GENETIC ALGORITHMS FOR ACCESSING ENGINEERING PERFORMANCE

by

Luh-Maan Chang[1] and Lei Zhang[2]

ABSTRACT

The performance of engineering activities has significant impacts on the successfulness of implementing industrial construction projects. Improving engineering performance can lead to better project outcomes. Previous studies on engineering performance improvement have either focused on the use of certain techniques or products, or looked at specific engineering processes or areas. There has been a lack of a systematic and analytical approach that improves engineering performance based on the understanding of the relationships between engineering inputs and project outcomes. The paper proposes a generic model, which integrates genetic algorithms with artificial neural networks, for modeling engineering performance measurement and improvement in industrial construction projects. Due to their robust and efficient search ability in complex situations, genetic algorithms are employed to search for solutions to improving engineering performance with the searching criteria, fitness function, being the neural networks that establish the relationships between engineering inputs and project outputs.

KEYWORDS: engineering performance, genetic algorithms, artificial neural networks

1. INTRODUCTION

Industrial construction projects have been experiencing unsuccessful implementation of projects for a long time. An industry survey (Post 1998) reported that one-third of the projects surveyed was over budget and nearly half was delivered late. The development of an industrial facility spans over five stages: pre-project planning, detailed design, procurement, construction, and start-up and commissioning (CII 1997). Early researches addressed the impact of engineering performance on the overall outputs of a project. For example, design errors, changes and omissions could constitute approximately 10% of the total installed costs of a project while construction mistakes account for only about 2% (Davis *et al* 1989). 25% of the facility owners surveyed by Post (1998) ranked detailed design as the weak link in the process of facility development.

The Research Team 156 (RT-156) of Construction Industry Institute (CII) studied the industrial project data collected by CII Benchmarking and Metrics Committee. The study reported that the detailed design phase was a prime source of project schedule delays and that about half of the project scope and development changes were initiated during the detailed design phase. The report also pointed out that design errors were the utmost source of field rework and that design-related field rework surpassed that initiated by both owner and constructor (Georgy *et al* 2000).

Since industrial projects involve huge amount of investment, even a small percentage of cost overrun or schedule delay will result in serious economic loss. Therefore, there is an urgent need to improve project outputs through improving engineering performance. This research aims at searching for approaches to improving engineering performance in industrial construction projects through integrating genetic

[1] Associate Professor, Division of Construction Engineering and Management, School of Civil Engineering, Purdue University, West Lafayette, IN 47907, 765-494-2246, changlm@ecn.purdue.edu
[2] Doctoral Research Assistant, Division of Construction Engineering and Management, School of Civil Engineering, Purdue University, West Lafayette, IN 47907, 765-494-0696, zhang41@ecn.purdue.edu

algorithms with artificial neural networks. Engineering refers to the detailed design phase of an industrial project.

2. PREVIOUS STUDIES ON ENGINEERING PERFORMANCE

Engineering is a systematic process with inputs and outputs. Engineering performance measurement deals with the output side. The ability to successfully perform the engineering and design activities on an industrial construction project depends on various project input variables (i.e., project attributes and conditions), which are essential in driving its engineering performance. There was a lack of analytical scheme that can approximate the cause-effect relationship between engineering inputs and outputs until the research work of Georgy (2000) and CII RT-156, which is part of the foundation of this research study.

CII RT-156 identified a total of 25 engineering input variables and ten engineering performance measures, as shown in Table 1 and Table 2 respectively. A neural-fuzzy system was developed for establishing the relationships between engineering inputs and engineering performance measures. A multi-attribute utility function was used to aggregate the performance measures into a composite index to indicate the engineering performance level (Chang *et al* 2001 and Georgy 2000).

Researchers in the past tried various approaches to improve engineering performance, but most of their approaches are qualitative in nature and have certain limitations. The limitations come from the fact that some approaches promote the use of a specific technique or product and some look at specific areas of engineering and design activities (Armentrout 1986, Atkin and Gill 1986, Breen and Kontny 1987, Choi and Ibbs 1990, Ginn and Barlog 1993). There is a lack of a systematic and analytical approach that looks at improving engineering performance based on the understanding of the relationship between engineering performance and its driving factors.

