COST ESTIMATING MODEL FOR SUSTAINABLE REHABILITATION OF ROAD PROJECTS

Final Report

METRANS Project # 11-25

July 2012

Principal Investigator

Tariq Shehab

College of Engineering
Department of civil Engineering and Construction Engineering Management
California State University, Long Beach

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ABSTRACT

There are about 3,000,000 miles and 50,000 miles of paved roads and highways in the US, respectively. Many of these roads and highways have approached the end of their design life and are considered to be in poor conditions. To upgrade these valuable infrastructure assets in a sustainable manner, state and federal governments have suggested the use of the rubberized asphalt technology. The use of this sustainable rehabilitation technique has been suggested to meet the current needs without compromising the ability of future generations to meet their own demands. This research develops a cost estimating system for the rubberized asphalt road rehabilitation projects. The proposed system uses information collected from 44 projects and applies neural networks for performing its task. It is believed to be a helpful tool that could be used in many road project applications such as preparation of accurate budget estimates and life-cost analysis. It is also considered to be an efficient tool that could be used to manage financial resources in limited budget environments.

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Abstract

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Introduction

Roads and highways are among the most important infrastructure systems in the US. They are used by about 88% of Americans for mobility purposes. The conditions of the majority of these roads and highways are considered to be in a bad shape (ASCE 2009). It has been documented that about 55% of arterial and major collector pavement conditions are either poor or mediocre (TRIP 2011). Furthermore, the Federal Highway Administration has reported that the percentage of "acceptable" ride quality, which is a measure of pavement conditions, has declined by up to 15% over the past several years (ASCE 2009). The poor condition of road and highway networks attributes to the death of about 35,000 persons per year and costs the economy about $80 billion per year in wasted time and extra fuel consumption (TRIP 2011 and ASCE 2009). To improve the condition of road and highway networks, it is estimated that about $200 Billion per year is required (ASCE 2009).

In order to plan ahead and allocate budgets to road and highway rehabilitation projects, their cost estimates are required. Interviews with California State officials revealed that current project cost estimating practices may lead to the production of over/under estimates by up to 50%. Obviously, this practice may lead to either improper utilization of available financial resources and/or interruption of projects' progress until more funds are approved in upcoming fiscal years. Interviews with California State officials have also revealed that most used cost estimating models were developed using information that were extracted from rehabilitation projects in which conventional pavement materials were used such as, asphalt and concrete.

Although many conventional pavement rehabilitation techniques have been used in the industry for very long time, other sustainable ones have become more preferred and encouraged to be used by local and federal governments. The encouragement to use sustainable rehabilitation techniques is mainly to ensure that future generations will meet their economic, environmental and social transportation needs in the best possible manner. It should be noted that many of these sustainable techniques involve the use of rubberized asphalt technology. The use of this technology does not only save the environment, but it also improves durability, crack propagation, fatigue and skid resistance of roads and highways (Xiao and Amirkhanian 2009). Other benefits of rubberized asphalt have been documented in the literature such as, high resistance to rutting and lower maintenance cost due to its high durability and performance criteria (Caltrans 2006). Environmental benefits of rubberized asphalt include diminishing heat island effects and providing a diversion for three quarters of all the scrap tires which would have ultimately been headed to a landfill (CalRecycle 2011). On average, a two-inch-thick RAC resurfacing project uses about 2,000 scrap tires per lane mile (CalRecycle 2011)

Although the rubberized asphalt rehabilitation technology has been developed in the late 1930s and used in California in limited patching applications in the early 1980s, it has not been used in full overlay applications until 2005 (CalTrans 2006). With the use of the rubberized Asphalt in full overlay road rehabilitation projects, comes a need for the development of project cost estimating model that assists to better manage this domain of projects.

Rubberized asphalt mixes could be produced using three main processes: 1) wet process; 2) dry process and 3) terminal blend. The most commonly used one in California is the wet process (Caltrans 2006). According to this process, rubberized asphalt is defined as a blend of asphalt, reclaimed tire rubber and certain additives. The rubber component must be 15%, at least, by weight of the mix (Caltrans 2006). This type of asphalt mix is produced at high temperature and under high agitation to keep the rubber particles suspended in the asphalt mix (Caltrans 2006). It should be noted that while dry mixes partially substitute standard aggregate content in conventional asphalt mixes with reclaimed tire rubber (i.e. the asphalt mixes contain aggregate and reclaimed tire rubber), Terminal Blend mixes contain rubber only but not agitated with the asphalt binder.

