

Neural Network Inverse Model for Quality Monitoring

Application to a High Quality Lackering Process

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Abstract: The quality requirement is an important issue for modern companies. Many tools and philosophies have been proposed to monitor quality, including the seven basic tools or the experimental design. However, high quality requirement may lead companies to work near their technological limit capabilities. In this case, classical approaches to monitor quality may be insufficient. That is why on line quality monitoring based on the neural network prediction model has been proposed. Within this philosophy, the dataset is used in order to determine the optimal setting considering the operating point and the product routing. An inverse model approach is proposed here in order to determine directly the optimal setting in order to avoid defects production. A comparison between the use of a classical multi-inputs multi-outputs NN model and a sequence of different multi-inputs single-output NN models is performed. The proposed approach is tested on a real application case.

1 INTRODUCTION

Product quality control is become a major issue in the mass customization context. Different policies, such as Total Quality Management (TQM) or Just in Time (JiT), have been developed in order to control quality. These two policies are related to the Lean Manufacturing (LM) concept (Vollmann et al., 1984).

These policies require the use of different tools, such as the seven basic quality tools (Ishikawa chart, check sheet, control charts, histogram, Pareto chart, scatter diagram, stratification) which allow to control quality a posteriori. This approach leads to reject or to downgrade a large part of the production (Thomas et al., 2013).

A first improvement was given by Taguchi (1989) which proposed to set up the parameters control in order to avoid the defects production. The aim of the Optimal Experimental Design (ODE) proposed by Taguchi is to provide a setting of the parameters robust to changing conditions. However, robust setting is generally non optimal when the actual conditions are considered. Well, for high quality production, the process works often near the

limits of its capabilities. In this case, non optimal settings are insufficient to limit the defects production (Noyel et al., 2013a).

Noyel et al., (2013b) have proposed to exploit the production data, collected and stored with traceability goal, in order to perform on-line quality monitoring. This approach exploits prediction models able to predict the defect occurrence risk as a function of the actual operating range and the product routing.

In order to improve this approach, another philosophy can be exploited. In the domain of automatic control, adaptive inverse control is based on inverse processes identification where the output of the process becomes the input of the model (figure 1) (Widrow and Bilello, 1993).

The design of the inverse model is often performed by using the neural network approach and this type of control has been applied with success to the control of many non linear process such as, synchronous motor (Liu et al., 2013), Maglev system (Hajimani et al., 2014) and robotic (Yildirim, 2004).

The main idea developed here, is to propose an on line quality monitoring approach based on

inverse neural model. The goal is to design a model able to determine the optimal setting from the tunable parameters, considering the operating point, the product routing and the defects occurrence risks.

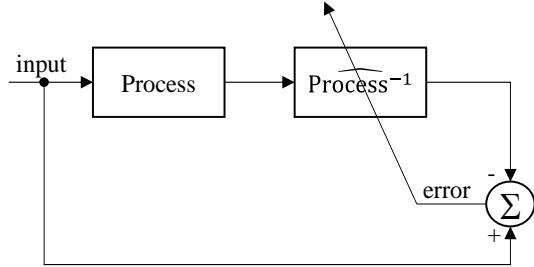


Figure 1: Inverse identification (Widrow and Bilello, 1993).

The main goal of such approach is to obtain directly a setting able to avoid defects. Moreover, if a pruning procedure is performed on the neural model, some inputs may be removed of the model. If one or more of these inputs correspond to defect types, this implies that a subsidiary benefit is to determine if a tunable parameter has an impact or not on some defect types occurrence.

First we will recall succinctly the quality monitoring problem. In a second step, the proposed procedure will be describe. Two approaches will be discussed:

- Using of one multi inputs multi outputs (MIMO) model;
- Using of several multi inputs single output (MISO) models;

The structure of the neural network and the tools used will be also presented. After, the industrial application case and the results obtained will be presented before to conclude.

2 QUALITY MONITORING

Quality monitoring needs to understand which factors have an impact on the defects production. Ishikawa (1986) has proposed the 6M method which classes these factors into 6 categories: Machine (technology), Method (process), Material, Man Power, Measurement (inspection), Milieu (environment). In the context of on line quality monitoring which needs to design a prediction model of the defect, it is more useful to classify these factors into controllable and non-controllable factors (Noyel et al., 2013b). The controllable factors group together the setup parameters when the non-controllable factors include the operating point

(environmental factors, process constraints...) and the routing product factors.

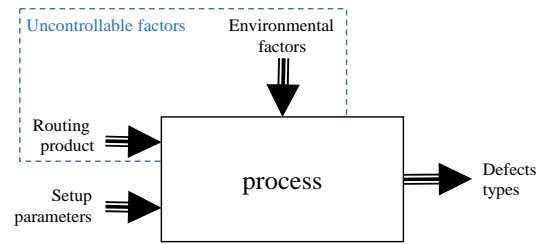


Figure 2: Data collection.

