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A case-based reasoning approach for estimating the costs of pump station projects

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Abstract The effective estimation of costs is crucial to the success of construction projects. Cost estimates are used to evaluate, approve and/or fund projects. Organizations use some form of classification system to identify the various types of estimates that may be prepared during the lifecycle of a project. This research presents a parametric-cost model for pump station projects. Fourteen factors have been identified as important to the influence of the cost of pump station projects. A data set that consists of forty-four pump station projects (fifteen water and twenty-nine waste water) are collected to build a Case-Based Reasoning (CBR) library and to test its performance. The results obtained from the CBR tool are processed and adopted to improve the accuracy of the results. A numerical example is presented to demonstrate the development of the effectiveness of the tool.

Introduction

To estimate is to produce a statement of the approximate quantity of material, time or price to perform construction. This statement of quantity is called an estimate, and its purpose is to provide information for construction decisions [1]. Adequate estimation of construction costs is a key factor in construction projects because it is one of fundamental management functions that need to be exercised at different project phases. The accuracy of an estimate is measured by how well the estimated cost is similar to the actual total installed cost. The accuracy of an early estimate depends on four determinants [2]: (1) who was involved in preparing the estimate; (2) how the estimate was prepared; (3) what was known about the project; and (4) other factors considered while preparing the estimate. So, the importance of cost estimating in the preliminary stages in the life cycle of any project is obvious and to a large extent the quality of the decisions taken will depend on the quality of the estimate.

AACE International's 18R-97 identifies five classes of estimates [3], which it designates as Class 1, 2, 3, 4, and 5 as listed in Table 1. A Class 5 estimate is associated with the lowest level of project definition or maturity, and a Class 1 estimate with the highest. Classes can be distinguished on five characteristics: degree of project definition, end use of the estimate, estimating methodology, estimating accuracy, and effort to

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Table 1 Cost estimate classification matrix [3].

Estimate class	Project definition (% of complete definition)	Purpose of estimate	Estimating method	Accuracy range (variation in low and high ranges)	Preparation effort (index relative to project cost)
Class 5	0–2	Screening	Capacity-factored, parametric models	L: –20 to –50% H: 30–100%	1
Class 4	1–15	Feasibility	Equipment-factored, parametric models	L: –15 to –30% H: 20–50%	2–4
Class 3	10–40	Budget authorization or cost control	Semi-detailed unit- cost estimation with assembly-level line items	L: –10 to –20% H: 10–30%	3–10
Class 2	30–70	Control of bid or tender	Detailed unit-cost estimation with forced, detailed takeoff	L: –5% to –15% H: 5–20%	4–20
Class 1	50–100	Check estimate, bid or tender	Semi-detailed unit cost estimation with detailed takeoff	L: –3% to –10% H: 3–15%	5–100

prepare the estimate. The main objective of this paper is to provide reliable cost estimating at the early stages of pump station construction projects utilizing case-based reasoning. The paper presents a parametric-cost model, dedicated to pump station projects. The proposed model is considered useful for preparing early conceptual estimates when there are little technical data or engineering deliverables to provide a basis for using more detailed estimating. The various cost drivers of pump station projects have been identified and collected from literature, instructed interviews and surveys.

Pump station components

The sizing of pump station components in the distribution system depends upon the effective combination of the major system elements: supply source, storage, pumping, and distribution piping. Population and water consumption estimates are the basis for determining the flow demand of a water supply and distribution system. Flow and pressure demands at any point of the system are determined by hydraulic network analysis of the supply, storage, pumping, and distribution system. Supply point locations such as wells and storage reservoirs are normally known, based on a given source of supply or available space for a storage facility. The reliability of the pumping station as a whole and of its individual components must be determined. Some typical factors and components which may be included in a reliability and availability evaluation are as follows

(1) Water demand and emergency storage.
(2) Preventative maintenance.
(3) Wear/life expectancy of subcomponent.
(4) Repair.
(5) Power transmission.
(6) Parallel operation and stand-by equipment.
(7) Emergency power.
(8) Surge protection.
(9) Pumps, valves and piping
(10) Motors.
(11) Controls.
(12) Time factors.