To better manage full overlay rubberized asphalt road rehabilitation projects, an accurate budget estimating system is proposed. This accurate system will prevent over and/or under estimation of project costs and accordingly, will ensure proper utilization of financial resources. Proper utilization of financial resources will not only maximize the number of rehabilitation projects performed and road miles improved, but will also ensure smooth continuation of rehabilitation projects and help to avoid waiting for more funds to be allocated in future fiscal years. Furthermore, the proposed system satisfies the industry need for the development of a specific cost estimating model that focuses primarily on rubberized asphalt road rehabilitation projects. It also augments the currents models described in literatures that are applicable only to conventional asphalt and concrete pavement rehabilitation projects (Chou et al. 2006, Kyte et al. 2004, Xin-Zheng et al. 2010, Irfan et al. 2010, Wilmot and Cheng 2003, Chou and O’Connor 2007, Bell and Bozai 1987). It should be noted that the use of proposed model is limited to projects in which wet rubberized asphalt mixes are used.

Model Development Methodology

The model was developed through three main steps. First, data was collected form a set of 44 projects that were constructed in State of California during the period of 2005-2008. Second, the collected data was analyzed, using Pareto technique, to determine the bid items that contribute to 80% of cost of projects. Third, information pertaining to these bid items were further processed, using neural networks, to develop and test the proposed cost estimating model. The following sections describe these processes in detail.

Data Collection

Data was collected using Office Engineer Database, which was developed by California Department of Transportation (Caltrans) and is posted on its website. Office Engineer is a quick reference database where Caltrans project information are saved. The database hosts projects that were advertised for bidding between the year 2000 and the present. To query for a specific type of projects, key words are entered into the online search field to generate a list of desired projects.

The set of projects extracted from the Office Engineer Database consist of 44 projects that were constructed in Los Angeles, Ventura, Orange, and San Diego counties during the period of 2005-2008. The cost of these projects range from $110,000 to $4.7 million. The projects contained up to 102 bid items. It should be noted that more sample projects would have been used in this study if overall rubberized rehabilitation projects were performed in California before 2005 and information pertaining to 2009 rubberized projects were available to the research team by the time this research work started in 2010.

Data Analysis

To determine the bid items that contribute to the majority of cost of projects, Pareto analysis which is sometimes referred to as 80/20 rule was used. Pareto analysis is a technique used to select a limited number of items that produce significant overall impact. Pareto analysis has been used to develop many cost estimating models for construction projects such as, bridges and utility pipes (Chou et al. 2005 and Shehab et al. 2010).

In order to perform Pareto analysis, each project was considered individually. The percentage contribution of each bid item was determined and, accordingly, the bid items were arranged in a decreasing order. The bid items that contributed to a minimum cumulative cost of 80%, in each project, were determined. Since not two projects are alike, this analysis revealed non-identical lists of bid items. For uniformity purposes, a common set of bid items needed to be determined for all projects. In so doing, all projects were re-analyzed. In this re-analysis process, it was noticed that about 75% of total cost, in all projects, are controlled by about 6 bid items. For each 1% cost increase, 5-8 additional bid items need to be considered. In other words, if 80% of cost needs to be maintained, about 40 bid items need to be considered.

Accordingly, the research team had two choices. The first one was to come up with a common set of bid items that is associated with a minimum of 80% of cost in all project cases. The second choice was to slightly reduce the 80% limit in a manner that does not greatly jeopardize the performance of the proposed model. In other words, it was a trade off between the number of bid items and their associated total cost. In an effort to simplify the use of the proposed model, the research team selected to focus on the bid items that contribute to 75% rather than 80% of total cost of projects. Accordingly, a total of common six bid items were selected. These common bid items are the quantity of rubberized asphalt (tones), quantity of cold plane asphalt (yd^2), quantity of thermoplastic traffic stripes (LF), quantity of thermoplastic pavement marking (LF), quantity of retro-reflective pavement marker (number of pieces) and quantity of inductive loop replacement (number of loops). These bid items contributed to 75%-96% of the cost in all project cases. While rubberized asphalt types and technology were explained earlier in this paper, retro-reflective pavement markers are devices that are used to improve safety on roads such as, cat's eyes. The following paragraphs explain the other four selected bid items.

In order to replace old pavement with new rubberized asphalt pavement the old pavement must first be removed. The process of removing this asphalt is referred to as cold planning. More specifically, cold planning is the process by which asphalt or concrete pavement is ground up and removed to a certain depth, usually 3-4 inches, in order to repair or re-profile pavement surfaces. Cold planning is used to re-establish pavement profiles and can also be done for the purposes of improving drainage flow from pavement irregularities, removing deteriorated pavements for future overlays, or be used to fine texture driving surfaces to improve skid resistance (CalRecycle 2011).

Thermoplastic is a plastic material that turns to a liquid when heated and freezes to a glassy state when cooled sufficiently. In asphalt pavement applications, thermoplastic material is used to draw lane striping, crosswalks, stop bars, turn arrows and lettering (Heydorn 2008). When used to draw lane striping the specification is referred to as "Thermoplastic Traffic Stripe", and when used in any other application it is referred to as "Thermoplastic Pavement Marking", both of which are key factors in the execution of a roadway resurfacing project. Thermoplastic materials are applied by locally heating the RAC surface, then laying out the material, and then heating the material in place until a permanent bond is created. Once material has cooled it is ready to accept traffic loads.

