An adaptive neuro-fuzzy inference system as a soft sensor for viscosity in rubber mixing process

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Abstract: Mixing rubber in an internal mixer is a complex nonlinear process in which viscosity of the rubber is one of the key quantities concerning end product quality. Since viscosity can’t be measured online, soft sensor methods for modelling viscosity are investigated to establish an online control of viscosity. This paper presents a black-box approach to modelling viscosity using an adaptive neuro-fuzzy inference system (ANFIS). As a result, models capable of depicting physical features of the process are found. On the basis of the results, needs for further research are outlined.

Keywords: rubber mixing, viscosity, neuro-fuzzy systems, ANFIS, soft sensors, identification

1 Introduction
Rubber mixing is a batch process performed in an internal mixer. One of the main objectives of the mixing is to achieve an optimal viscosity level for further processing.

Varying properties of natural rubber introduce a great amount of complexity to the mixing process. The process is being controlled using e.g. temperature, rotor speed and batch duration. A plain feedback control of viscosity is not possible since there is no online measurement. The viscosity information is only obtained from laboratory analysis after the batch has been discharged. A dominant system for controlling viscosity is therefore based on long-term tolerances and process operators’ expertise.

Ryzko et al. [3] stated that artificial neural networks provide a powerful means for modelling the complex nonlinearities of the rubber mixing process. This paper presents results from a research project aiming at a soft sensor for viscosity. So far, a black-box approach using an artificial neuro-fuzzy inference system (ANFIS) has been made. Self-organizing map (SOM) is utilized for clustering the multitude of recipes used in rubber mixing.

2 Process description
The research is being carried out at a Finnish tyre manufacturer producing several hundreds of different mixing recipes. The internal mixer under investigation is one with intermeshing rotors, variable rotor clearance and a volume of approximately 200 litres.

Natural rubber together with fillers and other synthetic additives is mixed in a chamber where two rotating rotors pose shear forces to the rubber. Mixing consists of several phases and takes typical-

![Diagram of rubber mixing process](image_url)
ly 5-10 minutes. Additives may be added also between phases. After the final mixing phase the batch is discharged to an extruder which moulds the material into a continuous web independent of batch boundaries. Samples for laboratory analysis of viscosity are taken from the web after the extruder. (Fig.1)

3 Theoretical background

3.1 ANFIS

An adaptive neuro-fuzzy inference system (ANFIS) is a fuzzy inference system formulated as a feed-forward neural network. Hence, the advantages of a fuzzy system can be combined with a learning algorithm.

Fig.2 shows a first order Sugeno fuzzy inference system with two inputs, two input membership functions, two rules and one output:

If \( x \) is \( A_1 \) and \( y \) is \( B_1 \), then \( f_1 = p_1 x + q_1 y + r_1 \)
If \( x \) is \( A_2 \) and \( y \) is \( B_2 \), then \( f_2 = p_2 x + q_2 y + r_2 \)

Each node on the first layer includes a membership function for one of the inputs. The membership functions are defined using a set of parameters referred to as premise parameters. The output of layer 1 is the membership grade of the input in a fuzzy set.

On layer 2, each node represents one fuzzy inference rule by performing a fuzzy AND operation on the membership grades defined in the premises of the rule. The outputs are firing strengths of the rules.

3rd layer includes the output membership functions which in Sugeno case are linear:

\[ O_i = w_i (p_i x + q_i y + r_i) \]

where \( O_i \) is the output from layer 3, \( w_i \) the firing strength of rule \( i \) (input from layer 2) and \( p_i, q_i \) and \( r_i \) are consequent parameters.

Layer 4 includes just summations of rule outputs and firing strengths, the former sum being divided by the latter on layer 5 to yield the overall output of the system.

There are two sets of parameters in the above fuzzy inference system. The overall output is linear in the consequent parameters on layer 3 but nonlinear in the premise parameters on layer 1. The hybrid learning algorithm detailed in [4] consists of a forward pass and a backward pass. In the forward pass, the linear parameters are updated using least-squares estimator (LSE). In the backward pass, error derivatives are calculated for each node starting from the output end and propagating towards the input end of the network. The nonlinear parameters are updated by steepest descent algorithm. [4]

3.2 SOM

A Kohonen self-organizing map (SOM) is a network capable of unsupervised clustering of input data. Specific to SOM is the ability to maintain the topology of the clusters, i.e. clusters close to each other have similar features.

