

Energy anomaly detection in tire curing by using data integration and forecasting techniques

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This study proposed a method of energy anomaly detection by using data integration and forecasting techniques to improve energy efficiency in tire curing. Proposed method integrates energy consumption with different factors (environments, equipments, operators, tire blanks and tire types). Artificial neural network model and Support Vector Machine model were used to forecast normal interval for energy efficiency ratio; instances dropping out of this interval indicate potential anomaly affairs. Compared with traditional method, proposed method is robust against environment changes, highly correlated to curing process and can discover curing energy anomalies (leakage of steam or nitrogen, idling, and improper curing parameters configuration) effectively.

Keywords: Artificial neural network (ANN), Data integration, Energy consumption anomaly, Energy saving, Support vector machine (SVM), Tire curing

Introduction

Demand for rational usage of energy is gaining more attentions in modern manufacturing business¹. Rubber vulcanization²⁻⁴, which consumes 80% of steam in the whole manufacturing process and large amounts of other energy materials, is the main energy consumption process in tire manufacture. Many factors that cause energy waste during tire curing include damage of valve parts leading to leakage of steam or nitrogen (N₂)⁵, damage of curing machine and its piping systems leading to heat loss, idling for waiting new tire blank, changing mold and curing bladder waste a lot of heat and electricity, and improper process parameters leading to excessive energy consumption or product quality defects⁴. Traditional methods to identify energy consumption anomaly utilize threshold comparison scheme⁶⁻¹⁰, which suffers due to one energy anomaly affair generating more than one alarms, no correlation of energy anomaly to a certain curing process, not robust with complicated and dynamic manufacturing environment, and thresholds are hard to be suitably set.

This study proposed a comprehensive framework for curing energy efficiency (CEE) to detect energy

anomaly affairs by using process-oriented data integration and regression model to integrate energy consumption with different factors (environment, equipment, operator, tire blank and tire), and also using artificial neural network (ANN) based regression prediction interval for energy efficiency ratio (EER).

Experimental Section

Comprehensive Framework for Curing Energy Efficiency

High-pressure saturated steam (190-210°C) is filled into a curing bladder of curing machine until temperature in curing bladder reaches a certain value. Then high-pressure (2.0-2.6 MPa) and high-purity N₂ is filled into curing bladder until pressure of curing bladder reaches a certain value, which is kept throughout vulcanization process. Finally, vulcanized tire is cooled by compressed air^{2-4,11} at a cooling station. The whole process consumes steam, electricity, N₂ and compressed air, and there exists strong correlations among the consumption of various types of energy. One anomaly affair may cause abnormal consumption of multiple energy substances. Therefore, anomaly affairs could be detected as the combined results of all types of possible energy substances consumed, and a comprehensive framework for CEE needs to be built for identifying energy anomaly affairs.

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An energy efficient manufacturing approach¹ is adopted to define CEE. Energy consumption of a curing process is categorized into direct energy [energy (steam, electricity, N₂, compressed air) consumed by a curing process] and indirect energy [energy consumed by activities (lighting, heating, ventilation, etc.)] to maintain environment of a curing plant. In this study, only direct energy is used to analysis CEE. Direct energy is divided into theoretical energy [minimum energy required to vulcanize one (or one group tires for multimode curing machine) tire, which is the minimum energy to heat one tire blank (or one group tire blanks) to vulcanizing temperature] and auxiliary energy [energy required by supporting activities (loading tire blanks, sealing, shaping, unloading tires, and cooling)].

CEE can be defined as $ER_{vul} = TE/DE$, where ER_{vul} is curing EER, TE is theoretical energy of a tire curing process, and DE is direct energy of a tire curing process. ER_{vul} ($0 < ER_{vul} \leq 1$) denotes EER of the whole curing process, and larger ER_{vul} indicates more efficient curing. However, ER_{vul} is a relatively stable value for a fixed assembly line (too low ER_{vul} means anomaly affairs with occurrence of energy wasting; too high ER_{vul} means anomaly affairs with scant manufacture). Process taking shorter time than standard criterion has larger ER_{vul} , but it may cause substandard tires and more waste of energy and materials in remanufacture.

Computational formula of TE is $TE = cm(t_2 - t_1)$, where t_1 is initial temperature of tire blank before curing, t_2 is vulcanizing temperature of process required, c is average heat capacity of tire blank (1.88-2.09 kJ/kg. °C), and m is mass of tire blank.

