# Management Information System for Predicting Quantity Martials

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***Abstract*** **– The purpose of this research work is to present in a systematic way the use of the integration method comprising the information system and prediction model towards optimizing the accuracy of Quantity Survey (QS) calculation. The main attention is paid to applied value of the considered methodology, to profitable interpretation and clarification of the results obtained. In order to achieve the goals, information system with the prediction model has been developed and integrated, which predicts the volume of concrete and steel materials using comprehensive experiments over a set of prediction shared algorithms. A new approach to prediction is proposed, based on the use of results of an automatic Information system capable to generate featured to improve the accuracy in the prediction problem. It was experimentally shown that in some cases this approach can be quite effective to significantly improve the quality of prediction and classification**

***Keywords*** **– Prediction, Information system, QS, Neural networks, Machine learning**

## 1. Introduction

One of the most popular areas of construction analysis in recent years is the development of QS software capable of automation the process of QS based on mathematical formulas. Such software is not considering any prediction model to handle the prediction of building materials quantities and prices, and in many cases it ignores the behavior of such objects based on data from previous trading periods. Such solutions could fail to provide accurate results for specific environments. In fact, to obtain any relevant results, the investigator should use the appropriate tools and correct algorithms to handle most of the variables in the dynamic areas. Scientists have set as their goal the development of superior software that could generate calculation of the required building materials of a specific object using fixed mathematical formulas. However the lack of research work dealing with the prediction of the essential quantity of concrete and steel materials is not recognized in the literature. This motivates this work to develop integrated methods of information system and prediction model.

DOI: 10.18421/TEM84-06
https://dx.doi.org/10.18421/TEM84-06

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*Received: 31 July 2019.*
*Revised: 05 November 2019.*
*Accepted: 12 November 2019.*
*Published: 30 November 2019.*



## 2. Literature Review

The invention of Mobile technology progress, allows the users and developers to access the BIM-model quickly and conveniently. This brings technology to a new level. In [1] focus on the benefit of using BIM technology to perform quantity survey processes, [2] states that qualitative methods and approaches, could provide a solid reference to the education systems for improving the QS program. The principal conclusion is that there is a strong argument for adopting and implementing a work placement approach in quantity surveying education courses. [3] Worked on a thesis titled “Conflicts in Building Projects in Tanzania: Analysis of Causes and Management Approaches”, the study observes the causes and organization methods of conflicts in building projects in Tanzania. [4] Described the impact of BIM on the QS profession and stated that BIM could provide significance solutions that will maintain and change the traditional work executed by the quantity surveyors. [5] State that, the programmed construction process for the bill of quantity (BOQ) allows the quantity surveyors to collaborate in the initial design phases for a specific building project. [6] Proposed comparison study on the importance of QS parts and roles in construction projects in Sweden and the UK. The outcomes of the study were dependent on the participant's interviews. [7] Described the QS framework that contains critical factors in improving the quality of QS activities, including BIM maturity, benefits, barriers, and business planning and change management. [8] Found improvement in achieving more profits once realizing the BIM for performing the QS process in actual service of using the BIM in 'Sri Lanka'. [9] States that the primary capabilities of quantity surveyors are seen only after improving service management. [10] Conducted a comparative experiment and research methodology to develop a conceptual framework related to MDS ability factors in adopting. [11] Provided a comprehensive survey on BIM technology, in particular, the 'Revit Software', as well as demonstrated the steps of using Revit software, and developed a list of benefits besides the using of BIM technology, and demonstrated a list of QS software. For more information related to prediction and classification could be found in [12],[13] As shown above most of the studies work on Analyze, Design and implement an automating QS process, however, none of the studies have been developing a comprehensive study in predicting quantity survey materials.

## 3. Problem Statement

Construction materials themselves are unpredictable since they depend not only on trade and industry events, but they are also influenced by the interior situation in different parts of the world. Therefore, it is extremely difficult to develop a mathematical model for processing such unpredictable, non-linear and non-parametric time series.