3. THEORIES

3.1 Artificial Neural Networks (ANNs)

ANNs are an information processing technology that simulates the human brain and nerve system. Their basic element is also called neuron (or node). All neurons are organized in layered structure and connected with weighted links. There is always an input layer where the initial stimulus happens, and an output layer where the final reaction of the system is shot out. ANNs' two major functions are learning and recall. Learning is the process of adapting the connection weights in an ANN to produce the desired outputs in response to inputs. Recall is the process of producing outputs in accordance to specific inputs using the knowledge obtained through learning (Tsoukalas and Uhrig, 1997).

3.2 Genetic Algorithms (GAs)

GAs are robust general-purpose search program based on the mechanism of natural selection and natural genetics (Holland 1972). Genes and chromosomes are the fundamental elements in GAs. A chromosome is a string of genes. In a real problem, genes are the variables that are considered influential in controlling the process being optimized, and a chromosome is a solution to the problem. GAs search for the optimal solution from populations of chromosomes. In this research, the genes are the 25 input variables in Table 1. A chromosome is a set of the 25 input variables. There is an objective function (preferably called fitness function) in GAs. The search process seeks the maximum or minimum value of the fitness function.

4. MODELS

The fundamental approach of the research is to employ GAs to search for the engineering performance inputs that lead to optimal engineering performance. The ANN system shown in Figure 1 serves as a complicated fitness function. Two models were built.

- Engineering Performance Index Model (EPI Model).
- GA-ANN-Integrated Search Model (GA-ANN Model).

4.1 EPI Model

EPI model is in essence the framework of CII RT-156. As illustrated in Figure 1 and Figure 2, EPI model is comprised of two parts. The first part is 10 neural networks that establish the relationships between the 25 engineering inputs and the 10 engineering performance measures respectively. The second part is a multiple attribute utility function that takes the outputs from the 10 neural networks in the first part as its inputs and translates them into a composite utility score, engineering performance index.

The 10 neural networks, after being trained, can predict performance measures for given engineering inputs. The 10 engineering performance measures depict, from different perspectives, the quality of outputs of engineering activities. However, if it is required to evaluate a project or to compare it with another one, it will be hard to make the judgment when 10 varying measures are presented. Therefore, there comes the need for a single composite measure that indicates the overall level of engineering performance and contains the information embedded in the 10 measures. Through multiple attribute utility function, an engineering performance index is defined on the scale of [0, 1] with 0 depicting the poorest engineering performance and 1 the best performance.

Thus, through the trained neural networks, if given engineering inputs, EPI model can make prediction on engineering performance through both a group of 10 different measures and an overall engineering performance index. The set of 10 measures gives a comprehensive view of engineering performance. The engineering performance index will be used as fitness function value in GA-ANN model.

4.2 GA-ANN Model

GA-ANN model, as shown in Figure 3, depicts a typical genetic search process. Its most distinguished feature is the fitness function, EPI model, where the GA-ANN integration happens. GA-ANN model searches the engineering inputs that lead to better engineering performance. The genetic search starts with an initial population. The initial population is comprised of a number of individuals. Each individual is a chromosome consisting of 25 genes, each of which corresponds to an engineering input in Table 1. For a given project, the input variables related to basic project attributes including general project attributes, general owner attributes and general designer attributes (refer to Table 2) will be kept constant throughout the genetic search; all other input variables subject to the changes in the actual project execution will be manipulated by genetic operations in order to form better combinations of the variables.

GA-ANN evaluates all individuals, keeps the good ones, reproduces the good ones, and sometimes transforms the good ones to make even better ones, … until satisfactory individuals are produced. First of all, the individuals in the initial generation are evaluated through the fitness function, EPI model. First, Each individual is presented to the 10 trained neural networks that predict its 10 corresponding engineering performance measures. Second, the multiple attribute utility function transforms the 10 predicted measures into a composite engineering performance index, which is the fitness function value of the individual.

