

Car paint thickness control using artificial neural network and regression method

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Received: 27 October 2009; Revised: 5 June 2010; Accepted: 29 November 2010

Abstract: Struggling in world's competitive markets, industries are attempting to upgrade their technologies aiming at improving the quality and minimizing the waste and cutting the price. Industry tries to develop their technology in order to improve quality via proactive quality control. This paper studies the possible paint quality in order to reduce the defects through neural network techniques in auto industry production lines. The inputs as effective factor in paint spray process identified for each thin layer on a plate. In the paint shop, defects generate that correlate with film thickness in paint process. In this work, a sheet of metal in demonstrated 50*20 using as a sample when Saipa Company, Iranian Auto Market Leader, is considered as a case study. In the present paper two models of NN is presented. The first model shows prediction of film thickness by 10 input for bell, air layers and 12 inputs variables for dry film thickness or final paint thickness and 6 output points for three layers and second model is predicting of paint appearing uniformity by average and standard deviation of film thickness. Finally the application of Neural Network and statistical method (Regression) in predicting paint thickness and the comparison of the results are presented.

Keywords: Neural networks; Paint spray process; Paint thickness; Paint problems; Proactive quality control

1. Introduction

Various methods have been applied to improve the paint spray process in vehicles. Most of these methods are based on inspections which can take place somewhere in the process (semi-manufactured products) or to end products of the factory. Solutions given to remove the defects are based on the same inspection, some of which are effective and lead to the removal of problems. These solutions, used in the production line, often rely on experience and are not systematic. Methodologically, inspection-based QC techniques are reactive rather than proactive to prevent quality problems in manufacturing (Lou, 2003). New generation of controlling introduced in manufacturing industry, intends to prevent quality problems through optimizing control process (Wu, 1989). Jacobin matrix, being successfully used in paint quality control system, is among the methods of predicting the thickness of paint. This matrix is based on fuzzy logic and employs the Rule Base of Initial Conditions (RBIC) (Filev, 2002). Industrial practice shows, the film thickness and uniformity are much lower than the standard (Koleske, 1995).

Paint or coating is generally applied to vehicles for two major purposes. One is protecting the surface of the metal plate from such elements as

rust, and the other is painting the vehicles according to the taste of the clients. The latter has for long been of great importance. Therefore, we tend to explain a paint spray process from the beginning to the end. This serves as the two mentioned significant purposes. There are the following general steps in today's paint workshops:

- Pre-treatment
- Electro deposition
- Sealer and Under Body Coating
- Primary or surface coat
- Top coat

Among these steps, top coat is of great importance because top coat is what we see on cars and call it the color of the car (e.g. white, red, green, beige, metallic or solid). Top coats are of two types: solid and metallic. In metallic paints there are metallic and mineral particles and pigments which cause the car to look shinier than the car with solid paints. Figure (1) shows topcoat flow diagram.

Top coat must have certain physical and chemical features which can be measured through various tests (Robert, 1961).

There are three elements influencing the quality of vehicles' paint as follows:

- a. Type of painting tools and equipment
- b. Paint hall conditions
- c. Paint conditions

Variables can affect the quality of the vehicle's paint. These variables can be divided in four groups as follows:

1. Paint spray variables (such as the amount of paint sprayed – the volume of air in the spray – paint spray pressure – pistol or bell's distance from the surface of the vehicle, solid paint in the spray – the speed of bell rotation and move – radius of the move – bell voltage).
2. Paint hall air variables (temperature and humidity – air speed)
3. Paint variables (viscosity – paint temperature and solid paint amount)
4. Surface of the vehicle related variables (vehicle's surface temperature – linear velocity – thickness of the plate) (Li, 2006)

In system identification, multi-variable non-linear system can be presented by:

$$E = f(x_i, y_i) \tag{1}$$

Where "E" is performance of system, f is unknown non-linear function, x_i are controllable variables (spray variables, air variables, some of paint variables such as, viscosity temperature of paint) and y_i (some of paint variables such as, amount of solvent or thinner and vehicle body variables) are disturbance variables. It is expected that optimal setting of the manipulated variable can eliminate the negative influence of the disturbances on coating quality.

2. Paint defects and their relationship with the thickness

Among the defects of the surface, dirt or particles, orange peel, running or sagging, pin hole, glass, fish eye or crating can be mentioned. When significant defects of high percentage in the production line and their causes are studied, it can be seen that in all cases, the thickness of the paint layer is an important factor. When the thickness is kept constant all over the surface of the vehicle, defects are minimized. For example, when the

paint layer thickens, running and pin hole defects, which are harmful to the paint, will happen. As the thickness lessens, such defects as pale, matt color, and orange peel may occur.

Being a chemical process, painting is a nonlinear model. In some cases there might be slight changes or deficiencies in the data provided. Therefore, Neural Network models can provide us with appropriate means in this survey because of the following reasons (shows in Figure 2).

3. The Structure of artificial neurons

The current trend in intelligent system research is concerned with artificial intelligent tools as neural network for solving complex problems with complexities and uncertainties, adequate domain knowledge and pertinent data. Neural networks have on their side the capability of learning and adaptation adjusting interconnections among the layers. Linear technology, however, cannot provide satisfactory control for processes with high nonlinearity or moderate nonlinearity with a large operating region. This would lead to the development of nonlinear process control in which a control law is designed for a nonlinear model of the process (Bodizs, 1999).

The following figure depicts the structure of an Artificial Neuron Model based on the biological neuron. In this model, the aggregate weight of the input is measured first, and is then compared to its internal threshold. It will be activated when the weight exceeds the threshold; otherwise it will remain inactive. Therefore, the structure of an Artificial Neuron consists of input, weight, addition function, transformation function, and output. In fact, the network of all the input gives weights and addition function calculates the aggregate of weight coefficients in the input, and transformation function, which is a required element in neural networks, provides a threshold for transformation of the input and transforming it into the output.

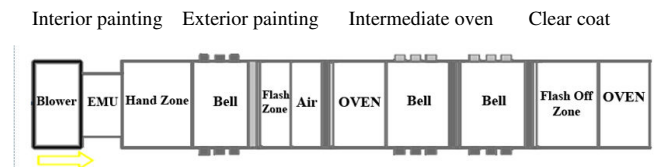


Figure 1: Topcoat flow diagram.

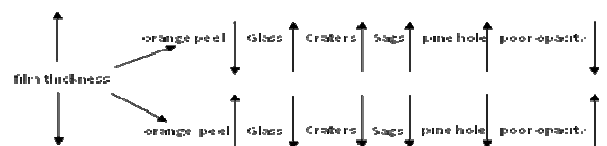


Figure 2: Paint defects and its relation to thickness.

In 1963, Rosenblat proposed single-layer perceptrons in which neuron models were connected to each other from the top. Single layer perceptrons are not capable of solving nonlinear problems. Thus multilayer networks are used to solve nonlinear problems such as processes. Multilayer networks have higher potentiality in solving problems, and have numerous applications.

It has a mathematical foundation that is strong if not highly practical. It is a multi-layer forward network using extent gradient-descent based delta-learning rule. Commonly known as back propagation (of errors) rule. The total squared error of the output computed by net is minimized by a gradient descent method known as back propagation or generalized delta rule. The derivation of activation function is denoted by $F(x)$. Let:

$$y_{-ink} = \sum_i z_i w_{jk} \tag{2}$$

$$Y_k = f(y_{-ink}) \tag{3}$$

The error will be minimized as:

$$E = 1/2 \sum_k [t_k - y_k] \tag{4}$$

By the use of chain rule we have:

$$\delta_k = -[t_k - y_k] f^1(y_{-ink}) \tag{5}$$

The weight updating for output unit is given by:

$$\Delta w_{jk} = \alpha \delta_k z_j \tag{6}$$

The weight updating for the hidden unit is given by:

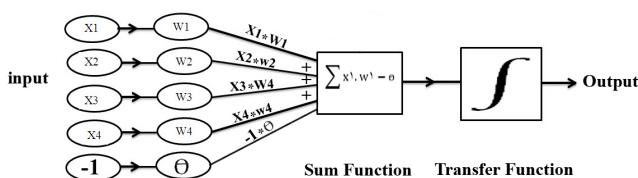


Figure 3: Neural network neuron model.

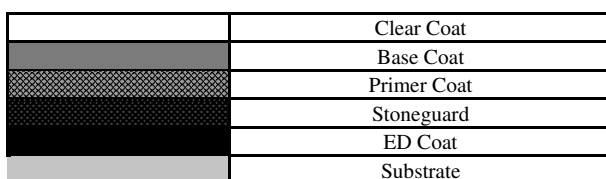


Figure.4: Schematic diagram of topcoat.

$$\Delta v_{ij} = \alpha \delta_j x_i \tag{7}$$

This is the generalized delta rule in the back propagation network during the training.

During back propagation of errors, each output unit compares its computed activation y_k with its target value t_k to determine the associated error for that pattern with that unit. Based on the error, the factor $\delta_k = (k = 1, \dots, m)$ is computed and is used to distribute the error at output unit y_k back to all units in the previous layer (Sivanandam, 2008).

4. Tools and method of data collection

For implementation of the model Saipa Company, the leader automotive car manufacturer in Iran was selected as a case study.

In order to collect the necessary data, metal parts of 50*20 cm were installed in the windows of cars, while being painted, called Gig. So it was made possible for us to collect accurate data from nearly 105 sound plates.

In the beginning of the study, the thickness of the top paint of the vehicles was measured. But, in fact, we were able to measure the thickness of the dried film. The thickness of the dried film of the top paint includes three layers. Base layer paint sprayed by bell, the layer sprayed by air gun, and the clear layer sprayed by clear gun. To measure these three layers separately and accurately, plates of 50*20 cm were made ready. All the plates were surface coated.

Three rows of tape of 5 cm width were used on them. After every paint spray time, one row of clear tapes was removed and its track was air painted. Then the next tape was removed, and finally after the clear tape, the last tape was removed. Under the last tape, there was only surface coating. Figure (4) shows schematic diagram of topcoat.

The basecoat contain all the color pigments and the clear coat serves as glossy scratch and UV resistance layer (Ramamurthy, 1993).

$$(a + b + c + p) - (a + c + p) = b \tag{8}$$

Bell layers are resulted from subtracting the following layers:

And the air layer, in turn was the result of the subtraction of the following layers.

$$(A + C + P) - (C + P) = A \tag{9}$$

5. Modelling

Variables involved in the process of Painting fall under four categories Table 1. Parameters related to bell and air layers are also stipulated in Table 2 (Li, 2004; Lou, 2001). A multi layer perceptron neural network was used in designing an intelligent model to predict the thickness of the Bell spray. This network includes input, hidden, and output layers.

This model has employed 10 input variables for Bell and Air layers, and 12 input variables for the final thickness of the paint, and 6 output variables. Each of these variables, as experts say, can determine the thickness of the paint.

Different network structure positions, regarding the number of layers and neurons, were considered. The best of them for Bell and Air layers with two hidden layers was 20 neurons for the first layer and 10 for the second, and as for the final layer was 1 hidden layer with 25 neurons. Six outputs for the first position and two for the second one were considered. Therefore, for the purpose of efficiency of the network, using the neural network was studied for all the three layers separately.

Each of the above mentioned positions was evaluated from two approaches.

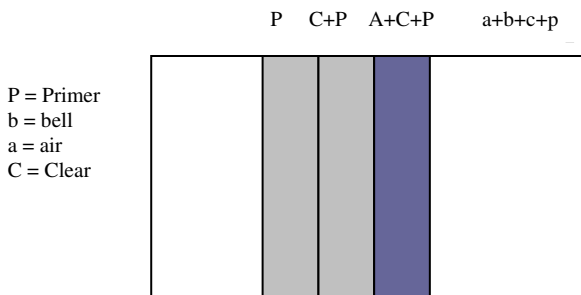


Table 1: Variables influencing the process of painting.

spray variables	1- distance between gun and body 2- shaping air pressure 3- bell voltage 4- spray pressure
paint variables	1- density or viscosity 2- temperature 3- paint type 4- solid or non-volatile materials percent
booth variables	1- temperature 2- humidity 3- particles 4- air current speed
movement variables	1- conveyer speed 2- pitch 3- automobile length
vehicle variable	1- panel temperature 2- substrate thickness 3- filmbuild

5.1. The first approach

As it can be seen from the figure, the first approach is predicting six points separately. In fact, here we tend to control thickness in each of the six points in several vehicles. Therefore, there will be six outputs and six errors for each case. To evaluate the results, first we calculated the mean error of estimation and the second root of the mean errors to the power of two, then calculated the algebraic mean of 30 samples. The results obtained from Air, Bell layers, and the final thickness, are shown in the tables. Results from regression method are put forward too.

5.2. The second Approach

The second approach deals with evenness of the paint on the surface. It means the less different the thickness of the paint layer in different points of the vehicle, the more even and beautiful the paint on the surface of the vehicle will be.

In straight forward terms, “the thickness of evenly sprayed paint results in more beautiful appearance.” Therefore, in this approach, the evenness of the paint on the surface of the vehicle is concerned, while in the previous one we studied six different points in 30 vehicles. Tables 3 and 4 show the results of using Neural Network and Regression for the same data.

6. Analysis of the results

The researchers believe that an appropriate index to show the usefulness of the neural network is its applicability. As it is not attended to by the management much, because it is costly, the diagram resulting from real values along with predictions were considered as sufficient. This diagram and its errors were then considered upon. A comparison was made for all the three Air, Bell layers, and the final thickness. To compare, first the mean of six points in 30 vehicles was calculated. This mean included the predicted and the real values.

Table 2: Input variables.

	Bell	Air
1	paint viscosity	paint viscosity
2	paint temperature	paint temperature
3	booth temperature	booth temperature
4	Down draft	Down draft
5	booth humidity	booth humidity
6	paint amount FM	paint amount
7	shaping air pressure of Air (LL)	Shaping air pressure of bell (LL)
8	Voltage	Air paint amount
9	magnetic field (HT)	shaping air pressure of Air (HL)
10	whole FMK paint amount	whole FMK paint amount

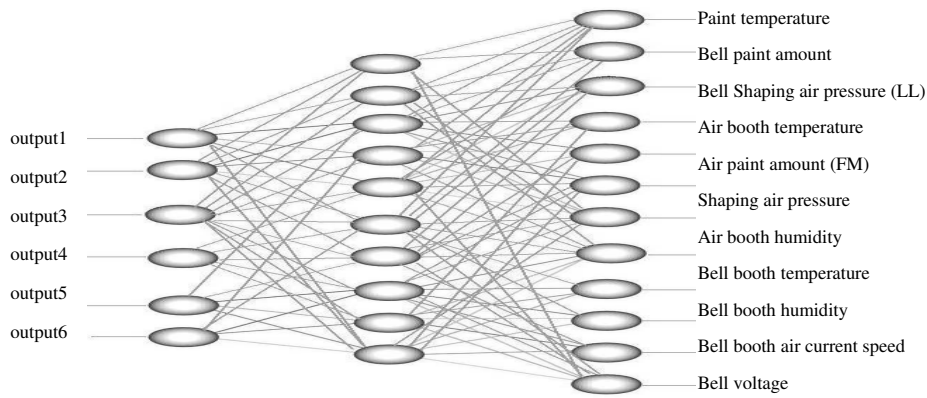


Figure 5: Neural network model.