Construction business regularly uses the traditional way to accomplish unique outcomes with limited resources under critical time constraints. The main difficulties that are seen in speeding up quantity survey calculation process are compressing the time to increase efficiency and produce a substantial competitive advantage. Manual quantity survey services are facing the following challenges:

1-Time used to perform the calculations of building materials is extensive.

2- The amount of errors in surveying measurement is hindering.

3- The high cost of purchasing and maintaining the QS software forced the tightly budgeted companies to perform QS work in traditional ways

In fact, most of the solutions performed by QS software are not accurate, whether they result in additional cost, i.e. extra materials not used or materials not sufficient to complete the constructions.

## 4. Proposed Solution

The proposed solution is realized on behave of developing an integration method comprising information system and prediction model towards optimizing the accuracy of Quantity Survey (QS) calculation. Figure 1 describes the structure of the proposed solution.

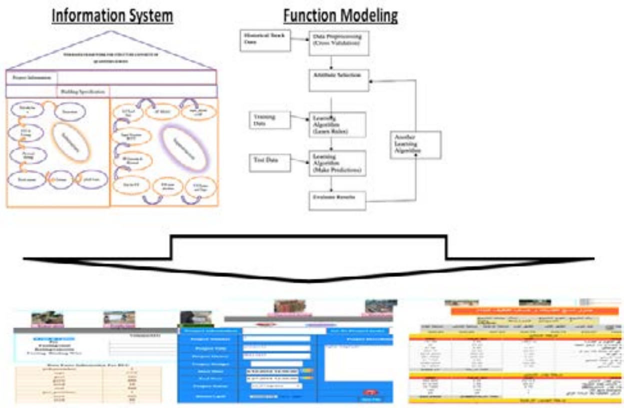


*Figure 1. Integration framework*

The Information system (IS) has been developed using C# and Asp.net within APIs, the information system code and could be found in:

*https://drive.google.com/drive/folders/1fnDk-VLSY1pOwqoXNnC-nsDQHtQkiY9_?usp=sharing*

And the interface of the IS could be found in http://saif2019-001-site1.etempurl.com

The class diagram of the developed IS demonstrated in figure 2.

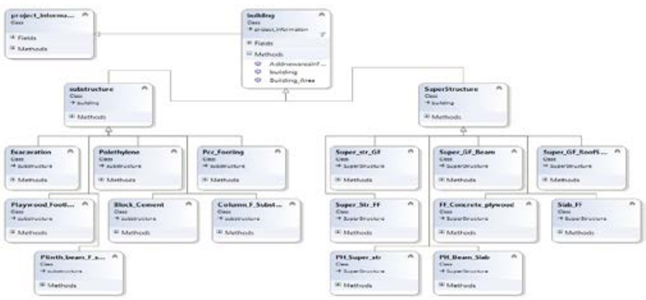

*Figure 2. IS class Diagram*

The function Modeling is used to make an adaptive system that learns to predict the quantity of the concrete and steel gave the historical data.

I.e. Area, IS calculation (concrete & Steel), date of constructions, actual concrete& steel data recorded from 2015 to 2018 in a specific construction company in sultanate of Oman. Hence the concrete and steel quantity is the output features, while the others are the input features.

## 5. Experiment

794 transactions have been used to create the models, the data set belongs to a consultant construction company in sultanate of Oman, the company has recorded 1803 transactions using excel application. The price of concrete and steel were missed in 1009 records. The data set have six attributes: Area of the building required the volume of concrete for each building area, the required volume of steel for each building area, date of the purchasing concrete & steel, Concrete Price for one m3, Steel Price for one Ton. Figure 3. shows a sample of the collected dataset.

