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Determining Empirical Relationship of Rubber Drying Process using Machine Learning

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***Abstract*—Rubber is considered an important material for humankind and it is one of the most important products in Southeast Asian countries. However, the production of rubber could harm the environment due to the conventional use of acid and salt. We propose a rubber drying process using heat and constructed a rubber heating tunnel. We also propose a strategy to determine the time it takes to dry rubber so that the rubber is sufficiently dried without overheating at different temperature levels. We found that this strategy could not make use of conventional curve fitting methods based on least squares since it cannot handle discrete or categorical input data very well. We propose a non-linear Machine Learning regression technique based on neural network and found that neural network has the ability to predict the output variable quite well despite the input variables contain discrete or categorical values.**

Keywords—empirical, relationship, rubber, regression, neural networks, heating

I. Introduction

Rubber is an essential material that has played a significant role in human development and its versatile form contributes to numerous important applications in various industries such as automotive, healthcare, construction, electrical and electronics, sports and recreation, textile, chemical, and aviation industry [1]. Due to its importance to mankind, several countries try to produce rubber. However, most of the rubber production in the world is from Southeast Asian countries such as Thailand, Malaysia, Vietnam, and Indonesia. This is because these countries have favorable climate for rubber trees. The high temperatures, abundant rainfall, and relatively consistent humidity are preferrable conditions to support rubber cultivation [2].

Since rubber is always in high demand throughout the modern history of mankind, the production of rubber is long known to cause harm to the environment. One of the main technologies for producing rubber in the form suitable for various industries required the use of mineral acid and ammonium salt to help the process of rubber drying [3]. The excess of the acid and salt is usually poured into natural land and waterways creating harmful environment for crops and animals to survive. In addition, farmers in different regions naturally produce different quality of liquid latex rubber. Local rubber farmers generally do not have sufficient knowledge and skills to calculate the appropriate amount of acid and salt to use. This imprecise control of acid and salt for rubber drying and production not only harms the environment but also creates poor quality dried rubber resulting in the decrease of the economic values and waste from low quality dry rubber. In addition, we also found that acid and salt actually are harmful to the bonding of the natural rubber during the coagulation process. Thus, a method of drying rubber without using acid and salt is necessary.

There are several conventional methods for drying rubber: air-drying, heat-drying, and smoke-drying. We study the heat drying method because of its controllability. Both air-drying and smoke-drying methods are not considered because the air-drying method depends on the outdoor environment which is often uncontrollable and the smoke-drying method creates a lot of smoke which is harmful to the environment and the color of the rubber. The heat-drying machine is similar to a typical bread-baking tunnel. In this paper, we call this machine a rubber heating tunnel. The liquid latex rubber collected from the rubber tree is poured onto the conveyor belt at the beginning of the tunnel. While the liquid latex rubber travels at the same speed as the conveyor belt of the tunnel, the rubber is heated inside the tunnel using infrared heater. The water molecules inside the liquid latex rubber gradually evaporate leaving the rubber molecules to be coagulated into a solid rubber. The rate that the rubber dries depend on the amount of heat provided to the rubber and the time it takes for the rubber to receive the heat. We are interested in finding the relationship between the temperature used and the time it takes to dry the rubber. Thus, we conducted rubber drying process at different temperatures and determine the time it takes for the rubber to dry. We noted the humidity of the rubber at different time and plot the relationship among the humidity, temperature and time as shown in Fig 1.

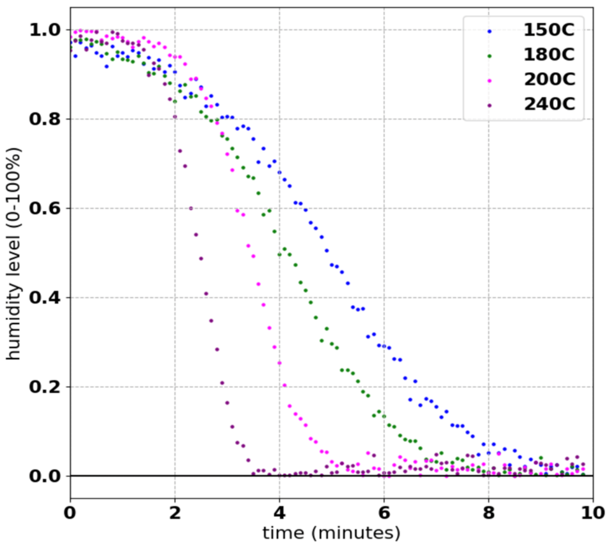

Fig. 1. the relationship among the humidity, temperature, and time during rubber-drying process.