Then, the initial generation goes through the genetic operations: selection, reproduction, crossover and mutation. First, the individuals with higher fitness function values get selected and the worse ones eliminated, which means that the engineering inputs that create better engineering performance are kept. Second, the selected ones are reproduced and crossovered. Lastly, a certain percentage of the individuals go through the mutation process which transforms a certain number of genes of the individuals. The mutation process might make the mutated individuals better or worse. Thus, the second generation is formed.

The second generation also goes through fitness evaluation, selection, reproduction, crossover and mutation. Some individuals better than those in the second generation are assembled and come into the third generation. The general trend is that the individuals become better and better from generation to generation. In other words, the level of engineering performance becomes higher and higher.

The genetic search process keeps going on until a certain termination criterion is met. Usually the termination criterion can be a desired fitness value, the maximum number of generations, or computation time. By the time the process stops, one or more sets of engineering inputs will be identified as the ones that lead to an engineering performance level close or equal to the desired level.

4.3 Relationships Between the Models

EPI model establishes the relationships between the engineering inputs and engineering performance measures and aggregates the measures into a composite index to indicate the level of engineering performance. GA-ANN model does the genetic search for better engineering performance using EPI model as the fitness function while EPI model provides engineering performance prediction for given engineering inputs.

5. ANTICIPATED APPLICATIONS OF THE MODELS

For past projects, GA-ANN model and EPI model work together to search better engineering performance and the corresponding engineering inputs. Then, the actual engineering inputs can be compared with the those searched by GA-ANN model and the comparison might be able to indicate what could have been done to achieve better engineering performance.

For future projects, GA-ANN model looks for the possible better engineering inputs and outputs for the project. These anticipated project inputs and outputs might act as the guideline and goal for the actual project execution.

6. DATA ANALYSIS

The project data for validating the proposed models are being collected by the authors. The result of data analysis is expected to be presented at the conference.

7. CONCLUSIONS

This paper proposed a systematic approach to improving the practice of engineering performance. The fundamental idea is to find the possible best practice of engineering activities for a given project. To pursue this, genetic algorithms and artificial neural networks are employed to build the models. Artificial neural networks provide the ability to establish the relationships between engineering activity inputs and engineering performance outputs, and genetic algorithms serve as a search engine to find the possible best engineering practice based on the relationships between engineering inputs and outputs identified through artificial neural networks.

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Table 1 Engineering Input Variables

Category	Variables
General project attributes	Project size (total installation cost)
	Contract type
	Relative size of project compared to projects of the same industry type
	Relative level of complexity
	Site conditions
	Legal and environmental conditions
General owner attributes	Owner profile and participation
	Newness of process technology to owner
	Owner previous experience with designer
General designer attributes	Split engineering practices
	Designer qualifications and capacity
	Newness of process technology to designer
Project schedule	Design schedule
	Design-construction overlap
Project information inputs	Completeness of scope definition
	Completeness of objectives and priorities
	Completeness of basic design data
	Quality of constructor input and constructability
	Quality of vendor data
Level of automation	Use of 3D CAD modeling
	Use of Integrated Databases (IDB)
	Use of Electronic Data Interchange (EDI)
Project changes	Percent TIC scope changes
	Change management procedure
	Change communication system

Table 2 Engineering Output Variables (Engineering Measures)

Category	Variables
Detailed design value	% design rework
	Design document release commitment

	% detailed design schedule delay
	% detailed design cost overrun
Fabrication and construction value	% fabrication and construction schedule delay due to design deficiencies
	% fabrication and construction cost overrun due to design deficiencies
	% construction hours for design problem solving and field design
	% estimated dollar savings due to constructability
Start-up and commissioning value	% start-up schedule delay due to design deficiencies
	% start-up cost overrun due to design deficiencies