So, in this context, three main types of data must be collected and stored: controllable and uncontrollable factors upstream of the process, and the defects types downstream of the process (figure 2).

Two ways may be used to search the “zero defect” goal:

- By optimizing the settings of various factors;
- By drifts monitoring and prevention;

The on line quality monitoring philosophy refers to the first way. The goal is to determine the best setting of the controllable factors, for each product or batch (taking into account its routing constraints), considering the existing conditions (current operating point) (Thomas et al., 2013).

3 ON LINE QUALITY MONITORING

The proposed approach is based on the design of a neural model able to determine the optimal setting of controllable factors. The neural network used here is a multilayer perceptron which seems to be perfectly adapted to our needs because it is an universal approximator (Cybenko, 1989, Funahashi, 1989).

3.1 Multilayers Perceptron

The classical multilayer perceptron (MLP) is a feedforward neural network including only one hidden layer using a sigmoidal activation function and on output layer using an activation function which can be linear for regression problem or sigmoidal for classification problem. Its structure is given by (for the output k):

$$z_k = g_2 \left(\sum_{i=1}^{n_1} w_{ki}^2 \cdot g_1 \left(\sum_{h=1}^{n_0} w_{ih}^1 \cdot x_h^0 + b_i^1 \right) + b_k \right) \quad (1)$$

with $k = 1 \dots n_2$

where, z_k are the n_2 outputs and x_h^0 are the n_0 inputs of the neural network, w_{ih}^1 are the weights connecting the input layer to the hidden layer, b_i^1 are the biases of the hidden neurons, $g_1(.)$ is the activation function of the hidden neurons (here, the hyperbolic tangent), w_{ki}^2 are the weights connecting the hidden neurons to the output k , b_k is the bias of the output neuron k , $g_2(.)$ is the activation function of the output neuron. Because of the problem is to obtain the optimal setting of controllable parameters, we are faced to a regression problem, so $g_2(.)$ being chosen linear.

No normalisation is performed on the dataset. This fact implies to use an initialisation algorithm able to take into account the different value ranges between the inputs (Nguyen and Widrow, 1990).

The dataset is a real industrial dataset polluted with outliers. So the learning algorithm used must be robust to these outliers (Thomas et al., 1999). In order to evaluate the generalization capabilities of the model, the dataset must be divided into learning and validation datasets. The learning dataset is used in order to adapt the parameters of the MLP when the validation one is used to estimate the performance of the model.

The accuracy of the neural model depends on the structure (number of hidden neurons, inputs and parameters). Too few parameters or hidden neurons, and the learning can't find accurate parameters. Too much parameters, and the learning can lead to the well-known overfitting problem. To avoid this problem, the learning is performed on a largely oversized structure with too much hidden neurons and a pruning procedure is used to reduce this structure (Thomas and Suhner, 2015). This

procedure presents the advantage to be able to discard some spurious inputs.

3.2 Tuning of Controllable Parameters

The main idea is to determine the optimal setting of the controllable parameters by using MLP model. This model is designed by using the dataset constituted by the controllable and uncontrollable factors collected upstream of the process, and the defects types collected downstream of the process. This model is designed under the inverse concept where the outputs of the model are constituted by some inputs of the process, when the inputs of the models includes some inputs of the process and its outputs (figure 3).

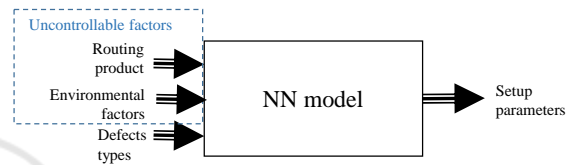


Figure 3: Inverse model design.

To do that, the classical and simplest approach is to design a multi-inputs multi-outputs (MIMO) neural network. However, in this case, the pruning phase don't allow to determine if a defect type (input) is related to a particular setup parameter (output).

To outperform this drawback, another structure is used, where different multi-inputs single-output (MISO) neural networks are designed sequentially. The figure 4 presents an example of such structure, where 3 setup parameters are considered.

