | E | NE | E | E |
| | 1 | E | E | E | NE | - | E | E | E |
| | 2 | E | NE | E | E | - | E | E | E |
| | 3 | E | E | NE | NE | - | E | E | E |
| 5 | 4 | E | E | E | E | - | E | E | E |
| | 5 | E | E | E | E | - | E | E | E |
| | 6 | E | E | E | E | - | E | NE | E |
| | 7 | NE | E | E | E | - | E | E | E |
| | 1 | E | E | E | E | E | - | NE | - |
| | 2 | E | E | NE | NE | E | - | NE | - |
| | 3 | E | E | E | E | E | - | E | - |
| 6 | 4 | E | E | NE | NE | E | - | E | - |
| | 5 | E | E | E | E | E | - | E | - |
| | 6 | E | E | E | NE | E | - | E | - |
| | 7 | E | E | E | NE | E | - | E | - |
| | 1 | E | E | E | E | E | NE | - | E |
| | 2 | E | E | NE | NE | E | NE | - | E |
| | 3 | E | E | E | E | E | E | - | E |
| 7 | 4 | NE | E | E | E | E | E | - | E |
| | 5 | E | E | E | E | E | E | - | E |
| | 6 | E | E | E | E | NE | E | - | E |
| | 7 | E | E | E | E | E | E | - | E |
| | 1 | E | E | E | E | E | - | E | - |
| | 2 | NE | E | E | E | E | - | E | - |
| | 3 | NE | NE | E | E | E | - | E | - |
| 8 | 4 | E | E | NE | NE | E | - | E | - |
| | 5 | E | E | E | E | E | - | E | - |
| | 6 | E | E | E | E | E | - | E | - |
| | 7 | E | E | E | E | E | - | E | - |

**Step 7: Determining the Effectiveness Probability of the Production Factors ($EPPF_{i-j}$)**

A qualitative evaluation between factors of each two plants in the sample database was calculated in step 5. To develop a fully useful table of past information, a quantitative measure of the effectiveness of production factors for each $PI_j$ is needed. To achieve such purpose the effectiveness probability of production factors should be calculate based on qualitative measurements of Step 6.

To clarify Eq. (2), the following lines describe the calculation of effectiveness probability of the production factors of the past experience 1 ($EPPF_{i-1}$) in the sample data matrix. As it is depicted in Table 6, $PI_1$ has different readiness level as other plants in the sample database. Thus, production factors of this plant should be compared to PFs of all the other plants in the sample database (Eq. (1)). As the result, first PF of the first plant is introduced as Effective in all of these compressions meaning that $PF_{1-1}$ has 100% probability of being effective in determining the readiness level of the first plant in the sample database. Furthermore, $PF_{2-1}$ is introduced as Effective in 6 of the compressions made, as the result, the effectiveness probability of the second production factor of $PI_1$ is 86% (6 : 7 = 0.86). Table 7 shows the final database with the effectiveness probability of all factors of all the sample data plants been calculated.

**Step 8: Introducing an Unrated Concrete Plant into the Algorithm**

The purpose of this algorithm is to calculate readiness level of a concrete plant to produce high quality concrete based on past information. After generating a complete database, in this step an unrated concrete plant is introduced to the algorithm in order to calculate its readiness level (e.g. Table 8). The only preparation needed by the algorithm in order to calculate the RL of the unrated plant is determining the quality level of its production factors.

$$\begin{aligned}&\text{Total number of compresions made for } PF_{i-k}\\&\quad = \text{Total number of cases in the data matrix}\\&\qquad - \text{number of cases with same RL as } PI_k\end{aligned}$$

$$EPPF_{i-k} = \frac{\text{Number of compresions in which; } EPF_{i\text{-}k} = \text{"Effective"}}{\text{Total number of compresions made for } PF_{i\text{-}k}} \tag{2}$$