Buildings will be designed in compliance with local codes and regulations. Building layouts must be designed logically considering the sequence of installation of initial and future equipment if future expansion is planned. Space will be provided for removing equipment for repair without interrupting other equipment. Equipment layouts must provide vertical and horizontal clearances and access openings for maintenance and repair operations. The foundation design is based upon soil analysis and recommendations of a geotechnical engineer experienced in the field of soils mechanics and foundation design. Information on ground water conditions and the classification of soil types will be obtained through borings at the pump station location. Equipment layout provides space for safe maintenance and operation of equipment. Floor drains and pump gland drains will be provided in pump areas. Below-grade equipment structures, which cannot be drained by gravity piping, will be provided with sump pumps. Engines may be located in separate buildings or in outdoor enclosures in warmer climates. Engines will be provided with adequate combustion air. Engines will have a cooling system, a fueling system, a lubrication system, an electric starting system with battery charging, safety controls, and an instrument and control panel as required for system operation. Fuel tanks will be located above ground where possible with fuel spill protection and containment. Pump stations are regulated by some general specifications including safety, and submissions to clarify designated specifications. All pump station equipment, panels and controls must be intrinsically safe, i.e., equipment and wiring must be incapable of releasing sufficient electrical or thermal energy to cause ignition of gases. Complete fabrication, assembly, foundation, and installation drawings, together with detailed specifications and data covering materials, parts, devices and accessories shall be submitted. The developer/contractor shall submit shop drawings. Shop drawings shall include equipment descriptions, specifications, dimensional and assembly drawings, parts lists, and job specific drawings.

Cost factors of pump station

There are a large number of factors that affect the cost of pump station networks. In order to identify the most important and effective factors, structured interviews were conducted and a questionnaire survey was distributed. A set of structured interviews were arranged with five experts; the experts then went through the first interview questionnaire one entry at a time, making comments on each one. Any given comment can affect the interview questionnaire by

Table 2 The first list of cost factors.

No.	Factor	Mean (μ)	Standard error (SE)
1	Project type	4.28	0.13
2	Location of project	3.75	0.13
3	Area services	2.95	0.15
4	The cost of utilities	2.23	0.14
5	Population no.	4.38	0.14
6	Project duration	2.15	0.15
7	Estimate year	2.00	0.15
8	Weather condition	1.48	0.14
9	Safety requirement	1.55	0.14
10	Soil condition	2.95	0.15
11	Ground water level	2.23	0.15
12	Capacity of station	4.08	0.14
13	Distance between pump station and source	4.18	0.14
14	No. of buildings	2.40	0.15
15	Dimension of wet well gate	1.73	0.14
16	Shape of well	1.95	0.15
17	Volume of well	2.83	0.15
18	Type of pipes	1.95	0.13
19	Diameter of pipes	1.93	0.14
20	Length of pipes	2.00	0.14
21	Type of pumps	3.63	0.15
22	No. of pumps	3.90	0.15
23	Rate of pump	4.00	0.14
24	Head of pump	4.30	0.14
25	Pump arrangement	3.98	0.14
26	Type of pump motor	4.18	0.14
27	Rate of pump motor	4.15	0.15
28	Types of header pipes	3.90	0.15
29	Diameter of header pipes	1.83	0.13
30	Source of electricity	2.08	0.14
31	No. of generators	2.08	0.14
32	Rate of generator	1.70	0.13
33	Material availability	2.00	0.14
34	Equipment delivery time	2.05	0.15
35	Cement Price	2.05	0.15
36	Steel Price	2.00	0.13
37	Pipe Price	2.33	0.14
38	Pump Price	4.10	0.15
39	Duration of operation & maintenance	1.88	0.14

- The deletion or addition of factors.
- The quantification of factors.
- Re-categorization of factors.

Then, a questionnaire survey was prepared and used to identify the final list of factors essential for the parametric-cost estimating of pump station construction projects. This questionnaire is composed of two main sections. The first section includes the respondent's personal data, while the second section is the principal component of the questionnaire, and includes the list of factors against a scale designed to indicate levels of importance. This final list of cost drivers is used in developing the parametric-cost estimating model. The data collection took place from April to October 2009. The survey contains the suggested factors that are believed to have the most important effect on the preliminary cost of pump station projects. In the survey, the experts are requested to indicate the degree of importance associated with each factor on a five point *Likert Scale* consisting of five categories: "low", "low medium", "medium", "medium high", and "high" importance. Also, the experts were requested to offer their opinion concerning other factors that might be appropriately included in the survey. The first list of factors is included in Table 2. Only 40 survey sheets were completed and returned out of 55 forms distributed. Based on completed survey forms, 14 of 39 factors have high weights. After completing the basic statistics that measure the frequency of responses (on the five point *Likert scale*) for each of the 39 factors, the values were used to develop common statistical indices such as mean (μ), standard deviation (σ), and standard error (SE). Table 2 lists these factors along with their mean and standard error.