Computational formula of DE is $DE = \sum_{i=1}^n m_i Q_i$, where n is number of energy substance types; m_i is consumption of i th type of energy substance, different energy substance should be converted into same unit of measurement; and Q_i is heat conversion of i th type of energy substance. Measuring unit and heat conversion rate, respectively, of referred energy substances are as follows: high-pressure saturated steam, kg, 2675 kJ; high-purity N₂, Nm³, 19660 kJ; compressed air, m³, 1170 kJ; and electricity, kWh, 3601 kJ. For all energy substances, consumption can be automatically acquired by smart meters.

Integration Data Model for Curing Energy Efficiency (CEE)

In tire curing process, process parameters are set by operators in advance, then one or one group tire blanks

are conveyed into curing machine, which consumes energy substances and materials to maintain reaction environment for certain time, and finally tire products are obtained. Energy consumption is correlated to operator's technical level, property of curing machine, curing parameters, type of tire blank, temperature of environment, etc. Therefore, a process-oriented data model by integrating above conceptual objects is proposed (Fig. 1). Impacts of conceptual objects are as follows: i) energy substances (electricity, steam, nitrogen and etc.) are the basis to compute direct energy consumption; ii) tire blank (weight & heat capacity) is the basis to compute theoretical energy consumption; iii) environmental temperature is the basis to compute theoretical energy consumption, and both its temperature and humidity would impact curing energy consumption; iv) operator's technical proficiency (measured by technical grade, work age and age) would impact curing energy consumption; and v) tire product quality is the basis to determine whether a process is anomalistic or not.

Regression Method for Curing Energy Efficiency (CEE) and Performance Evaluation

Energy efficiency of vulcanization (ER_{vul}) is treated as a statistic of process-oriented data model, so ER_{vul} can be predicted previously. Regression model of CEE is given as $y_t = f(X_t)$, where y_t is prediction value of ER_{vul} in current period, $f(\cdot)$ is regression function; X_t is vector that impacts CEE and can be observed at the start of tire curing process, including factors of operator, environment, tire blank, curing machine etc. Data mining techniques can be used to fit $f(\cdot)$. Training samples can be extracted from historic database. As $f(\cdot)$ depicts the relation in normal condition, data with substandard products (and other known anomalies) should be excluded from training samples. There are many existing data mining algorithms for fitting $f(\cdot)$, such as ANN^{12,13}, Support Vector Machine (SVM)¹⁴ etc. Optimal algorithm for this specific application should be determined through performance analysis. According to unbiasedness criterion and minimum-variance criterion, absolute mean error (M_e) and standard deviation of absolute error (S_e) have been used to evaluate prediction accuracy, and are defined as¹⁵