**Table 7.** Effectiveness probability of factors

| PI | $EPPF_{1-j}$ | $EPPF_{2-j}$ | $EPPF_{3-j}$ | $EPPF_{4-j}$ | $EPPF_{5-j}$ | $EPPF_{6-j}$ | $EPPF_{7-j}$ | RL |
|---|---|---|---|---|---|---|---|---|
| 1 | 100% | 86% | 71% | 86% | 71% | 100% | 86% | A |
| 2 | 100% | 83% | 67% | 100% | 100% | 100% | 100% | B |
| 3 | 100% | 50% | 67% | 50% | 67% | 100% | 100% | B |
| 4 | 86% | 57% | 71% | 57% | 71% | 86% | 86% | E |
| 5 | 86% | 86% | 71% | 100% | 100% | 86% | 86% | D |
| 6 | 83% | 50% | 100% | 67% | 100% | 83% | 83% | C |
| 7 | 86% | 57% | 100% | 86% | 100% | 86% | 100% | F |
| 8 | 100% | 83% | 67% | 67% | 100% | 100% | 100% | C |

**Table 8.** Information of a sample unrated plant

| | $PF_1$ | $PF_2$ | $PF_3$ | $PF_4$ | $PF_5$ | $PF_6$ | $PF_7$ |
|---|---|---|---|---|---|---|---|
| Unrated Concrete Plant | 4 | 5 | 2 | 9 | 8 | 7 | 4 |

**Step 9: Evaluating Similarity between the Unrated Plant and Past Information**

Researchers have shown that past information really does help when complex decisions based on uncertain or confusing information have to be made (Mostafavi et al., 2010). Based on this concept, it can be interpreted that the readiness level of an unrated concrete plant is the same as the most similar past information.

In order to evaluate similarity between the unrated concrete plant and a concrete plant from past information, the quality levels of their production factors should be compared. If a PF quality level in the unrated concrete plant is similar or higher than the same PF quality level of a plant from database, the influence of that PF in the readiness level of the both plants is assumed to be the same. In other hand, if a PF quality level in the unrated concrete plant is lower than the same PF quality level in a plant from database, that PF can have a negative effect on similarity of readiness level of the unrated plant and the plant from database. This evaluation should be done for every production factor in each concrete plant in the sample database.

**Step 10: Calculating Score of Similarity, Score of Difference, and Total Score for Past Information**

Based on the evaluation of similarity between the production factors of the unrated plant and past information, for every production factor in each plant in the sample database, scores of similarity, difference, and total score should be calculated (Eq. (3)). Score of similarity indicate the similarity between the quality level of PFs of the unrated plant and the past information. In other hand, score of difference indicate the difference between the quality level of PFs of the unrated plant and the past information.

These scores provide quantitative measurements of similarity between the unrated plant and the plants in the sample database. Table 9 shows scores which have been calculated based on similarity of the sample unrated plant and each plant in the sample database.

**Step 11: Calculating Overall Scores for Readiness Levels**

Scores of similarity, difference and total has been calculated for each plant in the sample database.

$$
\begin{aligned}
&\forall\, PI_j \in Data\ matrix\\
&\text{If } LPF_{i-\text{Unrated Plant}} \geq LPF_{i-j} \rightarrow\\
&\qquad\begin{cases}\text{Score of Similarity for } PF_{i-j} \rightarrow SPF_{i-j} = LPF_{i-j} \times EPPF_{i-j} \times WPF_i\\ \text{Score of Difference for } PF_{i-j} \rightarrow DPF_{i-j} = 0\end{cases}\\
&\text{If } LPF_{i-\text{Unrated Plant}} < LPF_{i-j} \rightarrow\\
&\qquad\begin{cases}\text{Score of Similarity for } PF_{i-j} \rightarrow SPF_{i-j} = 0\\ \text{Score of Difference for } PF_{i-j} \rightarrow DPF_{i-j} = \left(LPF_{i-\text{Unrated Plant}} - LPF_{i-j}\right) \times EPPF_{i-j} \times WPF_i\end{cases}\\
&\text{Score of Similarity for } PI_j \rightarrow SPI_j = \sum_{i=1}^{7} SPF_{i-j}\\
&\text{Score of Difference for } PI_j \rightarrow DPI_j = \sum_{i=1}^{7} DPF_{i-j}\\
&\text{Total Score for } PI_j = SPI_j + DPI_j
\end{aligned}
\tag{3}
$$

The next step is calculating these scores for each alternative which are introduced in step 1. Overall scores for alternatives are calculated using the scores which were calculated for each plant in the sample database. The overall scores are the average of scores for plants with the same readiness level. As Table 10 shows, higher score for an alternative means that the unrated plant has the most similarity to the other plants with the readiness level. Thus, it can be expected that the unrated plant will have the same readiness level of producing high quality concrete.