Updating of clusters in SOM is based on a similarity measure between points in the input space. The following algorithm gives a rough idea:

1. Given an input point, select the cluster with the largest similarity measure between the input point and the cluster.
2. Update the cluster towards the current input point with a small learning rate. Update also the neighbouring clusters to the same direction with an even smaller rate. [4],[5]
4 Modelling and results

This paper describes the first phase of the research, in which data from the discharge moment was used, so a static mapping between final state of a batch and viscosity was sought. Input data included measurements such as chamber temperature, rotor speed, torque, energy and pressure. Output data was collected from laboratory viscosity measurements. Because the laboratory samples were taken from a continuous rubber sheet after the extruder, some phase shift in coupling the lab results with batch data may have occurred.

Different combinations of the abovementioned input quantities were tested. Best results were achieved using temperature, torque, fill factor, rotor clearance, pressure and rotor speed. The last four are recipe-specific parameters kept constant within a recipe.

The data available covered roughly 3000 batches, 90% of which were used for teaching the ANFIS and 10% for testing. Because the data included various recipes, attempts were made to group the recipes into 3-5 clusters and to create different models for each cluster.

Self-organizing map was used to group similar recipes to clusters. Table 1 shows results from three clusters with models of their own compared with a model covering all recipes. The numbers are root mean square error (RMSE) values of the test data set and scaled so that RMSE for all recipes is equal to 1. It can be seen that a general model performs well compared with the cluster-specific models. This probably follows from the fact that clusters B and C include more complex and versatile recipes thus difficult to model.

Fig. 3 A scatter diagram of viscosity calculated by ANFIS vs. viscosity obtained from laboratory. The straight line indicates optimum.

<table>
<thead>
<tr>
<th></th>
<th>All recipes</th>
<th>Cluster A</th>
<th>Cluster B</th>
<th>Cluster C</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE (scaled)</td>
<td>1.0</td>
<td>0.7</td>
<td>1.3</td>
<td>1.2</td>
</tr>
</tbody>
</table>

Table 1 RMSE-values for four different models: one for all recipes and one for each cluster. Smaller value means better performance. Values are scaled.

Fig. 3 shows how well viscosity values calculated by the all-recipe model correlate with laboratory values. The figure includes one point for each batch in both training and testing data.

One advantage of an ANFIS network over a multilayer perceptron is the possibility to view input-output relations. Fig. 4 shows the fuzzy inference surface of viscosity in terms of torque and temperature that can be interpreted physically as follows: Comparing batches in which discharge temperature is equal, increasing torque indicates increasing viscosity. On the other hand, comparing batches with equal torque at discharge, higher tem-
temperature means higher viscosity. This sounds sensible from the physical point of view.

5 Conclusion
Taking into account the inaccuracies in process measurements and data collection, an artificial neuro-fuzzy inference system could implement a relatively accurate model for the viscosity. Deviations between the model output and laboratory measurements are small enough for the model to be utilised in control. Before that, however, several ways to improve the performance of the model are listed in the following subsection.

5.1 Needs for further research

5.1.1 Dynamic model
The research presented herein is the first phase in a project aiming at soft-sensor and control of rubber viscosity. In the first phase, data collected merely at the moment of batch discharge was used. Thus, no dynamics could be included in the models. The temperature or power profile during the batch may however have an impact on the final viscosity, which can only be identified by collecting measurement data during the batch.

5.1.2 Outlier detection
A production-scale system inevitably produces disturbance situations where the system is in an abnormal state. These disturbances produce outliers to the data, which may have a deteriorating effect on the optimisation. Methods of detection and removal of outlier points will be considered as the research is being continued.

5.1.3 Semi-physical model
In the described ANFIS model, no a priori knowledge was taken into account. Nevertheless, there are numerous physical dependencies concerning rubber mixing known in the literature. These physical features can either be introduced to a certain neuro-fuzzy model structure or be used as a basis for a physical model which is then further tuned using a learning algorithm.

5.1.4 Viscosity control
Measurements are seldom useful without control. When a satisfactory soft sensor for viscosity is found, the next phase will be designing a control strategy to improve the quality and runnability of the process.

Fig. 4 Surface describing fuzzy inference from torque and temperature to viscosity.
References:


