INTERNATIONAL JOURNAL OF ADVANCE RESEARCH, IDEAS AND INNOVATIONS IN TECHNOLOGY

ISSN: 2454-132X
Impact factor: 4.295
(Volume 5, Issue 3)
Available online at: www.ijariit.com

Prediction of building structure age using machine learning

Neha Mahajan
mahajanneha999@gmail.com
Usha Mittal Institute of Technology, Mumbai, Maharashtra

Darshana Patil
darshpatil12321@gmail.com
Usha Mittal Institute of Technology, Mumbai, Maharashtra

Apurva Kotkar
apurvakotkar96@gmail.com
Usha Mittal Institute of Technology, Mumbai, Maharashtra

Kumud Wasnik
kumudwasnik@gmail.com
Usha Mittal Institute of Technology, Mumbai, Maharashtra

ABSTRACT

Determining the service life of building structure is a critical step for the evaluation of maintenance of the building. If the service life of a building is known then proper maintenance and refurbishment steps can be taken. Previous studies focused only on physical obsolescence whereas new concept focused on other new six criteria. The objective of this paper is to use the entire six criteria for the evaluation of obsolescence for the prediction of the age of building a structure using machine learning. A prediction model for predicting age is developed by combining the six obsolescence criteria, absolute weights, diagnostic scores, and machine learning. As obsolescence is predicted using all six criteria, the manual calculation is reduced to provide more accuracy. This prediction model has built using python language, Django as a framework and PyCharm IDE. To make this prediction system more adaptable the website is created and hosted on webhost000.com by combining prediction model and UI of the website which displays the predicted age for respective diagnostic scores. Hence predicting age is useful for taking actions to prevent future degradation.

Keywords— *Service life, Obsolescence, Diagnostic scores, Prediction model, PyCharm IDE, Django, Adaptable*

1. INTRODUCTION

Nowadays, we have heard many cases of infrastructure collapsing. The recent example is the Andheri Bridge. This is because no proper attention is paid towards the maintenance of infrastructure. Although building are long lasting, continuous maintenance and refurbishment is required. So prediction of age of building is must to predict the future chances of collapsing and thus preventing the damage. Therefore our proposed system predicts the age of the building which helps in preventing the collapsing of building. The aim of this paper is to develop a prediction model for predicting buildings age based on rate of obsolescence. To achieve the aim, implementation is divided into three modules. First, a literature review was done to decide the method of determining the age. The first module comprise of interface which is used to collect diagnostic scores. Second module has been implemented for obsolescence prediction using machine learning algorithm of Multiple Linear regression. Third module uses obsolescence value to predict age of building.

Our objectives of the study are listed as follows:

- To predict the lifespan by estimating the age of the infrastructure
- To take preventive measures for damage
- To reduce cost spend after damage
- Reduce the risk factor of life

2. EXISTING SYSTEM

2.1 Using a combination of various structural materials and environments

It attempts to assign useful life values for buildings having various combinations of main (structural) materials and environments. The base case is taken as reinforced concrete because that will probably be the most common building material today. The predominance of structural steel and timber is likely to be seen only in older buildings. A building will have different materials of different qualities in a variety of microenvironments. Poor quality of construction could reduce useful life by up to 20 years; this would depend on the combination of material and environment.

Table 1: Main Structural Elements [6]

Material	Foundation	Walls	Columns & Beams	Floors	Roof
Reinforced Concrete	✓		✓	✓	✓
Masonry	✓	✓			
Steel			✓*		✓
Timber				✓*	✓

This method does not give expected accuracy as it has considered only two parameters that is. Materials and Environment. So a system that takes into consideration various factors is required.

Table 2: Deterioration factors [6]

Material	Moisture	Heat	Settlement	Chemicals	Biological
Reinforced Concrete	corrosion, ingress of chemicals			CO_2, chlorides, sulphates	plant roots
Masonry	softening	movement cracking	movement cracking		plant roots
Steel	corrosion			chlorides	
Timber	biological attack				termite attack

Table 3: Useful life estimator [6]

Case	Main Material	Environment	Useful Life (years)
Base Case	Reinforced concrete	dry[3], non-aggressive	60
Variations in	Structural steel[1]	dry[3], non-aggressive	80
Material	Masonry and/or Timber[2]	dry[3], non-aggressive	100
Variations in	Reinforced concrete	wet[4], non-aggressive	40
Environment	Reinforced concrete	wet[4], aggressive[5]	30

2.2 Mathematic model for predicting the building service life

This method proposed a mathematical model to determine the physical and useful life of buildings, with the latter being deemed to be discounted physical life, where the discount rate is taken as the sum of the obsolescence factors. In other words, the useful life will be shortened owing to various obsolescence factors. The relationship is given by [3]

$$O_i = \sum_{j=1}^{m} X_j = \sum_{j=1}^{m} S_j \times W_j,$$

This method requires a lot of manual calculations and it sometimes does not give accurate results. So a system is required that will reduce or automate the mathematical calculation.