**Step 12: Accounting for Users' Attitude**

Users of this algorithm may choose between three kinds of attitudes toward the final result. This enhance productivity of the algorithm process by considering the alternatives' ranking sensitivity to each user attitude and helps users place high degree of confidence on the outcomes of the algorithm.

1- Choosing based on similarity: In this case the user only considers similarity between unrated plant and past information.

2- Choosing based on difference: In this case the user only considers difference between unrated plant and past information.

3- Choosing based on total score: In this case the user uses a combination of scores of similarity and difference.

**Step 13: Selecting the Readiness Level of the Unrated Plant**

In this step of the algorithm, the scores are ranked based on the user's attitude and the alternative with the highest score is selected as the readiness level for the unrated plant. Steps 12–13 can be performed for different attitude scenarios by the user.

## VERIFICATION OF THE ALGORITHM (CASE STUDY)

In order to verify the algorithm, it has been applied to a research about the quality of ready-mixed concrete plants in Isfahan province located in the middle part of Iran. This study was part of a national project conducted by Building and Housing Research Center. The aim of this study was to evaluate the current condition of ready-mixed concrete plants in the country and define best ways to improve the quality of concrete production in Iran. The field work of this project started from June 2013.

**Table 9.** Calculated scores for each plant in the sample database based on their similarity to the unrated plant

| PI | Scores | | | RL |
|---|---|---|---|---|
| | Similarity | Difference | Total | |
| 1 | 60.00 | -24.71 | 35.29 | A |
| 2 | 80.67 | -10.00 | 70.67 | B |
| 3 | 52.00 | -13.33 | 38.67 | B |
| 4 | 50.14 | -14.29 | 35.86 | E |
| 5 | 76.00 | -5.14 | 70.86 | D |
| 6 | 70.33 | -24.33 | 46.00 | C |
| 7 | 79.14 | -15.43 | 63.71 | F |
| 8 | 102.33 | -8.00 | 94.33 | C |

**Table 10.** Overall scores for the readiness level of the unrated plant

| RL | Overall Scores | | |
|---|---|---|---|
| | Similarity | Difference | Total |
| A | 60.00 | -24.71 | 35.29 |
| B | 66.33 | -11.67 | 54.67 |
| C | 86.33 | -16.17 | 70.17 |
| D | 76.00 | -5.14 | 70.86 |
| E | 50.14 | -14.29 | 35.86 |
| F | 79.14 | -15.43 | 63.71 |

Five major cities and more than 100 concrete plants were planned to take part in this project. The project started from the city of Isfahan, one of the cities with the most production of concrete in Iran, and more than 20 concrete plants were thoroughly examined in the first step in this city. Near to 150 factors which a concrete plant should consider to produce high quality concrete has been collected. These factors identified using national and international standards and codes about the maintenance of raw materials used in concrete, concrete mixture procedures, necessary tests before, during and after production of concrete, and other factors introduced in literature. Based on the collected factors, 18 sets of checklists were provided to gather information about the plants readiness to produce high quality concrete. The level of each PF has been calculated based on professionals' lingual views. Also, the final product of each concrete plant has been tested in a verified lab and using the concept of the error rate of concrete compressive strength, readiness level of the plants has been calculated. The readiness levels of the evaluated plants and quality levels of their PFs are tabulated in Table 11.

A survey among the professionals in the field of concrete technology was conducted by the authors in order to define the weights of production factors. Based on this survey, equipment calibration was considered to have very high importance. The reason was that using out-of-calibration equipment- such as: batching system and truck mixer- highly, more often affect the quality of the concrete in Iran and considered one of the major problems in the way of producing high quality concrete in the country. The following factors are considered to be highly important: “raw materials”, mix-design” and “workmanship”. On account of the fact that these factors are the main part of producing concrete, they are considered to be highly important. Other factors are considered to have moderate importance. Moreover, the user attitude in this case study has been set to “choosing based on total score”.