$$M_e = \frac{1}{n} \sum_{t=1}^n |\tilde{y}_t - y_t| \quad \dots(1)$$

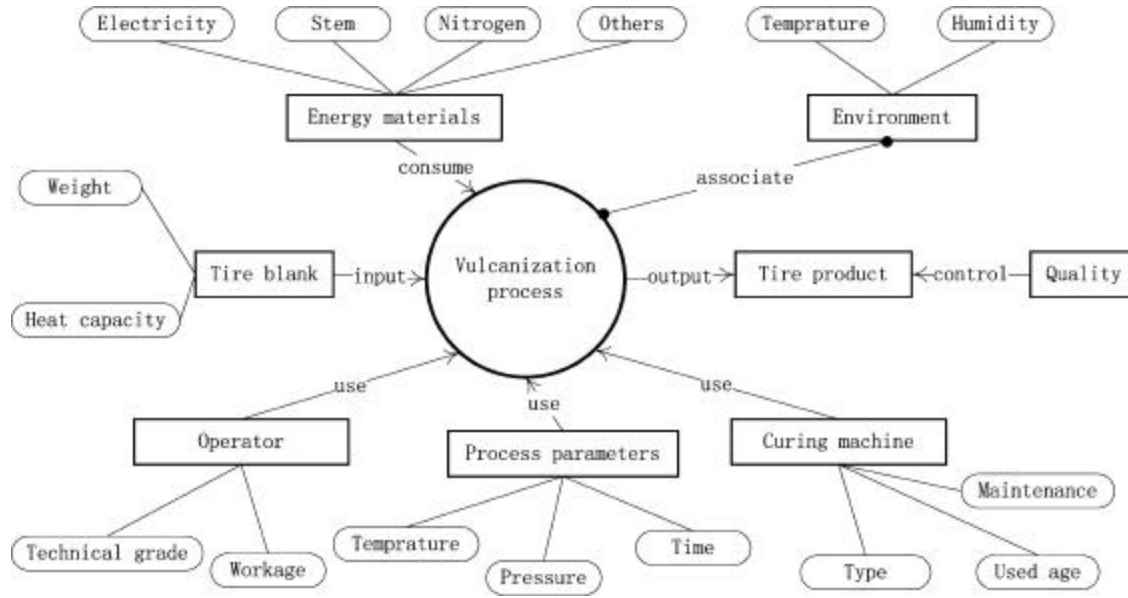


Fig. 1—Process-oriented curing data model

$$S_e = \frac{1}{n-1} \sqrt{\sum_{t=1}^n (|e_t| - M_e)^2} \quad \dots(2)$$

where $\tilde{y}_t$ is predicted value and y_t is observed value of ER_{vul} , $e_t = \tilde{y}_t - y_t$ and n is the number of training samples. Small values of M_e and S_e imply better prediction performance of $f(\cdot)$. The least squares criterion, $\text{Min} \sum e_t^2$, is generally selected as the objective function.

Method to Predict Interval of Normal Curing Energy Efficiency (CEE)

The function $f(\cdot)$ only gives the point prediction of ER_{vul} . Identifying anomaly affairs need a confidence interval, in which ER_{vul} generating from normal process is expected to drop. If observed value is not in the range determined by confidence interval, energy anomaly alarm would be triggered out. For $(n+1)$ th process, predicted value of ER_{vul} is denoted as $\tilde{y}_{n+1}$, and observed value is denoted as y_{n+1} . Assuming that $\tilde{y}_{n+1}$ and y_t are random statistic with same normal distribution, $e_{n+1} = y_{n+1} - \tilde{y}_{n+1}$, then e_{n+1} also has normal distribution, and expectation of $E(e_{n+1}) = 0$ or $e_{n+1} \sim N(0, s^2)$. Standard deviation s^2 is generally prior unknown, but it can be evaluated from training samples as

$$\tilde{s}^2 = \frac{1}{n-1} \sum_{t=1}^n e_t^2 \quad \dots(3)$$

where n is number of training samples. Building statistics z is given as

$$z = \frac{e_{n+1} - E(e_{n+1})}{D(e_{n+1})} = \frac{y_{n+1} - \tilde{y}_{n+1}}{\tilde{s}} \sim N(0,1) \quad \dots(4)$$

Given a significance level of α , confidence level is $1-\alpha$, then confidence interval of y_{n+1} is given as $\tilde{y}_{n+1} - Z_{\alpha/2} \tilde{s} \leq y_{n+1} \leq \tilde{y}_{n+1} + Z_{\alpha/2} \tilde{s}$. A curing energy anomaly may occur once the observed CEE y_{n+1} is not in the confidence interval, and operator should stop to troubleshoot, or improve his operating practices, to avoid wasting more energy.

In this study, ANN and SVM are employed for regression analysis (RA). ANN provides a flexible framework for computing a wide range of linear and nonlinear problems^{12,13,16}. ANN generates universal approximation that can approximate a large class of functions with a high degree of accuracy. SVM build their approximation function based on underlying concepts that rise from Statistical Learning Theory (SLT). Rather than based on Empirical Risk Minimization (ERM) as ANN, SVM makes use of Structural Risk Minimization (SRM) that seeks to minimize an upper bound on the generalization error, which appears to be computationally less demanding since ERM is intended to deal with large sample sizes. Thus, SVM focuses on a trade-off between model accuracy during training and prediction stages^{14,17}.

Table 1. Prediction performance of regression functions by different algorithms

Algorithm	M_e	S_e	$\text{Max}(e_i)$	$\text{Min}(e_i)$
MLP-NN	0.821	0.614	4.05	0.003
RBF-NN	1.323	0.985	4.89	0.001
SVM	1.038	0.986	5.82	0.001

Results and Discussion

This study applied proposed framework and analyzed CEE of rubber vulcanization process to an industrial case study of a rubber tire factory. Data obtained from production procedures were used for simulation and application analysis of proposed methods, including RA, validation off-line and monitoring on-line.