Cost Estimating Model Development

To develop the cost estimating model, information pertaining to the six selected bid items need to be further processed across all project samples. To process this information, two model development techniques were considered: 1) regression and 2) neural networks (NNs). Due to the great prediction performance of neural networks and its proven capabilities, compared to regression techniques, in many civil engineering applications (Shehab et al. 2010, Shehab and Farooq 2009, Kim et al. 2005, Wilmot and Mei 2005, Khan et al. 1999, Hegazy and Ayed 1998), they were selected for the development of the proposed system. This superior performance is partially attributed to the lack of enough data that may be required to perform reliable regression analysis (Shehab et al. 2010).

Among the different types of neural networks, back-propagation paradigm is considered to be the most commonly used in many engineering applications (Shehab et al. 2010, Shehab and Farooq 2009 and Wilmot and Mei 2005). Back-propagation neural networks consist of an input layer, one or more hidden layers and one output layer (Figure 1). Each layer contains a number of neurons that are interconnected between different layers. Many references such as, Skapura, 1996; Tsoukalas and Uhrig, 1997; Looney, 1997 provide further information about structures and raining process of this type of network.

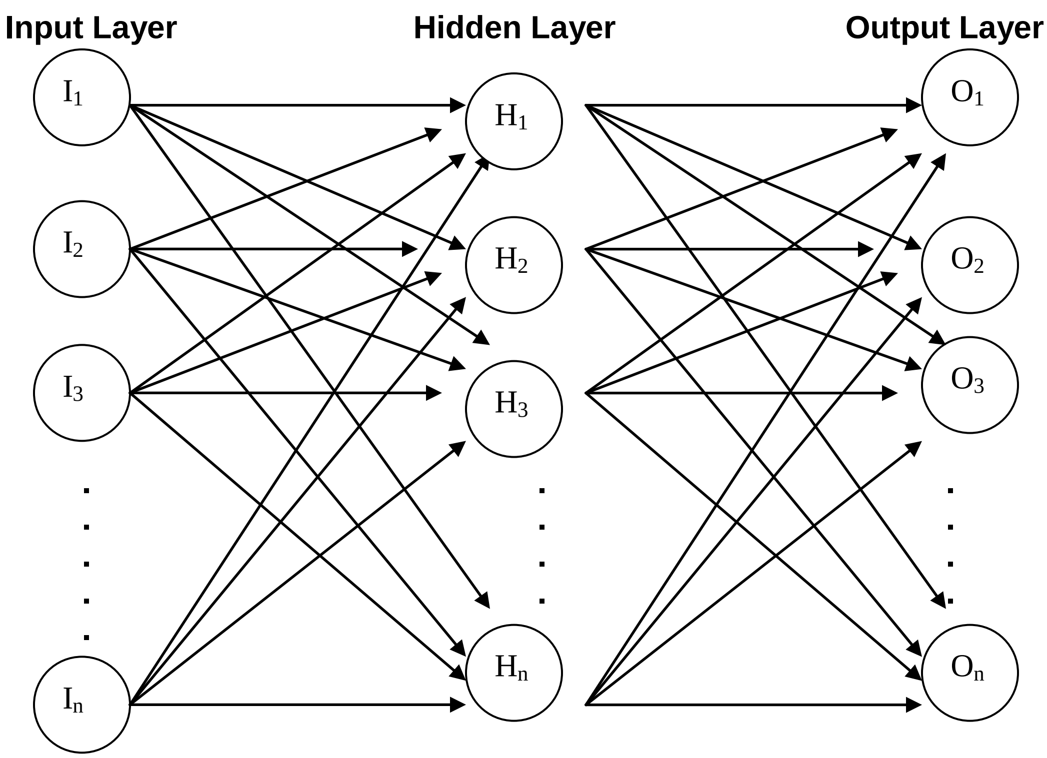

Fig. 1. Back-Propagation Neural Networks

To train the proposed back-propagation cost estimating neural network, the input layer was built with six neurons. Each neuron is associated with one of the most important project bid item that was determined using Pareto analysis (i.e. quantity of rubberized asphalt, quantity of cold plane asphalt, quantity of thermoplastic traffic stripes, quantity of thermoplastic pavement marking, quantity of retro-reflective pavement marker and quantity of inductive loop replacement). While the output layer consists of one neuron that reports the predicted cost of projects, the hidden layer consists of 21 neurons. It should be noted that the near optimum number of hidden neurons that provide reliable estimates is determined using trial and error process (NeuroShell-2 2004).