The SE is particularly useful in measuring the sufficiency of the sample size (based on collected data) as reported in Montgomery et al. [4]. It should be noted that the sample size is acceptable as long as SE does not exceed 0.2. In statistical terms, SE can be calculated according to Eq. (1).

$$\mathrm{SE} = \sigma/\sqrt{n} \tag{1}$$

The factors whose mean value (μ) was calculated to be less than 3.0 were discarded in order to keep the most important ones. As such, a total of fourteen factors were determined as cost drivers of pump station projects as per Table 3.

Fourteen cost drivers have been concluded to have the most impact on the costs of pump station projects in Egypt. These fourteen factors are used to develop the parametric-cost estimating model using case-based reasoning (CBR). The average rate of importance, which was detected from the survey responses, is considered as the basis for calculating the average weights of the different factors as listed in Table 2. Subsequently, a second survey was prepared to collect historical data records, which are used by the neural network for training and testing in order to be ready for prediction of future projects. This survey was sent to the participants who responded to the first survey. A total of 44 pump station projects (cases) were collected in the second survey. These projects were divided into two sets: the first set (38 projects) is used to build the case-based reasoning library, while the second set is used to test its performance (six projects).

Table 3 Identified cost drivers.

No.	Cost driver	Mean (μ)	Weight
1	Project type	4.28	0.86
2	Location of project	3.75	0.75
3	Population no.	4.38	0.88
4	Total capacity of station	4.08	0.82
5	Distance between pump station and source	4.18	0.84
6	Type of pumps	3.63	0.73
7	No. of pumps	3.90	0.78
8	Individual pump capacity "Rate"	4.00	0.80
9	Head of pump	4.30	0.86
10	Pump arrangement	3.98	0.80
11	Type of pump motor	4.18	0.84
12	Rate of pump motor	4.15	0.83
13	Types of header pipes	3.90	0.7
14	Pump price	4.10	0.82

Case-based reasoning application

An overview of CBR

In CBR systems, expertise is embodied in a library of past cases. Each case contains a description of the problem, plus a solution and/or the outcome. The knowledge and reasoning process used by an expert to solve the problem is not recorded as in the case of expert systems, but is implicit in the solution. To solve a current problem it is matched against the cases in the case base, and similar cases are retrieved. The retrieved cases are used to suggest a solution which is reused, tested and revised. Finally, the current problem and the final solution are retained as part of a new case. The typical case-based methods also have another characteristic property. They are able to modify, or adapt, a retrieved solution when applied in a different problem-solving context. A general CBR cycle may be described by the following four processes:

1. Retrieve the most similar case or cases.
2. Reuse the information and knowledge in the new case to solve the problem.
3. Revise the proposed solution.
4. Retain the parts of this experience likely to be useful for future problem-solving.

A new problem is solved by retrieving one or more previously experienced cases, reusing the case in some way or another, revising the solution based on reusing a previous case, and retaining the new experience by incorporating it into the existing knowledge-base [5]. The four processes each involve a number of more specific steps as depicted in Fig. 1. A lot of research efforts have been made in construction industry using case-based reasoning. These include: estimating the productivity of cyclic construction operations [6], cost estimating [7,8], construction negotiation [9], and construction disputes [10].

Modeling using CBR

The methodology for the application of CBR in parametric-cost estimating problems in the pump station sector consists of a number of steps. First, cases are defined by means of the fourteen cost drivers (attributes) and the cost of the project (output). Thirty-eight pump station projects (cases) are stored in the case-based (also known as the case library). Next, a method of similarity assessment amongst the cases is specified. As such, the CBR model becomes ready for use. Six test cases (denoted by target cases) are then fed into the CBR system. The system retrieves similar cases from the case-based data, generates similarity scores, and implements final prediction methods. After all similarity assessment methods are exhausted, the resulting predictions are reviewed and the one that generates the best prediction is adopted. CBR Works 4.0 Professional™ package is used to build a CBR library. It starts with identifying project features/attributes [11]. This includes identifying both the fourteen input features (cost drivers of pump station projects) and the single output feature (project cost) as per Table 4. Fig. 2 depicts screen shots of the proposed CBR system, dedicated to estimating pump station projects' costs.

