ARTICLE IN PRESS
AUTCON-02145; No of Pages 9
Automation in Construction xxx (2016) xxx–xxx

Contents lists available at ScienceDirect
Automation in Construction
journal homepage: www.elsevier.com/locate/autcon

Improving consumption estimation of electrical materials in residential building construction

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ARTICLE INFO

Article history:
Received 24 August 2015
Received in revised form 24 August 2016
Accepted 25 August 2016
Available online xxxx

Keywords:
Building material consumption
Estimation
Electrical systems
Intelligent systems
Artificial neural network
Data mining
Feature selection
Information extraction

ABSTRACT

Estimating the amount of materials necessary for deploying electrical systems in buildings is a difficult task since these systems are complex and highly correlated with the design of other building systems. In Brazil, the usual method for estimating the consumption of electrical materials relies on constant rates per electrical points, incurring in large estimation errors. Furthermore, these rates can only be used in advanced project phases. This paper proposes a novel method for estimating the consumption of electrical materials, based on artificial neural networks (ANNs), by using information from early project stages. A dataset with project attributes was used to construct the ANN estimation models. In order to evaluate these new models, their estimates were compared to results from linear regression and constant rate models. Results showed that the ANN models have better performance when compared to other methods, supporting that ANNs are well suited for nonlinear and multidimensional problems. This investigation, therefore, supports that the method proposed could also be used by construction companies for estimating the consumption of other materials.

1. Introduction

Cost estimation in early construction phases is a critical aspect for the success of a project. In general, existing estimation models predict the global cost of the project in a feasibility study stage, when limited information is available. The estimation is then upgraded when the design evolves, and more information is made available until the project is finished and its cost is confirmed [1]. Particularly, cost estimations done during feasibility studies and design processes are important to support decision making. Overall, when decisions involve building systems, models for estimating material consumption, and not only the global cost, are required.

The construction industry presents different characteristics from the manufacturing sector, for example, production occurs at the construction site, making it harder to forecast and plan processes, materials, and costs. This increases the importance of the familiarity and experience of a company with the type of project they are working on, in order to make decisions in early stages. However, when this knowledge is not enough, it is necessary to use accurate information from past projects, which must be readily available [2].

Currently, in Brazil, consumption estimation is done using constant rates. For example, it is considered that each power outlet will consume 33 m of 2.5 mm^2 wires. The main reference handbook for these rates, which is also used for public biddings, is the Price Composition Table for Estimates (TCPO - *Tabela de Composições de Preços para Orçamentos*) [3,4], published in 1955 and currently in the 14th edition. The TCPO presents rates for material consumption, labor and machinery productivity. The use of these one-dimensional rates leads to significant estimation errors since material consumption estimation is a multidimensional task and a non-linear problem. For example, a power outlet in a 50 m^2 apartment should consume less wire than a power outlet in a 200 m^2 apartment, due to the shorter trajectory.

In early project stages, estimating material consumption of electrical systems is very hard since their design depends on various characteristics of architectural and structural design, and even on the building layout, which is yet not available [5]. Trajectories of conduits and conductors are complex and make material consumption harder to quantify. Many Brazilian construction companies do not quantify this consumption at the end of the design phase and use reference consumption data based on the comparison with previous projects [4]. In this case, decisions on design are made blindfold and

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http://dx.doi.org/10.1016/j.autcon.2016.08.042
0926-5805/

Please cite this article as: R. Milion, et al., Improving consumption estimation of electrical materials in residential building construction, Automation in Construction (2016), http://dx.doi.org/10.1016/j.autcon.2016.08.042

the consequences regarding consumptions and, therefore, project costs are not properly analyzed. The use of simple comparisons without understanding how variables influence material consumption can lead to large errors [6].

Although material consumption estimation is not a commonly addressed subject, the estimation of global construction costs is a very explored subject with similar characteristics to this investigation, such as multidimensional nonlinear inputs and outputs. Several tools were used to create cost estimation models, such as case-based-reasoning (CBR) [7,8], multiple regression analysis [9], genetic algorithms [10] and artificial neural networks (ANNs) [11]. Although ANN models are considered black boxes, where details of their structure are too complex or not even available, their results are undoubtedly more accurate than those from other tools already used [2,12]. ANN models were also used with success for estimating the consumption of concrete in structures [13].

This study presents a method for estimating the consumption of electrical materials by using ANNs. The method can use information available from feasibility studies or preliminary designs.