| 1: Area Numeric | 2: concreate Numeric | 3: steel Numeric | 4: Date Nominal | 5: concrateactual Numeric | 6: steelactual Numeric | 7: pricconceperim3 Numeric | 8: pricsttelperton Numeric |
|---|---|---|---|---|---|---|---|
| 584.0 | 408.8 | 38.93 | 201... | 464.0 | 94.0 | 27.0 | 177.0 |
| 591.0 | 413.7 | 39.4 | 201... | 422.0 | 48.0 | 25.0 | 175.0 |
| 598.0 | 418.6 | 39.87 | 201... | 420.0 | 41.0 | 30.0 | 180.0 |
| 605.0 | 423.5 | 40.33 | 201... | 448.0 | 65.0 | 26.0 | 176.0 |
| 612.0 | 428.4 | 40.8 | 201... | 476.0 | 88.0 | 27.0 | 177.0 |
| 619.0 | 433.3 | 41.27 | 201... | 439.0 | 47.0 | 24.0 | 174.0 |
| 626.0 | 438.2 | 41.73 | 201... | 457.0 | 60.0 | 26.0 | 176.0 |
| 633.0 | 443.1 | 42.2 | 201... | 507.0 | 106.0 | 22.0 | 172.0 |
| 647.0 | 452.9 | 43.13 | 201... | 455.0 | 46.0 | 24.0 | 174.0 |
| 654.0 | 457.8 | 43.6 | 201... | 487.0 | 73.0 | 20.0 | 170.0 |
| 661.0 | 462.7 | 44.07 | 201... | 545.0 | 127.0 | 29.0 | 179.0 |
| 668.0 | 467.6 | 44.53 | 201... | 468.0 | 45.0 | 31.0 | 181.0 |
| 675.0 | 472.5 | 45.0 | 201... | 493.0 | 66.0 | 27.0 | 177.0 |
| 682.0 | 477.4 | 45.47 | 201... | 486.0 | 54.0 | 32.0 | 182.0 |
| 689.0 | 482.3 | 45.93 | 201... | 555.0 | 118.0 | 29.0 | 179.0 |
| 696.0 | 487.2 | 46.4 | 201... | 491.0 | 50.0 | 25.0 | 175.0 |
| 703.0 | 492.1 | 46.87 | 201... | 508.0 | 62.0 | 26.0 | 176.0 |
| 710.0 | 497.0 | 47.33 | 201... | 523.0 | 74.0 | 21.0 | 171.0 |
| 717.0 | 501.9 | 47.8 | 201... | 513.0 | 59.0 | 26.0 | 176.0 |
| 724.0 | 506.8 | 48.27 | 201... | 556.0 | 98.0 | 22.0 | 172.0 |
| 731.0 | 511.7 | 48.73 | 201... | 518.0 | 55.0 | 32.0 | 182.0 |
| 738.0 | 516.6 | 49.2 | 201... | 537.0 | 70.0 | 21.0 | 171.0 |
| 745.0 | 521.5 | 49.67 | 201... | 537.0 | 65.0 | 20.0 | 170.0 |
| 752.0 | 526.4 | 50.13 | 201... | 618.0 | 142.0 | 31.0 | 181.0 |
| 759.0 | 531.3 | 50.6 | 201... | 557.0 | 76.0 | 28.0 | 178.0 |
| 766.0 | 536.2 | 51.07 | 201... | 586.0 | 101.0 | 29.0 | 179.0 |
| 780.0 | 546.0 | 52.0 | 201... | 642.0 | 148.0 | 32.0 | 182.0 |
| 787.0 | 550.9 | 52.47 | 201... | 617.0 | 119.0 | 24.0 | 174.0 |
| 794.0 | 555.8 | 52.93 | 201... | 558.0 | 55.0 | 20.0 | 170.0 |

*Figure 3. sample of data set*

A web API service has been developed to calculate the required quantity of concrete and steel for a giving area. Figure 4. shows the API interface to perform this step.