It is worth noting that features/attributes are essentially used by CBR to differentiate between the projects stored in the case library. Also, as part of defining the features, the relative weights as between input attributes are provided, which have been obtained from the first questionnaire survey. These weights are fundamental to the retrieval process. When the structuring process for features is completed, building the case library proceeds with the collected pump station projects. Similarity is a key concept in CBR, expressed as follows: "similar problems have similar solutions" [12]. In other words, estimating the cost of a new target case (a new pump station project) is contingent upon its similarity to the cases stored in the case library. As discussed earlier, the fourteen input features/attributes can be classified into many types; each has a different means of measuring its similarity.

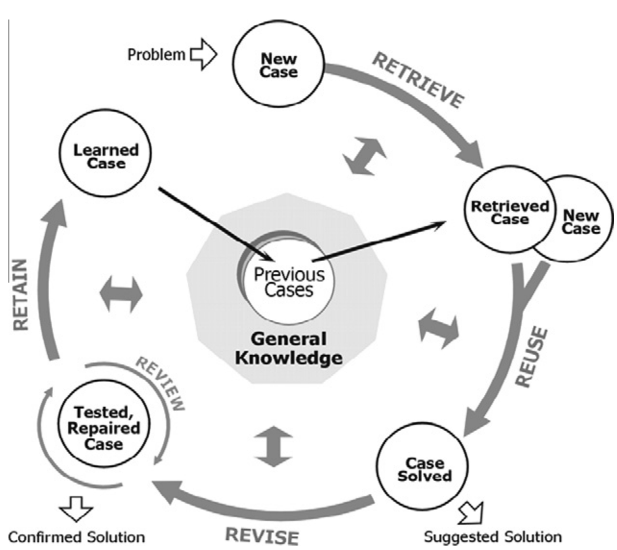

Fig. 1 Typical CBR cycle [5].

Testing application performance

Whenever a new/queried project exists, exemplified by any of the six tested project cases, the retrieval mechanism performs a search based on a weighted nearest neighbour algorithm.

Table 4 Input/out features of the CBR system.

Factor name	Value	Type
Inputs		
Project type	Water or wastewater	Ordered symbol
Location of project	New Cairo-6th of October-10th of Ramadan-Bader	Ordered symbol
Population no.	5500–950,000 people	Integer
Total capacity of station	2500–571,000 m^3/day	Integer
Distance between pump station and source	1–22 km	Integer
Type of pumps	14 type of pump	Ordered symbol
No. of pumps	2–8	Integer
Pump capacity (rate)	15–1250 l/s	Integer
Head of pump	10–125 m	Integer
Pump arrangement	Vertical–Horizontal-deep	Ordered symbol
Type of pump motor	13 Type of engine	Ordered symbol
Rate of pump motor	11–2000 kW	Integer
Types of header pipes	Steel-cast iron	Ordered symbol
Pump price	8000–1470,000 LE	Integer
Output		
Cost of project	(1–46) million LE	Integer

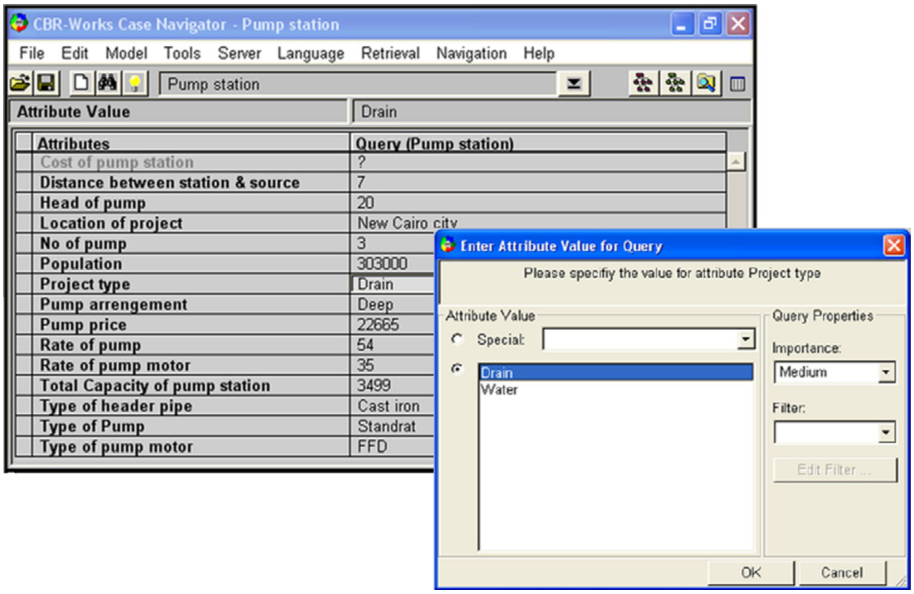

Fig. 2 CBR user interfaces screens.