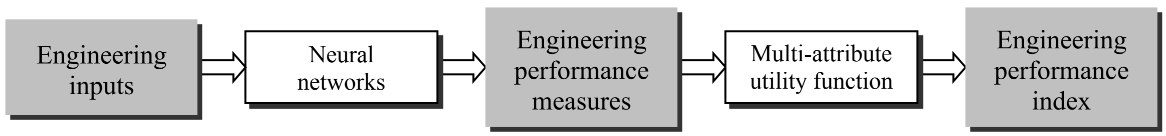

Figure 1. EPI Model -- General Idea

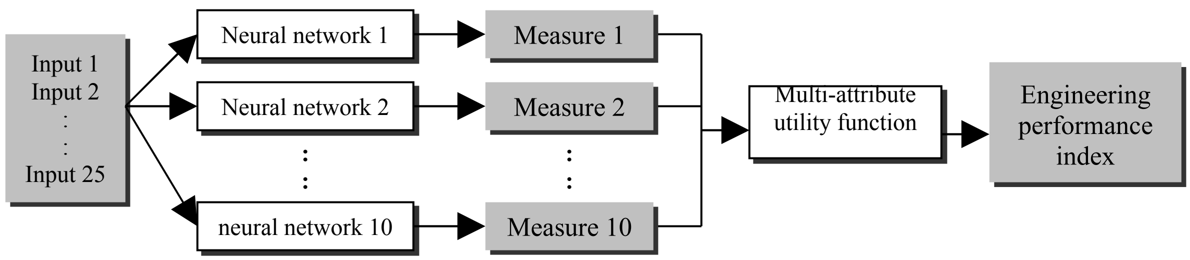

Figure 2. EPI Model -- Breakdown

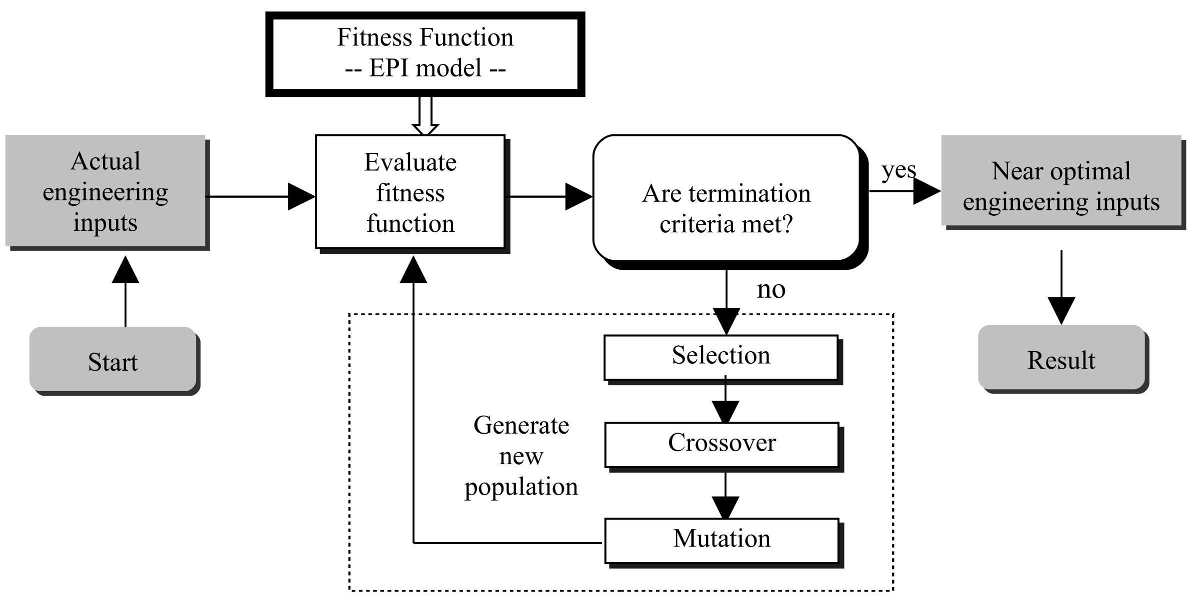

Figure 3. GA-ANN Model