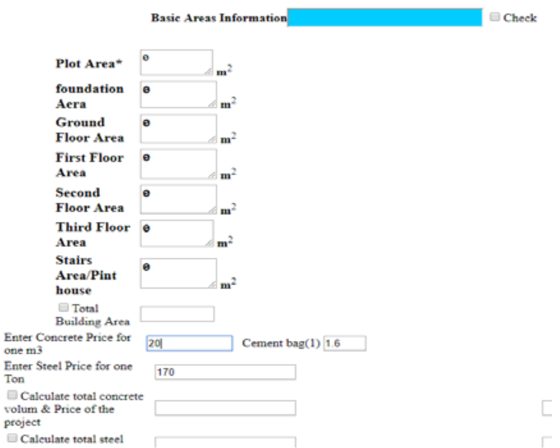


*Figure 4. API interface*

Up to this stage, two new features have been added to the data set. So we could see the variation of actual quantity and the quantity calculated by the information system that used standard QS formulas to perform the calculations. The results endorse our argument discussed in the introduction section, which determined the fact of having perfect accuracy of the required quantity. For running the prediction experiment in order to find the optimal solution over the set of algorithms we used 974 recodes and split into two data set 828 for the training and 164 for the validation. Figure 5 and figure 6 demonstrate the statistics of the two data sets.

| CSV | Area | concre... | steel | concra... | steelac... | pricco... | pricstte... |
|---|---|---|---|---|---|---|---|
| Max | 800 | 560 | 53.33 | 646 | 147 | 32 | 182 |
| Sel Max | | | | | | | |
| Min | 150 | 105 | 10 | 107 | 11 | 20 | 170 |
| Sel Min | | | | | | | |
| Mean | 465.3841 | 325.7688 | 31.02562 | 360.1003 | 65.39976 | 25.92995 | 175.9299 |
| Sel Mean | | | | | | | |
| Stdev | 187.3803 | 131.1662 | 12.49199 | 135.0185 | 32.00451 | 3.71668 | 3.71668 |
| Sel Stdev | | | | | | | |
| Count | 828 | 828 | 828 | 828 | 828 | 828 | 828 |
| Sel Count | | | | | | | |
| Sel Part | | | | | | | |

Set: Training

*Figure 5. statistics of the training dataset*

| CSV | Area | concre... | steel | concra... | steelac... | pricco... | pricstte... |
|---|---|---|---|---|---|---|---|
| Max | 794 | 555.8 | 52.93 | 642 | 148 | 32 | 182 |
| Sel Max | | | | | | | |
| Min | 150 | 105 | 10 | 116 | 12 | 20 | 170 |
| Sel Min | | | | | | | |
| Mean | 514.9589 | 360.4712 | 34.33062 | 394.4932 | 68.36987 | 25.81507 | 175.8151 |
| Sel Mean | | | | | | | |
| Stdev | 173.966 | 121.7762 | 11.59772 | 124.8926 | 31.66049 | 3.872099 | 3.872099 |
| Sel Stdev | | | | | | | |
| Count | 146 | 146 | 146 | 146 | 146 | 146 | 146 |
| Sel Count | | | | | | | |
| Sel Part | | | | | | | |

Set: Validation

*Figure 6 statistics of the Validation dataset*

To select related features, the correlation analyzing process has been implemented to see what features affect the desired output. Figure 7. shows the histogram information.

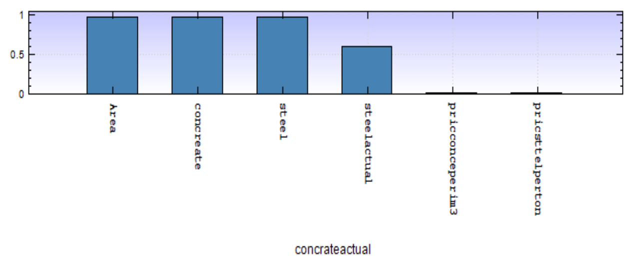


*Figure 7. Correlation process*

For instance, the price of concrete and the price of steel do not contribute much to affect the concrete and the steel quantity. So we get rid of such features as they are likely only to take up valuable computing power in the adaptive system. Therefore an extract filter has been used to remove such features. Figure 8 and figure 9 show the results after the correlation impact.