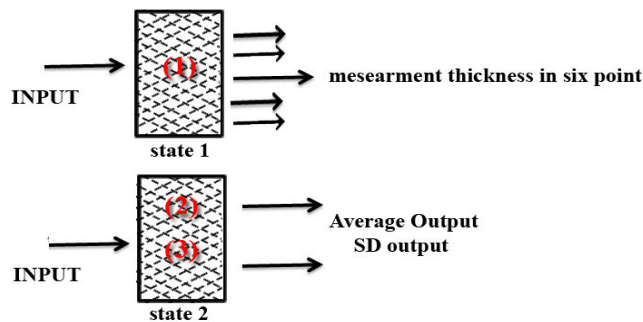


Figure 6: Different states of prediction.

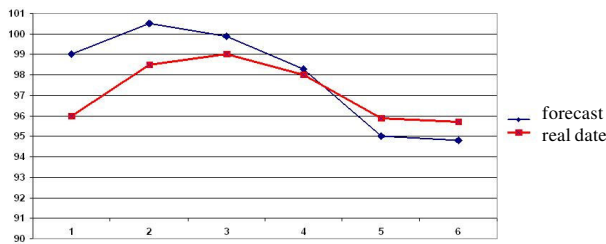


Figure 8: Prediction thickness through neural network model and real data.

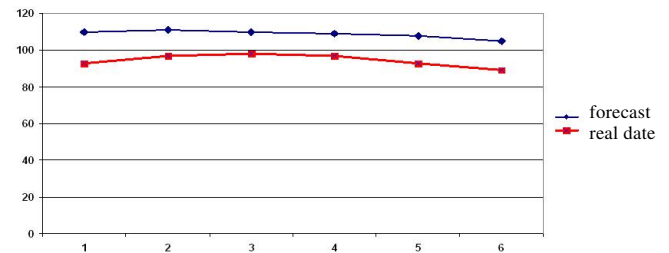


Figure 9: Predicting thickness through regression model and real data.

Table 3: Results associated to prediction of film thickness by neural network in six points.

Errors related to Air layer	Bias	0.52	-0.55	-0.04	-0.47	0.20	0.08
	MAD	2.33	2.84	4.19	2.79	3.02	2.42
	RMSE	3.74	4.42	6.22	3.91	4.02	3.61
Errors related to Bell layer	Bias	-0.26	1.84	0.39	0.22	-2.82	0.43
	MAD	3.26	3.76	3.24	4.27	5.03	4.10
	RMSE	4.02	4.77	4.33	5.34	6.53	4.98
Errors related to final layer	Bias	0.70	0.80	-0.30	-0.90	-2.13	-2.99
	MAD	14.39	16.35	12.75	14.10	15.33	17.62
	RMSE	19.91	21.65	18.80	19.85	18.85	21.00

Table 4: Results associated to prediction of film thickness by regression in six points.

Errors related to Air layer	Bias	-0.21	-0.14	0.34	-0.35	-1.08	-0.76
	MAD	3.07	2.62	2.28	1.83	2.27	3.14
	RMSE	3.87	2.95	2.83	2.30	2.80	4.32
Errors related to Bell layer	Bias	-2.67	-1.77	-1.71	-0.87	-0.35	-1.11
	MAD	4.38	4.10	4.16	3.57	3.22	3.35
	RMSE	5.35	4.90	4.86	4.67	3.93	4.19
Errors related to final layer	Bias	-14.67	-15.27	-17.16	-17.41	-17.86	-17.40
	MAD	17.29	18.22	19.86	20.67	21.04	19.81
	RMSE	24.20	25.63	27.41	28.25	27.46	25.95

Table 5: Comparison of two methods.