**Table 11.** Information of the case study project

| Plant | $PF_1$ | $PF_2$ | $PF_3$ | $PF_4$ | $PF_5$ | $PF_6$ | $PF_7$ | RL |
|---|---|---|---|---|---|---|---|---|
| 1 | 8 | 4 | 2 | 7 | 9 | 6 | 7 | A |
| 2 | 4 | 2 | 3 | 5 | 4 | 4 | 4 | D |
| 3 | 2 | 4 | 3 | 6 | 5 | 3 | 4 | E |
| 4 | 3 | 6 | 6 | 4 | 6 | 4 | 9 | B |
| 5 | 3 | 4 | 2 | 7 | 6 | 2 | 4 | E |
| 6 | 3 | 3 | 1 | 8 | 9 | 5 | 9 | B |
| 7 | 4 | 3 | 1 | 8 | 9 | 2 | 4 | E |
| 8 | 6 | 3 | 3 | 6 | 7 | 2 | 3 | F |
| 9 | 4 | 3 | 7 | 6 | 7 | 4 | 4 | C |
| 10 | 4 | 2 | 1 | 6 | 5 | 3 | 7 | D |
| 11 | 3 | 2 | 1 | 6 | 7 | 2 | 4 | F |
| 12 | 7 | 6 | 5 | 8 | 8 | 6 | 7 | A |
| 13 | 5 | 3 | 9 | 8 | 7 | 2 | 4 | C |
| 14 | 3 | 4 | 3 | 8 | 9 | 4 | 9 | B |
| 15 | 8 | 4 | 5 | 7 | 9 | 6 | 7 | A |
| 16 | 5 | 4 | 9 | 7 | 6 | 3 | 5 | C |
| 17 | 5 | 3 | 6 | 7 | 8 | 3 | 2 | B |
| 18 | 4 | 3 | 1 | 8 | 9 | 2 | 4 | B |
| 19 | 5 | 3 | 6 | 7 | 8 | 3 | 2 | D |
| 20 | 6 | 4 | 2 | 8 | 7 | 7 | 3 | C |

Because the computational process of the algorithm is time consuming and arduous, the computerized program of the algorithm is generated using “Microsoft Visual Basic for Applications” for the users to take advantage of the algorithm results more easily. This program facilitates the analysis of different user attitude modes. Therefore, the user can compare different attitudes’ results. The user enters the input data in terms of lingual terms based on the collected information about the concrete plant characteristics through program interfaces. Then, based on the input data and through the database, similarity and difference between the input data and the database information are evaluated; then scores of similarity and difference and the total are calculated and the most fit readiness alternative will be obtained. The results include the readiness alternatives’ ranking, a compression between the current situation of the concrete plants and the best and the worth situations, and the ranking of which production factor has the most effect on the plant readiness to produce high quality concrete.

To test validity of the algorithm, using the data from Table 11, information of 17 plants were used as database in the algorithm. The data from the other 3 plants were separated; their readiness levels, which were calculated previously based on lab tests, were hidden and they were feed as unrated plants to the algorithm. Figure 1a,b demonstrate some interfaces through which the user can enter input data. The linguistic inputs of the case study were entered in the program for analysis.

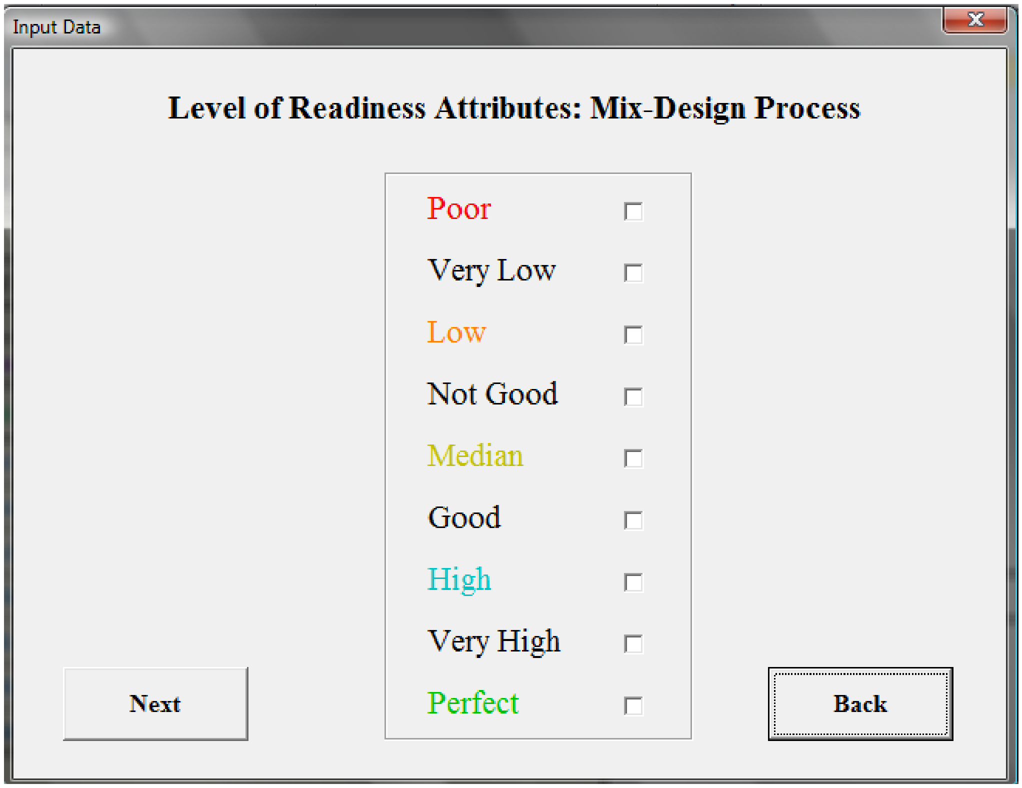
Validation of the algorithm would be proven if the readiness level of the unrated plants has successfully been predicted by the program with total correspondence to lab tests results. The results of the program were successful and the readiness levels of the unrated plants were accurately predicted, thus validate the algorithm correctness. Figure 2a,b illustrate the program outputs corresponding to the readiness alternatives’ ranking for an unrated plant from the case study project and the scores that has been predicted for each readiness alternative.