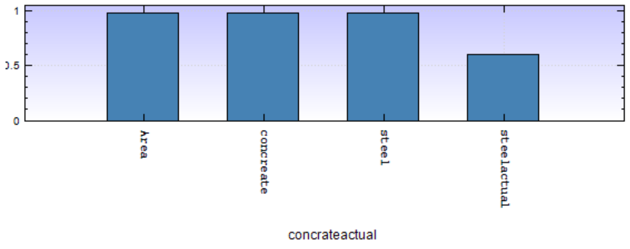


*Figure 8. Selected featured for predicting Concrete*

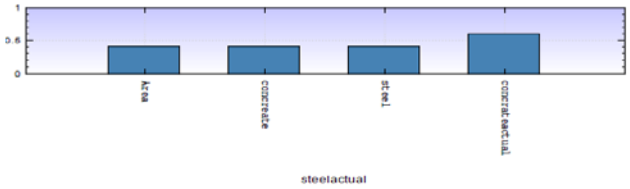


*Figure 9. Selected featured for predicting Steel*

To understand data in the individual features the histogram visualizer has been used, and figure 10 shows the histogram information for the concrete and its associated relation to other features. And figure 11 show the histogram information for the steel and its associated relation to other features.

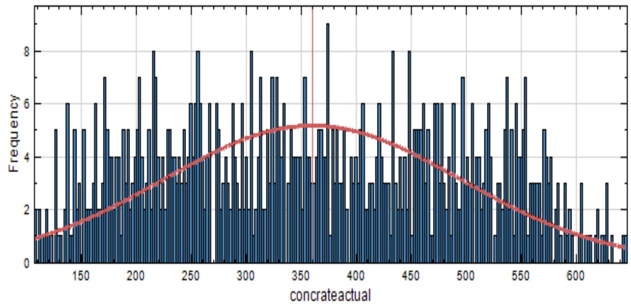


*Figure 10. Histogram for predicting Concrete*

As we can see most of the actual concrete are between 250 m3 and 350 m3 and about 200 of them are to be precise.

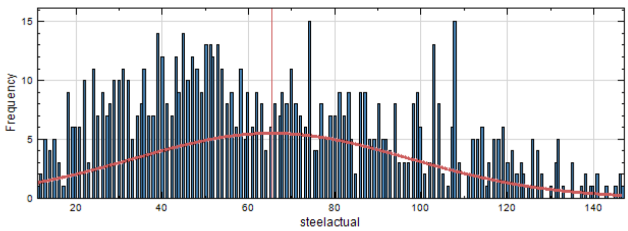


*Figure 11. Histogram for predicting Steel*

As we can see most of the actual steel is between 30 Ton and 60 Ton and for about 55 of them in order to be precise we remove all outlier, because an adaptive system is only as good as the data you feed it. Then we ran many experiments to evaluate the performance of three main algorithms Multilayer Perception, Linear Regression, and RandomForest. Figure 12. describes the evaluation results.

```
Analysing:  Mean_absolute_error
Datasets:   1
Resultsets: 3
Confidence: 0.05 (two tailed)
Sorted by:  -
Date:       7/31/19 12:15 AM


Dataset                     (1) functio | (2) func (3) tree
-----------------------------------------------------------
'2trainingsetfor_predicti (10)   0.33 |   0.70     4.11 v
-----------------------------------------------------------
                                (v/ /*) |  (0/1/0)  (1/0/0)


Key:
(1) functions.MultilayerPerceptron
(2) functions.LinearRegression
(3) trees.RandomForest
```

*Figure 12. Evaluation results over three algorithms*

From the obtained result, A multilayer perception (MPL) shows the best prediction results. Therefore we dig in detail and create the MPL model as shown in figure 13.

