Materials and Design 30 (2009) 1685–1690

Contents lists available at ScienceDirect

Materials and Design

journal homepage: www.elsevier.com/locate/matdes

Artificial neural network approach for predicting optimum cure time of rubber compounds

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ARTICLE INFO

Article history:
Received 15 May 2008
Accepted 9 July 2008
Available online 16 July 2008

Keywords:
A. Elastomers and rubber
C. Vulcanisation
G. Thermal analysis
Artificial neural networks (ANN)

ABSTRACT

Artificial neural network (ANN) technique has emerged as a powerful tool which can be used for many scientific and/or engineering applications such as process control and system modelling. ANNs are inspired by the nervous biological architecture systems consisting of relatively simple systems working in parallel to facilitate quick decisions. In this study, three different ANN architectures: multilayer perceptron (MLP), Elman network and generalized regression neural network (GRNN) were used for modelling cure curves of a selected rubber compound at different temperatures. The ability of selected ANN architectures on predicting optimum cure times of 11 different rubber compounds in a model tire was studied. Equivalent cure concept, that is traditionally used in rubber and tire industries, was also applied to pre-determine optimum cure times of the same compounds. The results of two techniques, i.e. ANN and equivalent cure concept were compared in view of percentage error criteria. It has been concluded that ANN could be used as a powerful and simple alternative technique for prediction of optimum cure time.

1. Introduction

The curing process is the final step in tire manufacturing, whereby a green tire built from plies made of rubber compounds and reinforcing fabrics. Curing and shaping of tires are accomplished by internal and external heat treatment. In curing process, green tire is placed into curing machine while a bladder permanently remains inside of the green tire and the desired shape of the tire is formed during its curing in press. The major operating variables of the curing process are the conditions of the supplied cure media, which are to be varied according to the specified temperature and pressure of the cure media as a function of time so that the rubber compounds may attain specified degree of cure. But in practice, the distributed nature of the heat transfer mechanism makes it difficult to have every compound reach the respective target level. Interior layers of a tire cannot be fully cured without causing the overcure of surface layers and the consequent reversion of vulcanized crosslinks. Accordingly, it becomes necessary to make trade-offs between different parts of the tire with respect to the attainable degree of cure [1].

Three main steps of rubber cure can be distinguished in the cure curve regions for a typical accelerated sulfur vulcanization process as shown in Fig. 1. In the first region, there is a scorch delay or induction period that provides a safe processing time. It is believed that the accelerator chemistry is mostly involved in this period. The second region is the curing period, during which network structure is formed. The third period is called overcure that may occur as reversion, equilibrium, or marching cure behaviours according to the compound characteristics. It is well known that overcure of many tire compounds results in reversion which is observed in rheometric cure curves that pass through a maximum torque value. Since reversion usually has an undesirable effect on product quality, it becomes necessary to optimize the curing process [2].

Typical cure curves can be obtained with a moving die rheometer (MDR) which is technically a curemeter. The curemeter is based on the fact that the crosslinking density is proportional to the stiffness of the rubber [3]. This equipment is used to measure the torque required to oscillate the die. As vulcanization proceeds at a specific temperature, the torque required to shear the rubber compound increases and a curve of torque versus curing time can be generated. The use of this curemeter and standardized values read from the curve is specified in ASTM D 2084. Some of these recommended values that are important to know for this study are

M_L: Minimum torque in N.m or lbf.in.
M_H: Maximum torque where curve plateaus are in N.m or lbf.in.
t_x: Minutes to x% of torque increase, t_x = minutes for torque value equivalent to $M_L + x(M_H - M_L)/100$.

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doi:10.1016/j.matdes.2008.07.010

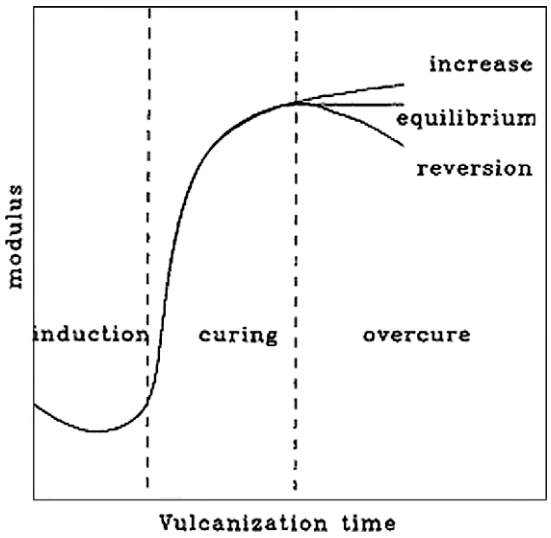

Fig. 1. A typical accelerated sulfur vulcanization cure curve obtained from a cure meter.