	Neural Network	Regression
	MAD Error	
Air layer	2.93	2.54
Bell layer	3.94	3.80
Final layer	15.09	19.48

Table 6: Results related to neural network uniformity.

		Mean	Standard Deviation
Errors related to Air layer	Bias	0.71	-0.66
	MAD	1.93	1.13
	RMSE	2.52	1.58
Errors related to Bell layer	Bias	-1.33	-0.35
	MAD	3.02	0.59
	RMSE	4.24	0.72
Errors related to final layer	Bias	-4.30	-0.76
	MAD	13.08	2.49
	RMSE	16.65	3.29

Then the difference between the means in both network models and the regression in each layer were calculated. The results are shown in the respective parts. Results obtained from evenness of the neural network on Table 6.

7. Conclusion

To improve quality film build and reduce defects, identification variables are essential. Variables influencing the process of painting in a painting hall in a topcoat booth were measured. A neural network model was proposed for the process and was subsequently analyzed through a neural network and regression method.

MAD, BIAS, and RMSE errors were measured for each layer. Real and predicted values were then compared for each layer in related diagrams. But in the final layer where the thickness of the paint is considered, thickness was not predicted pretty well. The maximum error of prediction in neural network for the final thickness of the paint was 2/99 microns and 17/86 in statistical method.

As there is a difference of 5 microns on different parts of a vehicle such as hood, door, etc. the error of the network can be accepted. According to Filev (2002), a film thickness measurement can be installed in a paint shop. Process information collects by devices (sensors, PLCs). Then real and predict outputs compare and finally variable based on error are adjusted. In addition neural network could predict successfully but in some points hasn't appreciated prediction and that points have higher division than another points. The introduced method can help for proactive Quality Control System rather than passive system.

References

Bodizs, A.; Szeifert, F.; Chovan, T., (1999), Convolution model based predictive control

roller for a nonlinear process. *Industrial and Engineering Chemistry Research*, 38(1), 154-161.

Browne, A., (1997), *Neural network analysis, architectures and applications*. IOP Publishing, Bristol, UK.

Filev, D., (2002), *Applied intelligent control- Control of automotive paint process*. IEEE International Conference on Fuzzy Systems, 1-6.

Gear, R., D.; Perich, R., (1961), *Liquid paint finishing defects*. Society of Manufacturing Engineers.

Koleske, J. V., (1995), (ed.), *Paint and coating testing manual*. 14th Ed., ASTM, Philadelphia, PA.

Li, J., (2004), *Adaptive molding integration optimization and control automotive paint spray process*. M.Sc. Thesis, Wayne State University.

Li, J.; Huang, Y., (2006), Bayesian-based on-line applicability evaluation of neural network models in modeling automotive paint spray operations, *Computers & Chemical Engineering*, 30(9), 1392-1399.

Lou, H.; Huang, Y., (2003), Hierarchical decision making for proactive quality control: system development for defect reduction in automotive operation, *Engineering Application of Artificial Intelligence*, 16(3), 237-250.

Lou, H. H.; Huang, Y. L., (2001), A neural network model of automotive topcoat spray for improve operation using limited data. *International Journal of Engineering Applications Artificial Intelligence*.

Ramamurthy, A. C.; Uriquidi – Macdonald, M., (1993), *Stone impact damage to automotive paint finishes – A neural net analysis of electrochemical impedance data*. IEEE International Conference on Neural Networks, 3, 1708-1712.

Sivanandam, S. N.; Sumathi, S.; Deepa, S. N., (2008), *Introduction to neural network using Matlab 6.0*. Tata McGraw-Hill publishing Company Limited, ISBN 0-07-059112-1.

Wu, S. M.; Ni, J.; Hu, S., (1989), *Next generation quality control in of the ASME winter manufacturing – Real time defect prevention*. Proceedings of the ASME Winter Annual Meeting, San Francisco, CA.