Data regarding the consumption of electrical materials from 59 different projects were collected to construct the ANN models. Data were analyzed so that better relationships between inputs and estimated outputs could be obtained. An outlier protection methodology was applied to make the models more robust. In addition, models were trained and validated through cross-validation. Results from the ANN models were compared to results from the TCPO, which is the current method used for estimating consumption, and to linear regression models, which is the simplest regression tool available, that estimates relationship between attributes, and could be easily used to solve linear problems. The developed estimation models presented better results than TCPO and linear regression models. Furthermore, the proposed models could be used in feasibility studies and not only when the number of electrical points is available.

It is expected that the proposed method will be used by construction companies to estimate material consumption and to support decision making in the design and deployment of electrical systems and other building systems.

1.1. Artificial neural networks

ANNs are studied by a knowledge area called intelligent systems, which includes other tools such as swarm intelligence, fuzzy systems, and intelligent agents. ANNs are computational algorithms inspired by the human brain and composed of set of processing units, the artificial neurons, interlinked by connections, namely, the artificial synapses. These connections are implemented by vectors and matrices, which are called synaptic weights. The most relevant features concerning ANNs are:

1. Adapting from examples: when an ANN is trained, its synaptic weights are adjusted with the examination of examples, so it maps given inputs into the correspondent outputs. Thus, ANNs acquire knowledge from experience.
2. Learning capability: Through the use of a learning method, the network can extract the existing relationship between the several variables comprising an application.
3. Generalization capability: After the learning process, ANNs can generalize the acquired knowledge and estimate solutions so far unknown [14].

ANNs can be employed in several problems in engineering and sciences, such as optimization, control, estimation, and classification problems. In this investigation, they were used as universal curve fitting tools, mapping the functional relationship between inputs and outputs. ANNs are useful to map complex processes that are difficult to model using traditional methods [15]. An ANN is made up of a set of artificial neurons. The general model for an artificial neuron is illustrated in Fig. 1. Signals ($x_1 \ldots x_N$) are input data, $w_1 \ldots w_n$ are the synaptic weights, θ is the neuron threshold, and y is the output of the neuron. This output is obtained by applying a function $g(.)$ to the signal u, which represents the linear combination of the inputs, i.e., the summation of the weighted inputs.

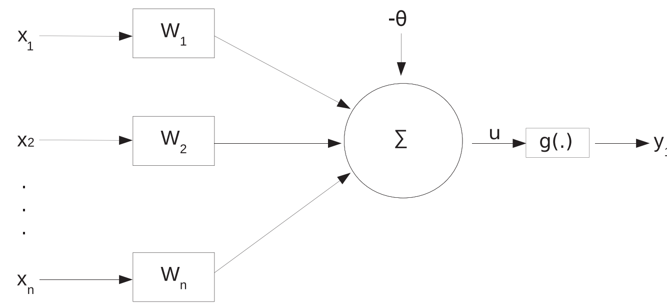

Fig. 1. Artificial neuron model.

The architecture of an ANN defines how its several neurons are arranged. These arrangements are structured by orienting the synaptic connections. In this study a particular architecture was used, the Multilayer Perceptron (MLP), with one hidden layer of neurons, the input and output layers, and with the information flux from the input layer to the output layer, known as the feed-forward structure. Fig. 2 illustrates an MLP.

The input layer is responsible for receiving the data, which can be measurements or signals from the external environment or samplings from experiments and simulations. The hidden layer contains the neurons, which are responsible for extracting the information required in the process. The output layer, also formed by neurons, is responsible for producing the output value.

An MLP with one hidden layer is capable of representing functions, working as a universal fitting tool [16]. Given a particular architecture, the number of neurons in each layer of the network has to be defined. The neurons of the input and output layers are defined by the number of input and output parameters, the number of neurons in the hidden layers can be set to achieve the best performance [17].

Training an ANN consists of applying a learning algorithm in order to adjust its synaptic weights and thresholds. There are several training algorithms and they can be classified as supervised, unsupervised, offline and online. In this study, the supervised backpropagation training algorithm was used. Such adjustment process aims to tune the network so that its outputs are close to the desired values. The supervised learning strategy consists in having available the desired outputs for a given set of inputs; in other words, each training sample is composed of the input signals and their respective outputs. Therefore, it requires a table with input/output data, where each sample is called an instance. In this case, the application of supervised learning only depends on the availability of such data. The supervised learning algorithm teaches the network what is the correct response for each instance presented. After the adjustments, the network can produce outputs from new inputs based on what was learned.

The synaptic weights and thresholds are continually adjusted through comparisons, made by the learning algorithm, between the produced outputs and the desired outputs. The differences are used as a guide for the adjustment procedure. Training algorithms have parameters to be set, such as the learning rate, which increases or decreases the adjustments that are done in each training iteration, and the momentum, which increases or decreases the learning rate in each iteration. The training process stops when the difference between the network response and the desired output stabilizes or

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