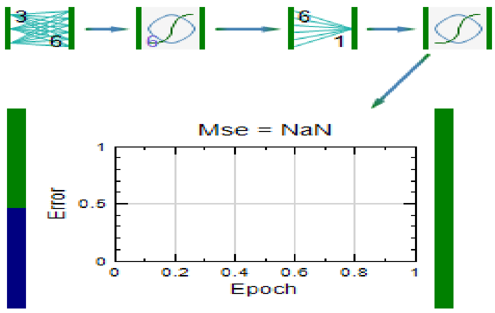


*Figure 13. MPL Model*

A multilayer perception (MPL) [13] it's a basic type of artificial neural network. The weight layers represent the long-term memory of the system. It's a set of weight that the signal that travels through the network and get multiplied with these weights. They get adjusted by the learning algorithm to produce the desired output signal by giving an input signal. The function layers can be seen as non-linear thresholds for the signal. They give the adaptive system its non-linear computing capabilities. Finally, the delta terminator is an error criterion. It takes two signals and compares them according to some metric. One input is set to the actual output of the system and one is set to the desired output. The delta terminator compares them and sends its results back through the system where that information is used to update the weight. It's called a "terminator" because it terminates the forward signal flow through the system.

As shown in Figure 14, 15, 16 we connect our main data as input and actual concrete/steel data which contains our desired system output. More information about the algorithm could be found in [13].

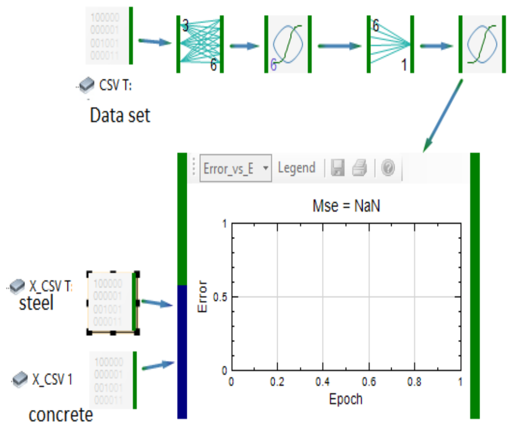


*Figure 14. Configuration of the proposed MPL Model*

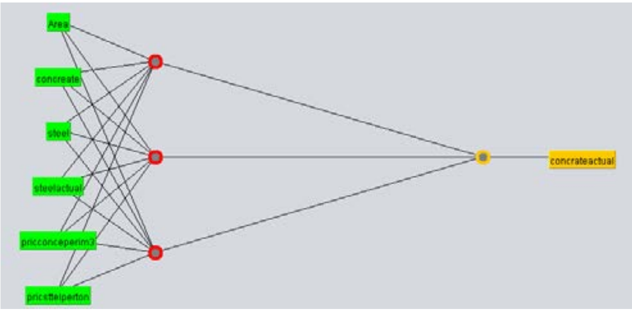


*Figure 15. Concrete MPL Layer*

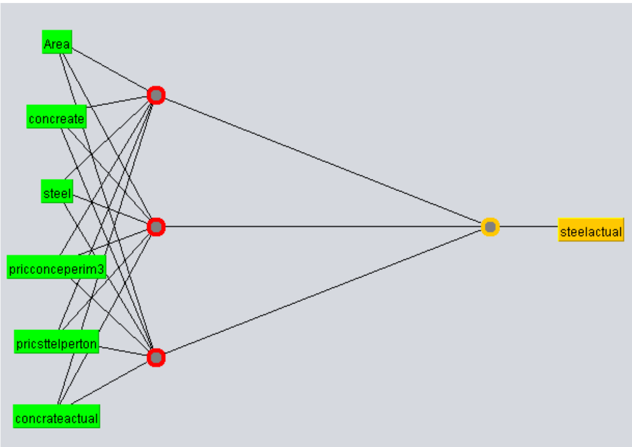


*Figure 16. Steel MPL Layer*

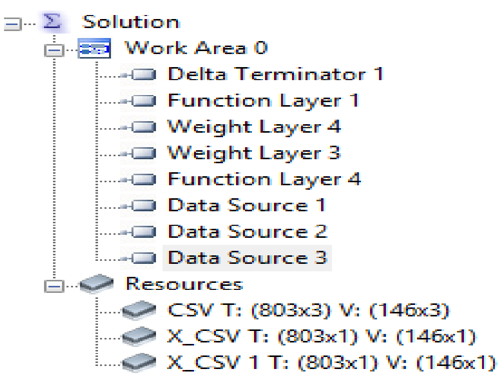


*Figure 17. Labels for the symbols for the MPL model*

We set the max epochs to 400 as a number of iteration. One epoch means showing the whole training data to the system once, so 400 epochs means that the training data will go through the system 400 times. And we set the batch length to decide how many samples are sent through the system at once.