II. Related Works

A. Curve-fitting Methods

Curve fitting is the process of obtaining a mathematical function that has the best fit to a set of data points. Curve fitting finds the best approximate relationship between one or more input or independent variables and an output or dependent variable [4]. The definition of the best fit must be clearly stated to match the requirements of the approximation. One of the most popular method to determine the best fit is called "least-squared fit" where the error or the differences between the approximated output and the true output variables are minimized with respect to the mathematical functions intended to the approximate the curve that fits the dataset. Normally, the relationship between the input variables and output variables are examined first to guess the characteristics of the relationship. Then the parameters or the coefficients used for adjusting the approximated function can be determined through the process of error minimization (best-fitting). The characteristics of the mathematical functions can be linear or non-linear.

For the least square curve fitting, we assume that we have an objective function *f(X, params)* where *X* is the vector of the values of input variables and *params* is a vector of parameters or coefficients used in the function. We would like to determine the function f and params that can minimize the error between *f(X, params)* and the observed values of *y* for each value of X. Our approximation for params is as follows:

$$\arg\min_{params}(f(X, params) - y)^2$$

There is a special case of using least square method called linear least square method which assume that the variable terms in X are linearly dependent on each other. In this case, we can assume the following linear relationship:

$$\begin{bmatrix} y_1 \\ y_2 \\ \dots \end{bmatrix} = \begin{bmatrix} X_1 \\ X_2 \\ \dots \end{bmatrix} C$$

We would like to find *C* that minimizes the error or residual between the observed values of y and the approximated values of *XC*.

$$\arg\min_{C}(XC - Y)^2$$

We can solve for C analytically by setting the first derivative of $(CX - y)^2$ with respect to C to be zero as follows:

$$\frac{d((XC - Y)^2)}{dC} = 0$$

$$2X^T(XC - Y) = 0$$

$$2X^TXC - 2X^TY = 0$$

$$X^TXC = X^TY$$

$$C = (X^TX)^{-1}X^TY$$

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The value of C can be solved analytically or numerically using linear algebra methods such as Gauss's Elimination and matrix decomposition.

This method is widely accepted as the standard method for curve fitting. However, this method requires that X must be linear and components of X must be determined appropriately or else all combinations of variables in X must be presented (including polynomials of variables) but this will affect the complexity and performance of the method.

B. Regression Methods

Regression is a type of Machine Learning technique for discovering the relationship between continuous independent variables or features and a continuous dependent variable or outcome [5]. Generally, regression is used for predictive analysis where the relationship is called a predictive model taking the continuous input variables to predict the output variable based on the input variables.

The predictive model of the regression technique (sometimes called regression model) is derived from the available data which is called training data. This model derivation is similar to that of curve-fitting methods which requires a pre-determined relationship model, and the model parameters are generally derived from the concept of the minimization of error or residual between the predicted output and the actual output in the training data [6]. However, machine learning regression models are different from curve fitting objectives functions that the regression models are not based on conventional mathematical functions which can be linear, polynomial, exponential or even trigonometric functions. Rather the regression models are combinations of basic linear models except that the combinations are often complicated and the coefficients or parameters used in the model are quite difficult to be solved analytically. Machine learning methods usually use iterative optimization methods such as gradient descents to solve for the parameters of the models. Since regression model is trained to obtain the relationship between independent variables and the dependent variable, the model can use the understood and best-fit model to predict the outcome from the unseen input data.

In [7], the authors used the standard curve fitting technique based on non-linear least square method utilizing residual minimization concept to determine the parameters of the objective functions provided by the authors. Eventually, the mathematical function that describes the lightning impulse test voltage waveform was obtained using the frequency-dependent k-factor objective function. The lightning impulse test voltage waveform generated by the least squares curve fit methods can fit to the waveform empirical data with approximately 10-15 percent error.