Regression Analysis (RA)

Due to great differences between various types of curing machines, RA should be respectively built up on each single machine. In this study, only one curing machine is chosen for training, testing and on-line validation for proposed methods. In order to ensure quality of training samples, data with substandard tire products are first excluded, and data ranges are mapped into the normal intervals [0, 1] by typical scenarios. This study selected 3280 historical records from factory in two continuous weeks. Selected data fields for training sample and their ranges were found as follows: weight of tire blank, 10-50 kg (including 5 types of tire blank); environment temp., 15-28°C (data covering 24 h for each day); curing temp., 160-170°C (reasonable range of curing temp.); curing pressure, 1.6-1.9 Mpa (reasonable range of curing pressure); curing time, 15-17 min (depending on type of tire blank); and workage of operator, 1-8 y (denotes as 8 y if larger than 8 y). Varying range of three key parameters (temp., pressure, and time) were collected by sensor terminals and recorded in Manufacturing Execution System (MES). Additionally, workage of operators, indicating individual proficiency, is a factor to energy efficient usage. For 3280 records, training set is composed of the first half samples, while testing set is composed of the others.

Three different data mining algorithms [multi-layer perception neural network (MPL-NN)^{12,13}, radial-basis-function neural network (RBF-NN)¹³ and SVM regression¹⁷] were utilized to train regression function of ER_{vul} . MLP-NN and RBF-NN can capture complex relationships between input and output variables. Broyden-Fletcher-Goldfarb-Shanno (BFGS) scheme

minimizing the sum of square error function is used in evolution update of neural network. MLP-NN and RBF-NN models with different kernels and structures were tested, and the most accurate and robust model was selected based on the performance evaluation defined in Eqs (1) and (2). Five different activation functions (logistic, identity, tanh, exponential, and sine function) were used for hidden and output neurons. Number of hidden neurons of MLP-NN was set between 5 and 12, and the weight decay for both hidden and output layer varied from 0.0001 to 0.001. Mean squared error goal of RBF-NN varied from 0 to 0.01, and spread of radial basis functions varied from 1.0 to 100.0.

SVM constructs a linear discriminate function separating instances (samples) as widely as possible. In the process of SVM regression models, high dimensional linear optimization problem is transformed into a dual convex quadratic programming problem. This study used ϵ -SVR method, wherein ϵ varied from 1.0 to 3.0, and penalty parameter C varied from 1 to 2000. Kernel was RBF function, and its spread varied from 1 to 100.

From testing results by using data mining algorithms, MLP-NN gave the best performance for regression prediction of CEE (Table 1). Generally, connection weights in ANN model indicate degree of impact to the target. Impact [degree (%) and direction (+ or -), respectively] of top 5 factors to energy efficiency calculated by MLP-NN method were found as follows: environmental temp., 35.6%, +; curing temp., 22.2%, +; weight of tire blank, 18.8%, +; curing pressure, 5.0%, +; and curing time interval, 3.2%, -. Since MPL-NN method obtains superior performance, it is chosen for off-line and on-line validation.

Off-line Validation

Records (3000) extracted from historical data set composed off-line sample set. According to product quality report, 76 abnormal records were found in off-line sample set. Abnormal affairs include leakage of steam or N_2 , idling, and improper curing parameters configuration.

Table 2—Detection results on off-line samples

Confidence %	N_a	N_d	N_f	N_m	R_f %	R_m %	R_s %
90	76	83	9	2	10.84	2.63	13.47
93	76	78	4	2	5.13	2.63	7.76
95	76	70	1	7	1.43	9.21	10.64
97	76	64	0	12	0.00	15.79	15.79
99	76	52	0	24	0.00	31.58	31.58

Table 3—Classified detection results on off-line samples

Confidence Level, %	Leakage of Steam or N_2 ($N_d = 34$)		Idling ($N_a = 23$)		Improper parameters configuration ($N_d = 19$)	
	N_m	R_m	N_m	R_m	N_m	R_m
90	0	0.00%	0	0.00%	1	0.53%
93	0	0.00%	0	0.00%	2	10.53%
95	2	5.88%	0	0.00%	5	26.32%
97	4	11.76%	0	0.00%	8	42.11%
99	7	20.59%	2	8.70%	15	78.95%

Table 4—Detection results of monitoring on-line

Confidence %	N_a	N_d	N_f	N_m	R_f %	R_m %	R_s %
90	24	25	2	1	8.00	4.17	12.17
93	24	24	1	1	4.17	4.17	8.33
95	24	24	1	1	4.17	4.17	8.33
97	24	22	0	2	0.00	8.33	8.33%
99	24	18	0	6	0.00	25.00	25.00%