We increase the batches to improve the training stability and to require less CPU time.

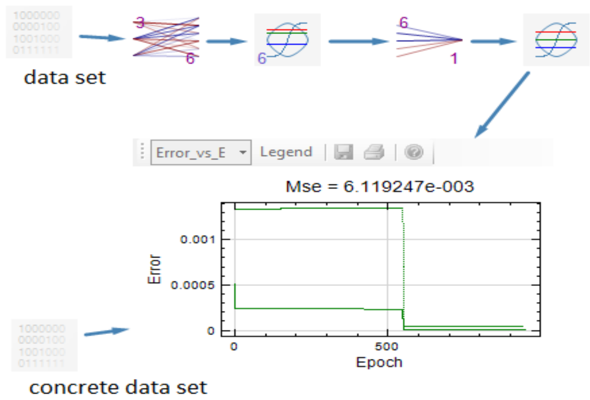


*Figure 18. Error indicator for prediction the quantity of Concrete*

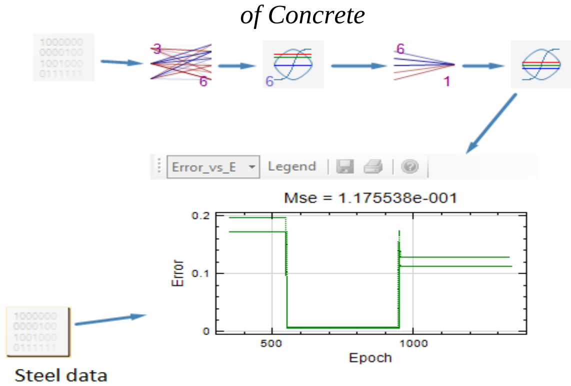


*Figure 19. Error indicator for prediction the quantity of Steel*

Figure 18 and 19 demonstrate two graphs indicators the error on training data and one on validation data for concrete and steel quantity prediction. Figure 20a and 20b show the evaluation metric using Linear and Manahan metrics.

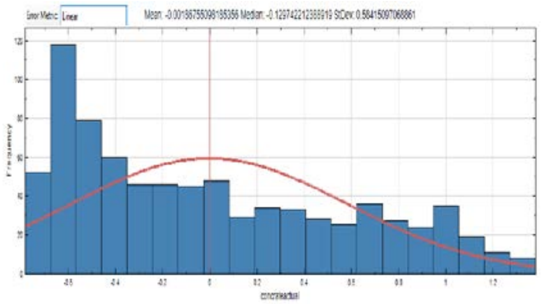

*Figure 20a. Error indicator using the linear indicator*

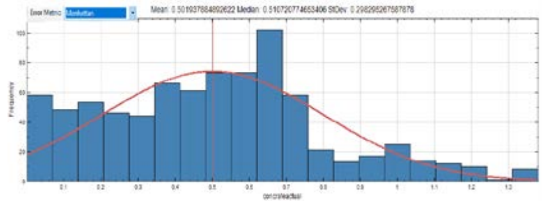

*Figure 20b. Error indicator using Manhattan indicator*

Linear metric showed the plain error as the desired output on the other hand Manhattan metric shows absolute error (desired output) which is more useful.

Figures 21, 22, 23, 24 show the confidence evaluation.