To train the above described neural network structure, the 44 sample projects were randomly divided into three parts without prior knowledge about their type and/or bid items listed as description of their scope of activities. These parts are 28 projects for training, 8 projects to monitor the performance of the training process and 8 projects to test and validate the trained network. It should be noted that these proportions were suggested by Neuroshell-2, 2004. The performance of the developed neural network is measured through three main criteria. These criteria are the coefficient of multiple determination (R^2), correlation coefficient (r) and percent within 5%, 5%-10%, 10%-25%, 25%-35% and over 35% (NeuroShell-2 2004). Table 1 demonstrates the performance of the developed network on the randomly selected training set (i.e. 28 projects). As shown in this table, the (R^2) and (r) values are 0.93 and 0.97, respectively, which indicate that the developed model well explains the variation in the predicted cost and Pareto analysis did actually reveal the most important bid items that positively contribute to the cost estimating process. Results presented in Table 1 show also that the cost of 85.7% of the training projects were predicted within a variation of 25%, as compared to their actual cost. It should be noted that this 25% cost variation is mainly attributed to the Pareto principle that predicted it upfront.

Table 1. Performance of the developed NN on the training set

Coefficient of multiple determination (R^2)	0.9339
Correlation coefficient (r)	0.9687
Percent of projects predicted within 5%:	17.857
Percent of projects predicted within 5% to 10%:	17.857
Percent of projects predicted within 10% to 25%:	50.0
Percent of projects predicted within 25% to 35%:	0
Percent of projects predicted over 35%:	14.286

Table 2 presents the performance of the developed network on the testing test that consists of 8 projects. It should be noted that since bid items of rubberized asphalt pavement rehabilitation projects vary from one project to another, as was explained in the data analysis section, the performance of the developed model was tested using 8 randomly selected projects that include different set of bid items which reflect the variation nature of road rehabilitation project components. As shown in this table, high (R^2) and (r) values are reported, which prove the generalization capability of the developed network. Furthermore, the cost of all projects included in the testing sample was predicted within a maximum variation of 25% compared to their actual cost. As can be noticed, these results match earlier expectations as explained by Pareto principle. Although 8 test projects might not be large enough to conclude the good performance of the developed model, they definitely demonstrate the high potential of the proposed cost estimating methodology.

Table 2. Performance of the developed NN on the testing set

Coefficient of multiple determination (R^2)	0.9350
Correlation coefficient (r)	0.9876
Percent of projects predicted within 5%:	25.0
Percent of projects predicted within 5% to 10%:	25.0
Percent of projects predicted within 10% to 25%:	50.0
Percent of projects predicted within 25% to 35%:	0
Percent of projects predicted over 35%:	0

Table 3 presents more detailed information about the predicted and actual costs of projects included in the testing sample. As shown in this table, while the cost of project no. 1 was almost predicted on target, the cost of projects no. 5, 6, 7 were predicted with more than 90% accuracy (i.e. 91%, 92.9% and 97.5%, respectively). As can be noticed also form this testing sample, the cost of four projects were over or under estimated (i.e. projects no. 2, 3,4 and 8). While the under estimated costs in cases of projects no. 2 and 8 could be mainly attributed to the Pareto principle, more in depth analysis was needed to understand the reason behind the over estimation in cases of projects no. 3 and 4. Upon further analysis of projects no. 3 and 4, it was noticed that both of them had very low number of loop detectors (i.e. 1.0) which is much less than the average number of loop detectors that the network was trained on (i.e. 50).

Table 3. Actual vs. predicted cost

Project #	Actual Cost ($)	Predicted Cost ($)	% variation
1	518556.6	521760.3	+ 0.62
2	696149	527658.6	- 24.2
3	767712	941289.3	+ 22.6
4	612997.8	762003.1	+ 24.3
5	947915.7	862735.8	- 8.9
6	1048287	973726.8	- 7.11
7	3096124	3017804	- 2.53
8	4720270	3738888	- 20.79

Conclusion

An artificial intelligence cost estimating system for full overlay rubberized asphalt pavement projects was developed. The system uses six bid items only and back-propagation neural network for performing its task. It augments current cost estimating systems that are applied to conventional asphalt pavement, concrete pavement and rubberized asphalt patching repairs only. The system was developed using a set of 44 projects that were built in California during the period of 2005-2008. The testing results reveal that although the system tends to underestimate the cost of projects, its accuracy ranges between -24% and 24%. While about 75% of testing projects were underestimated by 2.5%-24%, 25% of testing projects were overestimated by about

24%. The underestimation and overestimation performance of the developed system is mainly attributed to the Pareto assumption and unavailability of similar projects on which the neural network was trained, respectively. It should be noted that the these system presented results show big improvement compared to current cost estimating processes that may provide up to 50% inaccuracy.

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