Regression function trained by MPL-NN was used to test prediction performance on off-line sample, and results were as follows: M_e , 0.838; S_e , 0.664; Max (e_i), 5.487; and Min (e_i), 0.0. Three basic indexes (miss rate, false rate and mistake rate) evaluate detection performance. Total number of anomaly affairs is denoted as N_a , number of missed anomaly affairs by prediction model as N_m , and miss rate as $R_m = N_m / N_a \times 100\%$. Number of detected anomaly affairs by prediction is denoted as N_d , in which there are N_f false detection; then false rate is defined as $R_s = R_m + R_f$. MPL-NN method, executed with different confidence levels (90, 93, 95, 97 and 99%), gave experimental results on off-line samples (Table 2). Detailed results for anomaly detection by theoretical

computation and practical observation (Table 3) indicated that 93% is optimal confidence level for present case.

On-line Validation

To validate proposed method on-line, test data set is consisted of 1190 curing processes continuously observed in 2 weeks. Confidence levels (90, 93, 95, 97, and 99%) are tested respectively. Regression function learned by MPL-NN is used to test prediction performance for on-line sample, and prediction deviation errors are: M_e , 0.792; S_e , 0.664; Max (e_i), 5.487; and Min (e_i), 0.0. Detection result is optimal when confidence is between 93% and 97% (Table 4). Confidence level 95% is a compromising option. With confidence level 95%

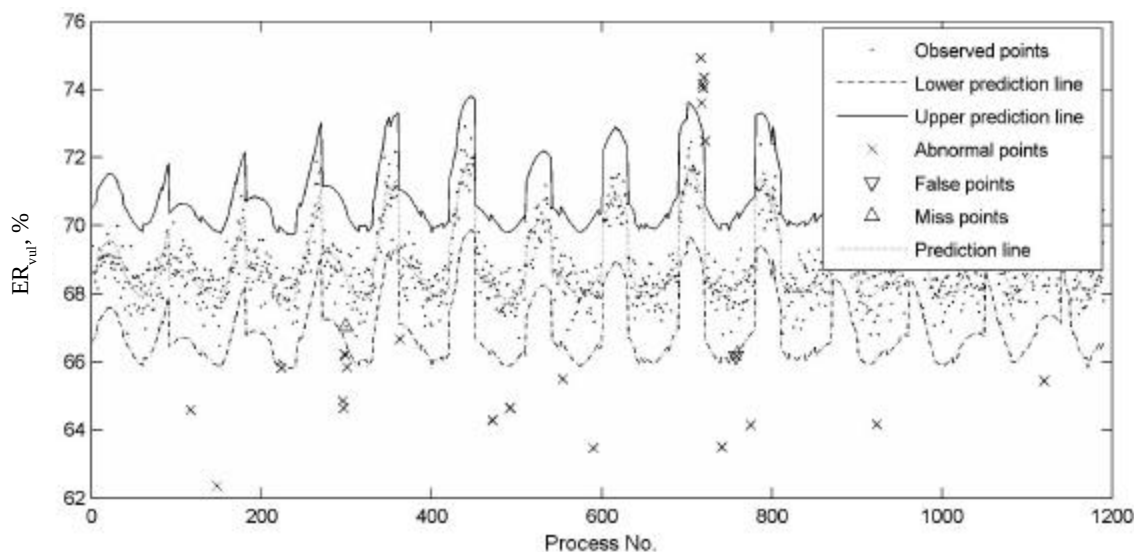


Fig. 2—Curing energy efficiency (CEE) monitoring on line (Confidence level, 95%)

(Fig. 2), cyclical variation of ER_{vul} is due to cyclically-varying environmental temperature every day. A few sudden changes of points were mainly caused by changes of tire blanks.

Conclusions

Proposed method for energy anomaly detection utilized a comprehensive index for describing energy consumption in rubber vulcanization, and builds a process-oriented data model and regression model, which correlates energy consumption with different factors (environment, equipment, operator, tire blank and tire). Energy anomalies are detected by judging whether practical value of energy consumption is in the prediction interval. Compared with threshold comparison method, proposed method locates anomaly affairs easily from energy consumption, is robust to dynamic environment, can effectively discover energy anomalies in tire curing as leakage of steam or nitrogen, idling, improper parameters configuration, etc., and can be extended to other industries for optimizing production system.

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