In [8], the authors used machine learning neural network technique to determine the non-linear relationship between input variables and output variables to solve the efficiency problem of standard curve fitting non-linear least square approximation whose solution converged very slowly. The authors used Extreme Learning Machine (ELM) model to approximate the relationship between the input variables and output variables of non-linear single variable mathematical functions. The results show that the mean square errors of this method can be reduced to less than 0.03 percent. However, the authors did not investigate the performance of the method on unseen data.

III. Machine Learning-based method for Determining Empirical Relationship of Rubber Drying Process

According to Figure 1, there are two input or independent variables, time and temperature, and there is one output or dependent variable (humidity of rubber). The data was collected from 4 rubber drying experiments at 4 different temperatures: 150, 180, 200, and 240 degree Celsius.

Using the standard least squares curve fitting method, we can try to fit the data to a known mathematical function. It is easy to see that the relationship between time and humidity level at a single temperature has the sigmoid-function form, and the relationship between temperature and humidity level has the linear form. By applying the least squares curve fitting on our empirical data, we found that the least squares curve fitting method could not fit the data well with the error of over 50 percent.

One of the reasons that least squares curve fitting method could not perform well on our data is that the method is designed to handle continuous data. The discrete temperature data used in the experiments are not suitable to fit a smooth curve to the temperature data using the standard curve fitting methods.

We naturally propose a machine learning based method to determine the relationship between independent variables and dependent variables. Since the relationship between the independent variables and the dependent variables involve non-linear relationship, it is natural to use non-linear model such as non-linear regression or neural network regression.

A neural network is a computational model inspired by biological neurons. The neural network consists of interconnected layers of neurons, representing computing nodes. Each neuron takes inputs, applies an activation function to the weighted sum of those inputs, and produces an output as the output of the activation function. All connections between linked neurons have associated weights and biases, which are modified during the training process to optimize the network's model that can offer the best fit relationship between the independent variables and the dependent variable.

In the context of regression, the neural network takes a set of independent variables as input, passes them through one or more hidden layers with nonlinear activation functions, and produces the predicted output or values of dependent variables. During training, the network adjusts its weights and biases to minimize the difference between the predicted values and the actual target values, typically using a loss function such as mean squared error (MSE) which measures the differences between the observed output values and the predicted output values [9,10].

We will train a neural network for regression by iteratively processing the training examples, computes the predictions, and compares them with the ground truth or observed values (forward propagation). The errors between the ground truth and the predicted values are used to adjust the weights and biases to minimize the errors in the subsequent iterations (backward propagation) with gradient descent.

The predicted output of a neural network node can be written as follows:

$$f(x) = \sigma(b + W^T X)$$

where σ is the activation function, b is the bias of the node, W is the weight vector related to input X which is the output of the nodes in the preceding layer. The output of each node in a hidden layer is forwarded to all nodes in the subsequent layer.

Given the learning rate α, the weight W can be adjusted starting from the end of the neural network to the beginning of the neural network with the following update process:

$$W = W - \alpha \nabla J(W)$$

where J is the error loss and ∇ is the gradient with respect to the linear parameter of each node m and n. We have

$$J = \frac{1}{n} \sum_i (y_i - (mx_i + b))^2$$

where i is the record index of the training data.

Neural network is well-known to have overfitting characteristics if the number of hidden layers and the number of nodes inside each layer are not selected properly. Selecting the number of layers and nodes in a neural network is a crucial task, as it directly impacts the network's performance and generalization capabilities. However, there is no standard method to determine the number of layers and nodes, since the optimal architecture gives out complex chain of mathematical relations and it depends on the specific problem involving the available data.

According to Figure 1, our data contains some sigmoidal characteristics. We then added the feature involving the term e^{-x} to our data.

IV. Experiment and results

We conducted 5 rubber drying experiments in a chemistry laboratory using 5 different temperature levels: 150, 180, 200, 220 and 240 Celsius. The data collected for the experiments using 150, 180, 200, and 240 degrees Celsius would be used for training and initial testing of the relationship model. The data collected from experiments using 220 degrees Celsius would be used for validating our trained model using this unseen data. A large number of rubber samples were collected from the rubber heating tunnel at different times starting from the beginning of the heating process. The data is collected and stored electronically in a CSV file. The humidity of the rubber was measured by chemists in Mahidol University rubber lab according to the standard humidity measurement procedure.

