Infrared Physics & Technology 77 (2016) 316–324

Contents lists available at ScienceDirect

Infrared Physics & Technology

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

Regular article

Non-metallic coating thickness prediction using artificial neural network and support vector machine with time resolved thermography

Hongjin Wang [a,*], Sheng-Jen Hsieh [a,b], Bo Peng [a], Xunfei Zhou [a]

[a] *Department of Mechanical Engineering, Texas A&M University, College Station, TX, United States*
[b] *Department of Engineering Technology & Industrial Distribution, Texas A&M University, College Station, TX, United States*

HIGHLIGHTS

- Active thermography is used to estimate the coating thickness at a low sampling rate.
- The effects of factors affecting surface temperature are analyzed non-dimensionally.
- ANN and SVRs are used to correlate surface temperature to the coating thickness.
- The SVM model generates more accurate coating thickness estimates than the ANN model.

ARTICLE INFO

Article history:
Received 7 October 2015
Available online 16 June 2016

Keywords:
Coating thickness
ANN
SVM
Thermography
Non-dimensional analysis

ABSTRACT

A method without requirements on knowledge about thermal properties of coatings or those of substrates will be interested in the industrial application. Supervised machine learning regressions may provide possible solution to the problem. This paper compares the performances of two regression models (artificial neural networks (ANN) and support vector machines for regression (SVM)) with respect to coating thickness estimations made based on surface temperature increments collected via time resolved thermography. We describe SVM roles in coating thickness prediction. Non-dimensional analyses are conducted to illustrate the effects of coating thicknesses and various factors on surface temperature increments. It's theoretically possible to correlate coating thickness with surface increment. Based on the analyses, the laser power is selected in such a way: during the heating, the temperature increment is high enough to determine the coating thickness variance but low enough to avoid surface melting. Sixty-one pain-coated samples with coating thicknesses varying from 63.5 μm to 571 μm are used to train models. Hyper-parameters of the models are optimized by 10-folder cross validation. Another 28 sets of data are then collected to test the performance of the three methods. The study shows that SVM can provide reliable predictions of unknown data, due to its deterministic characteristics, and it works well when used for a small input data group. The SVM model generates more accurate coating thickness estimates than the ANN model.

1. Introduction

Coating thickness measurement technologies are critical to quality control in surface modifications, as coatings can modify designed surface properties. By coating different materials, mechanism properties, electrical properties, or other properties may be improved to levels that satisfy application requirements. Coating thicknesses therefore significantly affect surface property improvements [1–6]. Therefore, rapid and accurate thickness measurements are used in several industrial sectors (e.g., packaging engineering, pipeline industries and manufacturing industries).

Thermography methods can serve as a useful alternative to existing non-destructive coating thickness measurement methods. The previous application of thermography involves in breast cancer detection, defect detection and thickness estimation [51–56,64–66]. Thermography approaches involve determining coating thicknesses based on differences in thermal properties between coatings and substrates, while eddy current testing methods are used to measure thicknesses based on different conductivity levels between coatings and substrates; magnetic field testing methods are based on differences in magnetic properties, radioactive testing methods are based on differences in radioactive

* Corresponding author.
E-mail address: sosososo1114@tamu.edu (H. Wang).

http://dx.doi.org/10.1016/j.infrared.2016.06.015
1350-4495/

penetration depths, and sonic methods (including both acoustic and ultrasonic methods) are based on mechanism properties [5–9]. The measurement principle used in thermography methods serves as an acceptable solution to measurements for certain coatings, where coatings and substrates have similar stiffness properties, radioactive penetration depths, electrical conductivity levels and magnetic properties or where the boundary between the coating and substrate is not distinct (e.g., polymer-to-polymer coatings used in biomedical products such contact lenses and tissue supports, and ferrous-to-ferrous coatings used in bearings, turbine blades and gear surfaces) [6,10–14].

The principle of coating thickness estimation with thermography lies in comparing the measured thermal signals (involving temporal response of surface temperature, its derivatives and phase angles) with pre-known knowledges about coating thickness. Usually, the pre-known knowledge are obtained based on heat conduction models for the special thermography tests. However, the non-linear and implicit relationship between surface temperatures and coating thicknesses constrains the application of thermography to coating thickness measurements. Researchers have employed several methods to conquer this limitation. One method pertains to the correlation developed by Aamodt [15,16]. Aamodt [15,16] reduced nonlinearity patterns between surface temperatures and depths using early detection methods wherein temperature data for depth estimations were collected over an extremely short period of time (based on their data, 0.5 s) under a transient pulse [15,16] using an extremely fast infrared camera or an infrared video recorder. Unlike Aamodt's correlation, Sun's algorithm [13] calculates coating thicknesses numerically and considers the effects of finite-duration pulses generated by flash lamps based on pulse thermography. Additionally, Sun's algorithm is implicatively correlative with coating thicknesses. Decker and Mackin [14] developed a thickness estimation model by fitting McKelvie and Mackenzie models under high-frequency thermal waves (from 3 Hz to 50 Hz). However, as the author [14] stated, the bias between the fitted model and the experimental data are larger than 10% for coatings from 38 to 114 μm. Lock-in methods also have been developed to estimate coating thickness based on phase angle changes or the amplitude changes. However, when the thickness of coating exceeds 1.5 times of the thermal diffusivity length, the difference in phase angle is small when coating thickness changes. Also, with the same phase angle, the samples may have different coating thickness. Besides, the uncertainties of results obtained based on heat conduction models are highly depended on the estimation of the thermal properties since these properties are used as pre-known inputs for coating thickness estimation. A method without requirements on knowledge about thermal properties of coatings or those of substrates will be interested in the industrial application. Artificial neural networks and Support vector machines are selected from the known machine learning algorithms based on the existed test about their ability and cost efficiency to handle regressions with high dimension, non-linear, covariance inputs [51,61–63].