The program has predicted the readiness level of B for the case (Figure 2a). Lab test verified that result and indicated the case compressive strength has between 20-10 percent error rate.

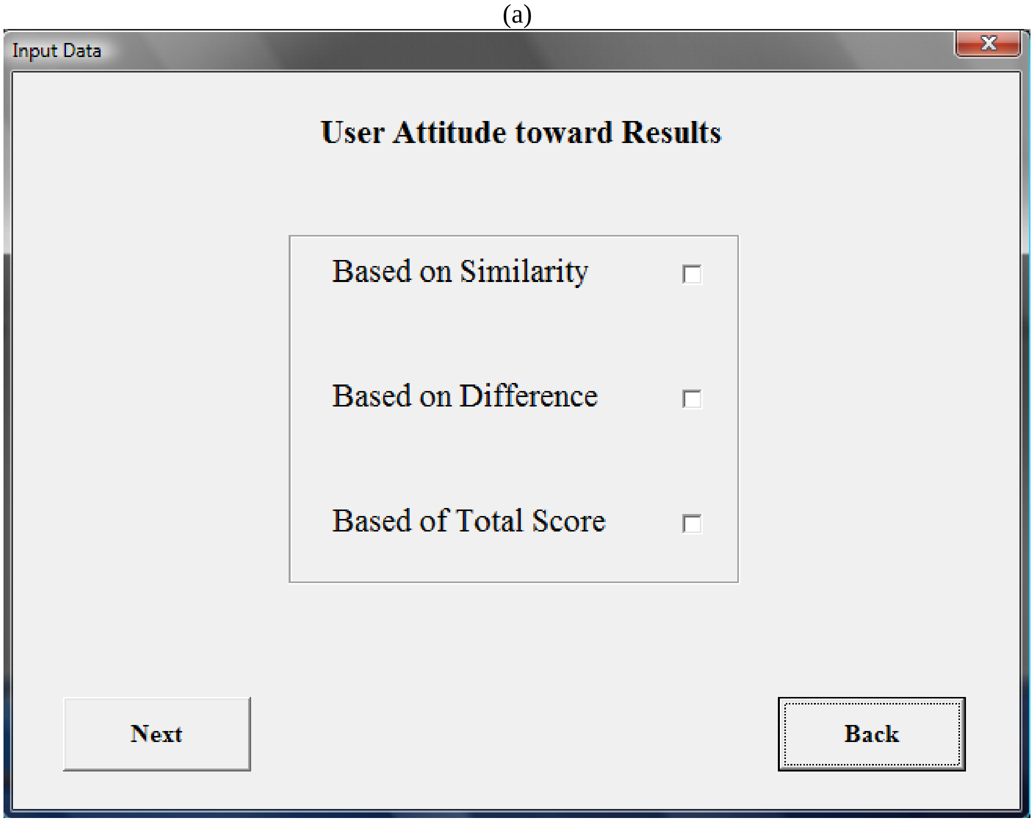
Figure 3 shows the result of the program regarding compression between the current situation of the test case and the best/worth situations available in the database. Figure 4 depicts the program output related to the ranking of production factors based on their effectiveness on the final results of the test case. As it can be seen, the test case can improve its level of readiness for producing high quality concrete by improving the quality level of its mix-design process. This result can help the concrete plant officials in order to choose the most effective production factor for making improvements.