The retrieval is truly a crucial aspect of any CBR system. The end result of a retrieval process is a set of similar/relevant or potentially useful projects. Each retrieved pump station project from the case library is associated with its similarity index or score. This score, which used to rank the retrieved projects, depends on how well the target case (queried project) and the retrieved case (stored project) match with each other. The retrieval of cases, based on a threshold score, is set beforehand. CBR Works 4.0 Professional™ has the ability to provide a cut-off for displaying the retrieved cases. For the considered CBR pump station, only the stored projects that have a similarity score of 0.70 or more can be retrieved from the case library and used for prediction purposes.

Even the retrieved pump station projects with the highest scores do not represent an exact match to the queried new project. In CBR terminology, retrieved cases that are out of context would require a certain degree of adaptation [13,14]. Typically, CBR systems use general or domain-specific knowledge to adapt the retrieved cases. In the CBR application at hand, four adaptation approaches were pursued. They are (1) null adaptation, (2) weighted adaptation, (3) neuro-adaptation, and (4) fuzzy adaptation. Each of these adaptation approaches uses the similarity scores for the retrieved cases in two ways to predict the cost of the new pump station project:

- Use the percentage of similarity to select the best cases similar to the queried project and take the value of projects' costs corresponding to the top ten rates of similarity scores [15]. This technique is referred to as the Without Similarity Index "*W/O SI*".
- Use the percentage of similarity to select the best cases similar to the queried project and take the value of projects' costs corresponding to the top ten rates of similarity scores multiplied by the percentage of similarity [16]. This technique is referred to as the With Similarity Index "*W/T SI*".

The following sub-sections describe the four adaptation approaches, which are tested against six unforeseen project cases to validate their performance.

Null adaptation

Null adaptation depends on the descending ranking of retrieved projects from the one with the highest score to the one with the least score that passes 0.70. Then, the cost of the project with the highest score is utilized as the estimate for the new project. Here an assumption is made that the stored project with the highest similarity score is very close in context to the new queried project and therefore its actual cost is the best indicator for the new project. The results of the null adaptation approach are shown in Table 5.

Weighted adaptation

In weighted adaptation, the entire set of retrieved pump station projects is utilized to conclude the estimate of the new project. The "weighted average" of the costs of retrieved projects is calculated and then is used as an estimate for the new project. Using the similarity scores of the various retrieved cases to represent the relative weights in calculating the average guarantees that the closest projects have more impact on the estimated cost than those with lower similarity scores that pass 0.70. For standardization, the top ten retrieved projects were utilized in the weighted adaptation process. The results of weighted adaptation approach are shown in Table 6.

Table 5 Null adaptation results.

Project case	Actual cost (LE in millions)	Predicted cost (LE in millions)	Absolute error (%)	
			W/O SI	W/T SI
1	4.00	6	50	44
2	9.80	8	18	28
3	21.20	25	18	5
4	12.20	18	48	20
5	6.80	4	41	41
6	10.60	7	34	46
Average absolute error (%)			35	31

Table 6 Weighted adaptation results.

Project case	Actual cost (LE in millions)	Predicted cost (LE in millions)	Absolute error (%)	
			W/O SI	W/T SI
1	4.00	11.2	180	90
2	9.80	13.3	36	1
3	21.20	22.2	5	25
4	12.20	13.8	13	19
5	6.80	16.2	138	69
6	10.60	16.7	58	4
Average absolute error (%)			72	34

Neuro-adaptation

Neuro-adaptation, which is probably the most complex, employs neural networks (NN) training on the retrieved projects. This is then used to predict the cost of the new queried project. There is an interesting analogy for neuro-adaptation: it works as if CBR acts as a filtering mechanism for the training set. It should be noted that NN needs a sizable training set in order to perform properly. The diversity and contradictions within the training set makes it harder for the NN to recognize trends. However, when the training set is more appropriate to a particular new case, employing only relevant cases in the NN training can be quite useful. In neuro-adaptation, the data of the retrieved projects that have the top ten rates of similarity scores are trained in NeuroInelligence™. Then, the predicted costs for the ten retrieved projects (which are trained in NN) are obtained. The absolute error is calculated using Eq. (2). The average absolute error for the six tested cases is 34%.