Artificial neural networks are widely recognized supervised learning machine algorithms that can be used to correlate hyper-nonlinear problems [17,18]. Hsieh's study [19] involved the use of artificial neural networks in non-metallic coating thickness estimations via time-resolved thermography, a form of thermography technology that uses a continuous constant heating source. However, there are several drawbacks of ANN models: they require considerable training time to make accurate predictions, and they typically fail to measure 'unknown' data due to their stochastic nature [20,21]. Therefore, a deterministic non-linear regression method may be preferred when limited training data are collected.

Support vector machines, another family of supervised learning models used in classification and regression analyses, are deterministic [22,23]. A principal difference between SVMs and ANNs lies in risk minimization mechanics [24–26]: SVMs employ the structural risk minimization (SRM) principle to minimize an upper bound on the expected risk, whereas ANNs apply traditional empirical risk minimization (ERM) to training data. In several fields [20,21,24–30], SVM models are more robust and deterministic than ANNs while SVM predictions are comparable to ANN results. However, SVM model accuracy levels depend heavily on the experimental data used. In each study listed above, SVM models performed differently. In addition, SVM models require considerable computation, as they are designed to solve non-linear equations [20,21]. The role of SVM regressions in thermography coating thickness estimations remains unclear, as this method has not been used for coating thickness detection or estimation in the field of thermography.

This study tests the performances of SVM models and ANN models in predicting coating thicknesses via time-resolved thermography. We created a non-dimensional surface temperature solution based on the Fourier-Bessel transformed heat conduction equation. This non-dimensional solution is used to understand effects of thermal conductive ratios between coatings on surface temperature increments to those of coating thickness changes and to design the experiments. Additionally, the solution is used to show how sensitive surface temperatures are to coating thermal conductivity and power amplitude levels. Sixty-one painted samples with coating thicknesses varying from 2.5 mil to 22.5 mil (63.5 μm to 571 μm) are tested on. Surface temperature increments during heating are used as inputs for both regression models. The number of hidden neuron nodes and training algorithms in ANN and C- and gamma coefficients of SVM are determined via k-folder cross validation. Optimal models for each method are determined based on average performance levels across all of the 'folders' to eliminate lucky partitions. Another independent testing set was also collected from 28 additional painting-coated samples to measure the performance of the ANN and the SVM models. Their accuracy, precision and costs are compared based on both training and testing performance levels.

2. Heat conduction during thermography and non-dimensional analysis for experiment design

Thermography is a technic that measure certain variables based on the surface temperature. This section describes thermal responses of the coated surface under continuous heating conditions. In this study, coating thicknesses vary from 10 μm to 1000 μm. The width and length of the sample is roughly 50 mm. The temperature of the coating surface can be determined by solving of the following equation if the laser's thermal effects are simplified to a constant spot heating source and if the coating is opaque to the light source:

$$\rho_1 c_1 \frac{\partial T_1}{\partial t} = \frac{1}{r}\frac{\partial}{\partial r}\left(k_1 r \frac{\partial T_1}{\partial r}\right) + k_1 \frac{1}{r^2}\frac{\partial^2 T_1}{\partial \theta^2} + k_1 \frac{\partial^2 T_1}{\partial z^2} \quad (1)$$

$$\rho_2 c_2 \frac{\partial T_2}{\partial t} = \frac{1}{r}\frac{\partial}{\partial r}\left(k_2 r \frac{\partial T_2}{\partial r}\right) + k_2 \frac{1}{r^2}\frac{\partial^2 T_2}{\partial \theta^2} + k\frac{\partial^2 T_2}{\partial z^2}, \quad (2)$$

with boundary conditions:

$$k_1 \frac{\partial T_1}{\partial z}(r, t, z = z_0) = -q(r, t) \quad (3)$$

$$k_2 \frac{\partial T_2}{\partial z}(r, t, z = 0) = k_1 \frac{\partial T_1}{\partial z}(r, t, z = 0) \quad (4)$$

$$q(r, t) = Au(t)\exp\left(-\frac{r^2}{2B^2}\right)\Big/ 4\pi B^2, \quad (5)$$

where $u(t)$ is a step function; B is the diameter of the heating spot, k is the thermal conductivity level, ρ is the density level and c is the heat