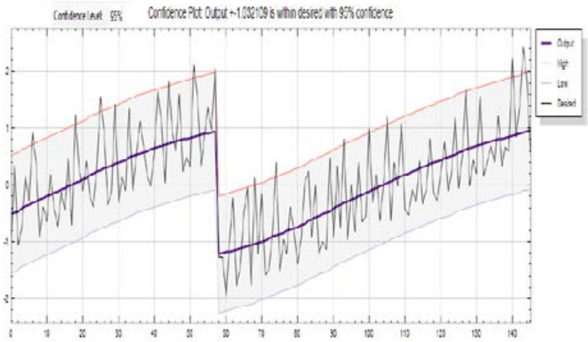

*Figure 21. Confidences According to the sample number(S)*

The purple line is the output of the system; the black line is the desired output; the red and blue lines are the confidence limits, According to the sample number(S), According to the desired value (T), According to error (E), According to output (O)

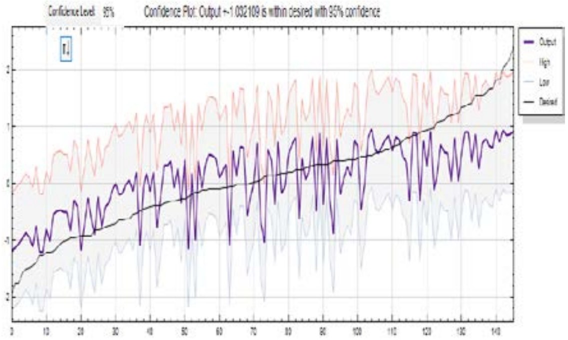

*Figure 22. Confidence According to the desired value (T)*

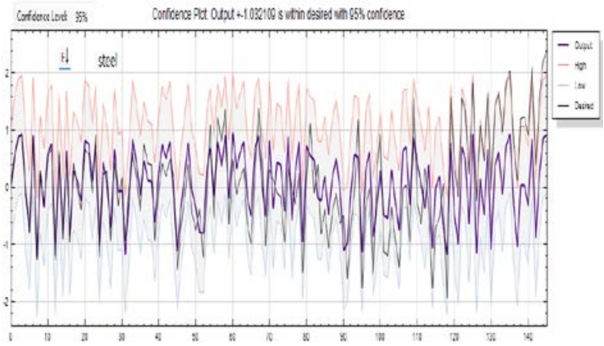

*Figure 23. Confidence According to error (E)*

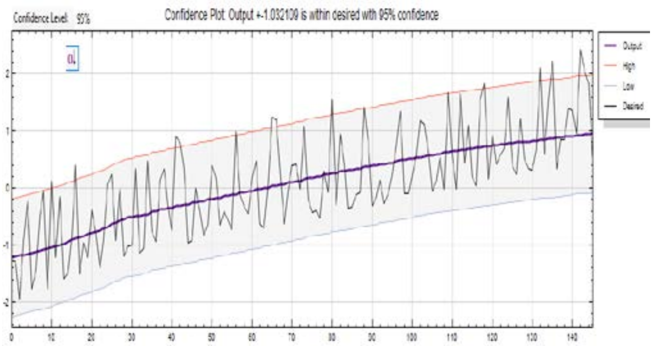

*Figure 24. Confidences According to output (O)*

The API service for the predicted model is coded in a DLL library as shown in figure 25.

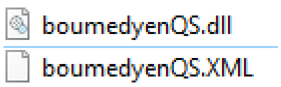


*Figure 25. Deployment library for the development prediction model using .net technology*

## Conclusion

Thus, in the present work, a new approach for prediction is proposed. It is based on the use of the results of an automatic Information system capable to generate extra features to improve the accuracy in the prediction problem. It was experimentally shown that in some cases this approach can be quite effective to significantly improve the quality of prediction and classification. Also in the work, a new method of feature selection is considered, based on solving a special optimization problem and finding the weights of attributes in the data set. The researchers applied and demonstrated all the described methods step by step: starting with fundamental analysis, using the neural networks, machine learning and Error metrics Linear and Manhattan as well as the confidence level of 95% for the sample number(S), desired value (T), error (E) and According to output (O) . Based on the Mean_absolute_error Comparision criteria with a 95% confidence level, The MultilayerPerceptron function overperform LinearRegression and trees.RandomForest. A QS information system and an adaptive system have been developed and released using the Net technology. All of the algorithms used, they allowed us to achieve satisfactory prediction accuracy results. The results show that our new development method by adding extra features extracted in the form of information system calculation i.e.concrete and steel is an effective method in improving the prediction problem.

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