## SUMMERY AND CONCLUSIONS

There is no ideal way to evaluate the overall quality of concrete or readiness of concrete plants to produce high quality concrete. Therefore, an appropriate way to predict concrete plants ability is to use past information. A probabilistic multi-attribute algorithm for evaluating the readiness level of concrete plants is proposed in this paper. This algorithm has many advantageous over other equivalents. The most important advantage is that the algorithm uses the error rate of concrete compressive strength to evaluate the ability of concrete plants instead of just predicting compressive strength. This gives the algorithm advantage of compensating effect of factors that might periodically increase the compressive strength but not the overall quality.




(a)




(b)

**Fig. 1.** a) Input interface regarding the level of readiness attributes (Mix-design process), b) Input interface regarding user attitude toward the results

**Probabilistic Multi-Attribute Algorithm**

Results Page

Readiness Level

Back

| Readiness Level | Ranking |
|---|---|
| B | 1 |
| C | 2 |
| D | 3 |
| A | 4 |
| E | 5 |
| F | 6 |

(a)

**Probabilistic Multi-Attribute Algorithm**

Result Page

Scores

Back

| Readiness Levels | Score of Similarity | Score of Difference | Total Score |
|---|---|---|---|
| A | 20.62 | -27.08 | -6.46 |
| B | 50.25 | -3.50 | 46.75 |
| C | 35.40 | 0.00 | 35.40 |
| D | 49.50 | -23.13 | 26.38 |
| E | 10.50 | -28.00 | -17.50 |
| F | 12.92 | -47.15 | -34.23 |

(b)

**Fig. 2.** a) Output interface corresponding to readiness alternatives ranking, b) Output interface corresponding to scores of similarity, difference and total for each readiness level

**Probabilistic Multi-Attribute Algorithm**

Results Page

Current situation via the Best/Worth situations

Back

| What is your current status | | | |
|---|---|---|---|
| Readiness Attribute | Highest Score | Lowest Score | Your Score |
| Raw materials | 8 | 2 | 5 |
| Mix-design process | 6 | 2 | 3 |
| QC and testing | 9 | 1 | 6 |
| Tools and equipment | 8 | 4 | 7 |
| Equipment calibration | 9 | 4 | 8 |
| Workmanship | 7 | 2 | 3 |
| Staff skills | 9 | 2 | 2 |

**Fig. 3.** Output interface corresponding to the compression between the current situation and the best/worst situations

**Probabilistic Multi-Attribute Algorithm**

Results Page

Ranking of Readiness Attributes Effectivness

Back

| Importance Effectivness | |
|---|---|
| Rank | Factor |
| First | Mix-design process |
| Second | Tools and equipment |
| Third | Raw materials |
| Forth | QC and testing |
| Fifth | Workmanship |
| Sixth | Staff skills |
| Seventh | Equipment calibration |

**Fig. 4.** Output interface corresponding to the ranking of readiness attributes based on their effectiveness

This algorithm is based on past information and a complete set of data can help the accuracy of its results. Seven production factors have been selected for the purposes of the algorithm but adding/removing PFs to the algorithm is feasible. Another advantage is that adding/removing attributes to the algorithm can be done without any change in the process or any extra calculation. Application of the algorithm in a case study reveals its robustness in evaluating the readiness level of concrete plants. Since the algorithm process is time consuming and is not understandable by a number of users, it has been programmed using the discussed steps. In this program, the user needs to determine the quality level of production factors for any specific concrete plant. Without the programmed algorithm, the user should know a basic knowledge of mathematics and data mining techniques for using this algorithm. It should be noted that the algorithm is a tool to assist professionals in the field of concrete. That is, the results of the algorithm should be examined carefully from other perspectives, since the process of evaluating the readiness level of concrete plants in order to produce high quality concrete and the quality of the concrete itself are complex processes.

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