$$\text{Error}(\%) = \frac{\sum_{i=1}^{10} RP^{i}_{\text{Actual}} - RP^{i}_{\text{Predicted}}}{RP^{i}_{\text{Actual}}} \times 100 \tag{2}$$

Fuzzy adaptation

This adaptation method is based on the use of the knowledge existing in cases that have been presented in terms of the fuzzy logic [17]. The quality of adaptation depends on the correlation between the selected input parameters and the output parameters to be adapted. The user can affect the adaptation quality by the selected input parameters. Its main advantage is the autoimmunization of the adaptation process, which allows the system to be applied by the inexperienced user. The results of the fuzzy adaptation approach are shown in Table 7. The value of the membership function μ is calculated for each selected numerical problem value. The value of μ ranges between 0 and 1. Membership function is calculated using Eq. (3) as reported by Hatakka et al. [18].

$$\mu = \frac{1}{1 + \left| \frac{X_{\text{med}} \cdot 10}{X_{\text{med}} - X_{\text{min}}} \; \frac{X \cdot 10}{X_{\text{med}} - X_{\text{min}}} \right|} \tag{3}$$

where

X: problem value of an input parameter.
X_{med}: middle value of the parameter in the five best cases.
X_{min}: minimum value of the parameter in the five best cases.
X_{max}: maximum value of the parameter in the five best cases.

Adapted output values are calculated on the basis of the average value of μ (of selected input data). If the problem values are smaller than the values in CBR, the adapted output value is calculated per Eq. (4).

$$Y = \frac{Y_{\text{max}} - Y_{\text{min}}}{10} + Y_{\text{med}} - \frac{Y_{\text{max}} - Y_{\text{min}}}{10 \cdot \mu} \tag{4}$$

where

Y: problem value of an output parameter.
Y_{med}: average value of the parameter in the five best cases.
Y_{min}: minimum value of the parameter in the five best cases.
Y_{max}: maximum value of the parameter in the five best cases.

It is worth noting that lowest average absolute error (9%) is obtained from the fuzzy adaptation method Without Similarity Index, while the fuzzy adaptation method With Similarity Index gives an average absolute error of 22%. In null adaptation, the average absolute error for Without Similarity Index (31%) is close to the average absolute error for With Similarity Index (35%). On the other hand, the difference in average absolute error in weighted adaptation is high, from Without Similarity Index (72%) to With Similarity Index (34%). As such, the fuzzy adaptation method Without Similarity Index is nominated to be the most suitable adaptation approach giving least average absolute error. This is within the range of

Table 7 Fuzzy adaptation results.

Project case	Actual cost (LE in millions)	W/O SI				W/T SI			
		Average cost (LE in millions)	μ	Predicted cost (LE in millions)	Absolute error (%)	Average cost (LE in millions)	μ	Predicted cost (LE in millions)	Absolute error (%)
1	4.00	5	1.00	4.80	20	4	0.31	3.26	18
2	9.80	8	0.27	4.20	57	13	0.16	8.88	9
3	21.20	20	1.25	20.20	5	22	0.41	20.82	2
4	12.20	15	0.40	13.00	7	13	0.23	10.54	14
5	6.80	12	0.16	4.40	35	9	0.29	6.26	8
6	10.60	14	0.20	10.00	6	10	0.47	10.07	5
Average absolute error (%)					22				9

Note: Average cost is the average of the best five retrieved projects.

budget authorization (Class 3), where accuracy ranges from – 20% to 30% as per Table 1.

Conclusion

The cost of a pump station depends upon a wide variety of conditions, including pump discharge, pump head, pump type, site conditions, desired usage, and structural design. In the preliminary cost estimate of a pump station project, the intent is not to determine the pump type or details of the station structural design, but rather to estimate the cost of a station that is capable of pumping the desired discharge at the necessary head conditions. The various cost drivers of this industry sector have been identified. A comprehensive process for the identification of these cost drivers was presented. The paper provided an overview of a newly developed CBR application that can be used as a parametric-cost model for pump station projects. The performance of the CBR model was tested via three adaptation methods; (1) null adaptation, (2) weighted adaptation, (3) Neuro-adaptation, and (4) fuzzy adaptation. The latter adaptation method outperforms the other methods with an average error of 9%. This average error is within the range of budget authorization. Although the proposed parametric-cost model is limited to pump station projects, which are classified as infrastructure projects, the approach can be extended to include other types of construction projects such as residential and industrial buildings.

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