3. PROPOSED SYSTEM

3.1 Find obsolescence

Obsolescence is a phenomenon that is widely used in relation to buildings. ”Obsolescence may be defined as a loss of utility of infrastructure due to the development of improved or superior products or services, although not utility loss due to natural deterioration or decay”. In our proposed system parallels are drawn between obsolescence, depreciation and discounting in order to develop a new method for predicting the impact of building obsolescence based on measurable context factors. These factors have physical, economic, functional, technological, social, legal and political characteristics. Useful life is defined as discounted physical life, where the rate of discount is determined from predicted future obsolescence. As part of the method, a new tool for determining the physical life of buildings is presented.

3.2 Prediction using Machine Learning

Machine learning is an application of Artificial Intelligence (AI) that provides systems with the ability to automatically learn and improve from experience without being explicitly programmed. Machine learning focuses on the development of computer programs that can access data and use it to learn for themselves. Linear Regression: Linear Regression is a well supervised learning algorithm which is used to predictions problems, it finds the target variable by finding the best suitable fit line between the independent and dependent variables.

3.3 Workflow

The workflow of our system is shown in figure 4, which shows the dataflow between modules. This workflow has been explained with the following steps. 1. User will enter the diagnostic score by selecting the appropriate level for each criterion through form 2. Values acquired from the form are passed to the obsolescence module. 3. Obsolescence module predicts the obsolescence rate and this value is passed to the Age Prediction Module. 4. Age Prediction Module will predict the age of the building.

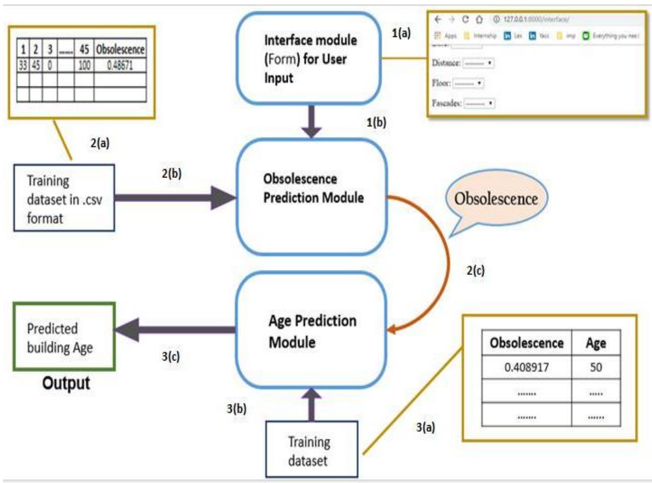

Fig. 1: Workflow

4. IMPLEMENTATION

4.1 Interface module

This module consists of a form where the user is supposed to enter diagnostic scores by selecting Levels from the drop-down list. Diagnostic Scores for the given criteria’s are described in the table given below. User has to enter the diagnostic score in the following manner.

Table 4: Useful life estimator

Levels	Criteria	Diagostic score
Level 1	0%	0%
Level 2	Between 1% to 15%	33%
Level 3	Between 16% to 30%	67%
Level 4	Above 30%	100%

Diagnostic score to individual criteria is weighted by a scoring system. For e.g. If the rating of the criteria is in between 1 % to 15% then entered diagnostic score should be 33%. These scores are stored in the database.

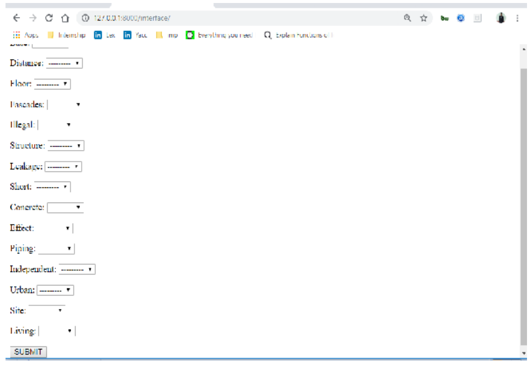

Fig. 2: User Interface (Form)

4.2 Obsolescence module

This prediction module accepts all scores for each criterion and predicts the obsolescence rate. Now, this module is trained on training dataset which consists of records containing scores for all criteria and obsolescence rate respectively. Multiple linear regression algorithm is used in this module. We are using Regression algorithm because we have to predict a value (that is. Obsolescence rate) depending upon the independent variables (that is. diagnostic scores). Since the obsolescence rate depends on many independent variables, therefore, multiple linear regression is best suited for prediction. Obsolescence is predicted in this module.