In rubber terminology, t_{90} is defined as "optimum cure time" for the rubber compounds. Rubber compounds that have different formulations differ also in curing behaviours. This difference is more evident in the compounds with fillers (usually carbon black) due to matrix–filler interactions. For filled elastomers, the maximum torque value usually decreases as the temperature increases. As a result of matrix–filler interactions and other effects such as the thermal instability of polysulfide linkages, the full cure at different temperatures may not represent the same network chain density [4]. So, it can be said that the torque values obtained during vulcanization of a rubber compound are related to compound formulation and curing temperature. On the other hand, curing temperature and the torque value that can be obtained at that temperature must be known to predict optimum cure time of a rubber compound.

Over the last 15 years ANN techniques have emerged as a powerful tool that could be used to replace time consuming procedures in many scientific and/or engineering applications [5]. However, there are relatively limited ANN studies met on rubber and tire literature and most of these studies focus on design of tire and tire curing equipments [6–8]. The ability of an ANN to evaluate the variability of rheometric properties of rubber compounds from their formulation was also studied [9]. Contrary to the previous study, in this study a model rubber compound was selected for modelling its cure curves in different temperatures using ANN. Then, the ability of selected ANN architectures on predicting optimum cure time of 11 different rubber compounds in a model tire was studied.

1.1. Artificial neural networks

An ANN is a mathematical model or computational model based on biological neural networks. The basic artificial neuron that processes the input information into output information is shown in Fig. 2. Neural networks are made of this type basic units arranged in layers. A unit collects information provided by other units (or by the external world) to which it is connected through weighted connections, known as synapses. These synaptic weights, multiply (i.e. amplify or attenuate) the input information [9–11]. Each of these units is a simplified model of a neuron and transforms its input into output response. This transformation involves two steps: First, the activation of the neuron is computed as the weighted sum of its inputs, and second, this activation is transformed into a response

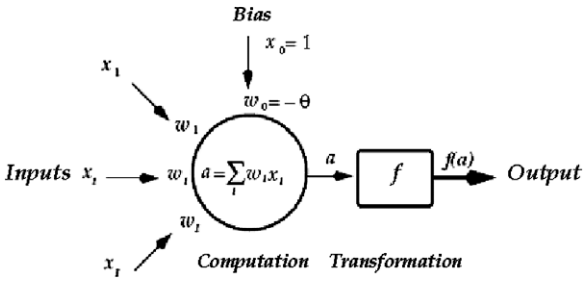

Fig. 2. Basic neural unit.

by using a transfer function. Formally, if each input is denoted x_i and each weight w_i, then the computation of activation is equal to a which is sum of $w_i x_i$ and the output is obtained as transfer function f. Any function whose domain is the real numbers can be used as a transfer function. The most popular ones are linear, step, threshold, logarithmic sigmoid and hyperbolic tangent sigmoid functions.

Elman's network is a recurrent network, whose output of hidden layer is feedback to input layer. The model is illustrated in Fig. 3 [12]. The activation in the hidden layer at time $t-1$ is copied into the context vector, which is the input to the network for time t. This is equivalent to having the hidden layer completely and recurrently connected, and back-propagating one step in time along the recurrent connections. The concept of the generalized regression neural network (GRNN) is based on nonparametric estimation commonly used in statistics. Nonparametric procedures and GRNN approach are the best solutions as the sample size grows large [13]. Relating to the radial basis function (RBF) networks that have the universal approximation property arise naturally as regularized solutions of ill-posed problems and are dealt well in the theory of interpolation [14]. Simple structure of RBF networks enables in learning stages, leads to a reduction in the training time and consequently such networks have been applied to many practical problems. The adjustable parameters of such networks are the center (the location of basis function), the width of the receptive fields (the spread), the shape of the receptive field and the linear output weights. GRNN can be treated as a normalized RBF network in which there is a hidden unit centered in every training case. Schematic diagram of GRNN architecture is shown in Fig. 4.

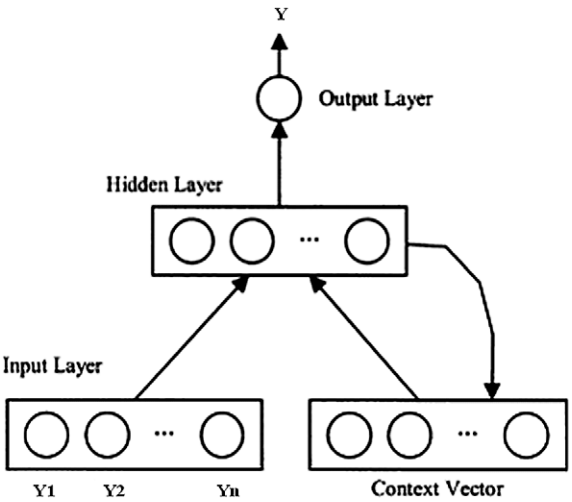

Fig. 3. Basic scheme of Elman network.