We constructed a multilayer perceptron (MLP) type artificial neural network (ANN) and trained it with the CSV file containing our empirical data using Python on a PC workstation with 2.4 GHz processor and 128 MB of memory. Our network consists of 3 input nodes and one output node. Our experiment uses 1 and 2 number of hidden layers with different number of nodes in each layer. The error loss was calculated according to the least squares error between the observed and predicted outputs as described in Section III.

The errors as used in the backward propagation steps along with gradient descent in order to estimate the weights that would minimize the errors with a learning rate of 0.000001.

The performance of our neural network regressor is measured as mean-squared errors and shown in Table 1. According to Table 1, the network performs best when we used 2 hidden layers with 4 number of nodes in the first hidden layer and 4 number of nodes in the second hidden layer,

TABLE I. PERFORMANCE OF NEURAL NETWORK REGRESSOR

Number of Nodes		MSE	
Hidden Layer 1	Hidden Layer 2	Seen Temp	Unseen Temp
4	-	0.1907	0.2078
6	-	0.0595	0.06142
8	-	0.0561	0.0621
10	-	0.0631	0.0591
4	4	0.0799	0.07325
4	6	0.0411	0.0466
4	8	0.0731	0.0534
4	10	0.0567	0.0606
6	4	0.1691	0.1969
6	6	0.0836	0.0588
6	8	0.0654	0.0765
6	10	0.1225	0.1396
8	4	0.1691	0.1968
8	6	0.0725	0.0647
8	8	0.2477	0.3060
8	10	0.0663	0.0685
10	4	0.0636	0.0569
10	6	0.0729	0.0717
10	8	0.0792	0.0709
10	10	0.0829	0.0674

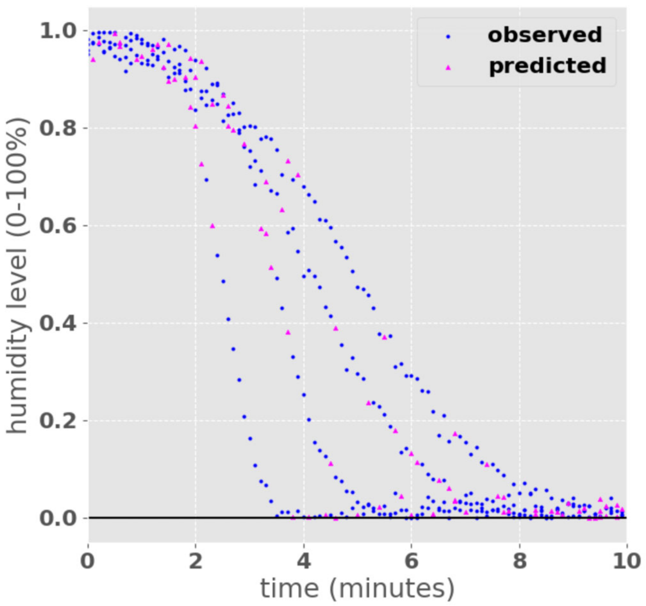

Fig. 2. The visualized relationship between observed output values and predicted output values.

We plotted the relationship between our prediction and observed values to visually confirm our results in Fig. 2. Our predicted values of the humidity are very close to the observed values. This supports our hypothesis that non-linear regression method using neural network could be used with this type of data that contains discrete or categorical values.

V. CONCLUSION

We propose an environmental-friendly method to dry rubber using rubber heating tunnel. It is important to determine the right amount of time to dry rubber at different temperature levels to obtain dry rubber without overheating. We determine the relationship between the independent and dependent variables by applying conventional curve fitting method and found that the conventional curve fitting method is not suitable for our data which contains categorical or discrete data type such as temperature level. We propose a non-linear regression method called neural network regression that can accept categorical or discrete input to predict continuous output. We found that we could predict the output variable quite well with small value of the mean square error when we use 2 hidden layers with the first layer having 4 nodes and the second layer having 6 nodes in the neural network.

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