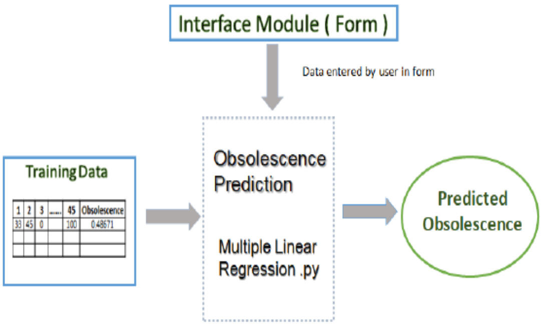

Fig. 3: Obsolescence module

4.3 Age prediction module

This prediction model accepts the obsolescence rate from the previous module. This is trained on training dataset which consists of a single obsolescence value and the respective age. Since age is dependent only on obsolescence rate therefore linear regression is best suited for this module. Age prediction module is shown in figure 4.

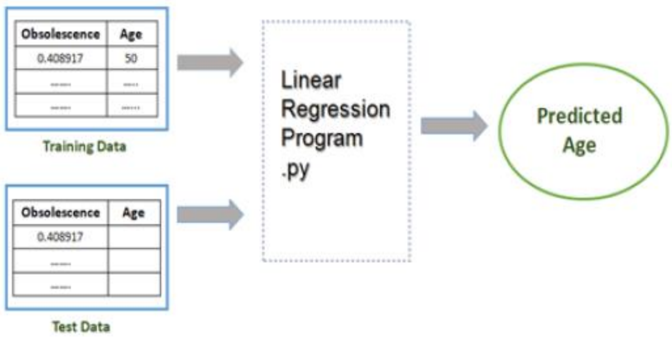

Fig. 4: Age prediction module

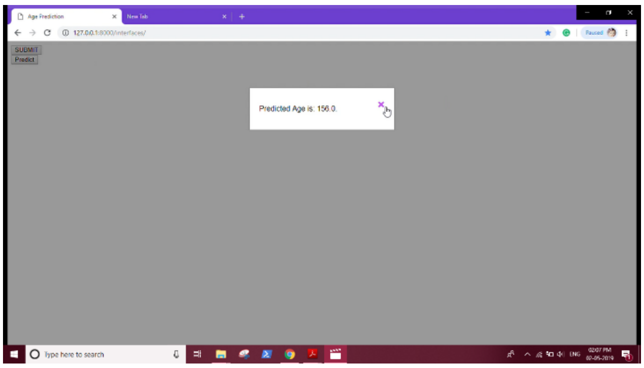

Fig. 5: Output screen

5. CONCLUSION AND FUTURE WORK

In this paper, we have demonstrated the effect of obsolescence rate on building. The system is able to determine the age of the building. The present study outshines the conventional evaluation of building that largely focused on physical obsolescence by taking into account economic, technical, social, functional and political obsolescence factors. These factors have helped us to build a robust prediction model. The model is accurately trained and gives a nearly accurate result on never-seen-before data. It reduces the efforts of manual calculation and hence reduces the calculation errors. Although the above study is only for already constructed buildings, this technique of determining the obsolescence an also be used while construction of a new building structure considering some more basic parameters. Also, changes in the machine learning algorithm can be done to obtain more accuracy in the results.

6. REFERENCES

[1] "Estimating the useful life of buildings", 36th Australasian University Building Educators Association (AUBEA) Conference, aaa2011.
[2] D. CA, "The Sustainability Implications of Building Adaptive Reuse", 2011.
[3] C. Chen, Y. Juan and Y. Hsu," developing A Systematic Approach to Evaluate and apredict"
[4] Building Service Life", Journal of Civil Engineering and Management, vol. 23, no. 7, pp. 890-901, 2017.
[5] J. SKOPEK," factors affecting building performance", aaai2013.
[6] W. Dias,"Factors Influencing the Service Life of Buildings", Engineer: Journal of the Institution of Engineers, Sri Lanka, vol. 46, no. 4, p. 1, 2013.
[7] P. Dias," Useful Life of Buildings", 2013.
[8] https://docs.microsoft.com/en-aus/azure/machinelearning/studio/algorithm-choice.
[9] http://www.learningaboutelectronics.com/Articles/Howaaa-to-retrieve-data-from-a-Django-form-Python.php
[10] http://www.learningaboutelectronics.com/Articles/Hoaaaaw-to-save-data-from-aform-to-a-database-table-in-Django.php
[11] https://www.kaggle.com/fadhli/predicting-house-fiprices-with-linear-regression
[12] https://medium.com/@contactsunny/linear-regression-in-python-using-scikit-learn-f0f7b125a204
[13] https:/towardsdatascience.com/create-a-model-to-predict-house-prices-using-python-d34fe8fad88f
[14] https://youtube.com