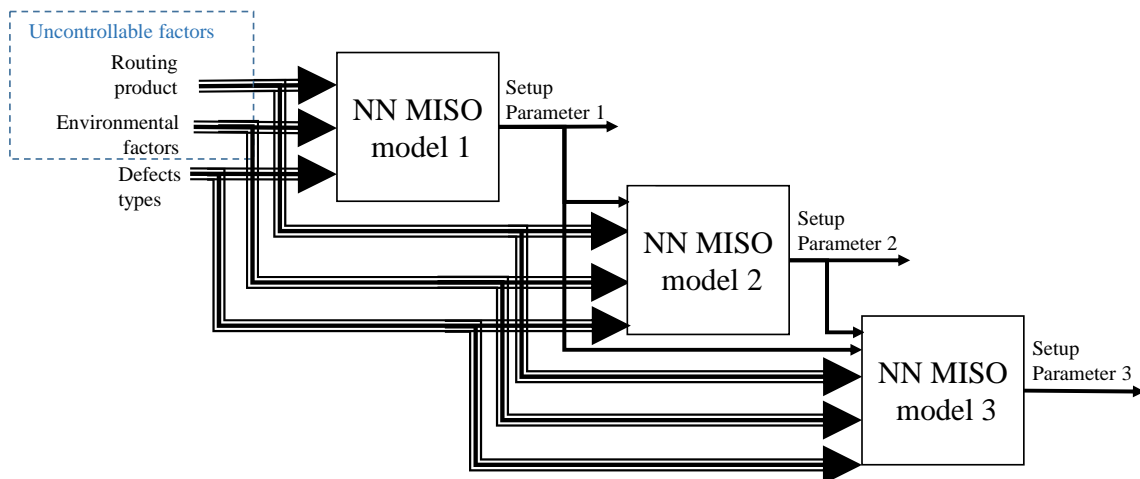


Figure 4: Sequential MISO NN models (case of 3 setup parameters).

Considering this structure, four advantages can be listed:

- Each NN model includes less parameters (only one output, possibly less hidden neurons, possibly more inputs pruned). This fact improves the learning and using speeds and limits the overfitting risk.
- The learning of each NN model is independent. This fact implies that the learning of these different model may be performed in parallel.
- The pruning step allows to pruned inputs in each NN model. This fact implies that a causal link may be discarded between some defect types (pruned inputs) and the considered setup parameter.
- Each NN model may use, as inputs, the outputs (setup parameters) of the upstream NN models in the sequential structure. This fact allows to improve the global accuracy of the structure.

The sequence of the different MISO NN models selected is the one which optimize the accuracy of the complete structure on the validation dataset.

In the sequel, the performances of the proposed structure will be tested and compared with those obtained with a single MIMO model on a real industrial case.

4 INDUSTRIAL APPLICATION

4.1 Presentation of the Process

The considered problem is a quality monitoring problem in a company which produces high quality lacquered panels made in MDF (Medium Density Fibreboard) for kitchen, bathroom, offices, hotel furniture, stands, shops... This study focuses on its main process which is a robotic lacquering workstation. This workstation is free of human factors, but defects rates are important and very fluctuant, and could expand from 10% to 45% from one day to another. This fact is mainly due to the high quality requirements, which implies that this workstation works at its limit capabilities. So, despite the design of an ODE in order to tune this robotic workstation, the company fails to reduce the defects rates.

That's why an on line quality monitoring approach is performed. Expert knowledge has allowed to list parameters able to have impact on the defects generations. These parameters can be classified into:

- Three environmental factors (temperature,

humidity, pressure).

- Five product routing parameters (number of passes, time per table, litre per table, number of layers, drying time)
- Three setup parameters (load factor, basis weight, number of products).

These different factors and parameters are able to have an impact on thirty different defects types.

Considering the inverse model structure, the dataset is constituted by three outputs (setup parameters) and thirty eight inputs (environmental factors, product routing parameters, and types of defects). The dataset includes 2167 data and is split into two datasets for identification (1088 data) and validation (1079).

In order to limit the risk of local optimum trapping, the learning of all the NN models is performed with twenty initial parameters sets and the best one is retained.

The selection criterion used is the classical Root Mean Square Error (RMSE) calculated on the learning and validation datasets:

$$RMSE = \sqrt{\frac{1}{N} \sum_{n=1}^N (z(n) - y(n))^2} \quad (2)$$

where $z(n)$ is the output given by the network for the data n and $y(n)$ is the corresponding target.

The first NN model designed is the MIMO one. The initial number of hidden neuron is set to twenty. Table 1 presents the RMSE values obtained with the best MIMO model for the three different outputs. These values highlight the difference between the variation ranges and amplitudes of the outputs. This fact may have an impact on the learning accuracy. During the learning, the criterion to minimize is the errors sum squared performed on the three outputs. In this case, the risk is that the learning algorithm favours one output over the others.

Table 1: RMSE values for the MIMO NN model.

	learning	validation
load factor	0.4057	0.4406
basis weight	191.8222	238.2346
products number	307.3382	381.0269

The results obtained with the MIMO model must be compared to those obtained with the sequence of MISO models.

To design the sequence of MISO models, it is necessary to determine in which order the setup parameters must be considered. The selected order is the one which maximize the sequence accuracy.

Table 2: RMSE values for the different MISO NN models.

		1 st MISO model	2 nd MISO model			3 rd MISO model		
supplementary inputs			load factor	basis weight	products number	basis weight	load factor	load factor
						products number	products number	basis weight
Load factor	learning	0.3698		0.3509	0.2339	0.2381		
	validation	0.4336		0.4466	0.2856	0.2805		
basis weight	learning	177.3311	185.1477		182.785		178.9352	
	validation	230.4716	226.6402		224.0547		228.0947	
products number	learning	297.5479	223.1687	365.6229				218.7272
	validation	361.2214	264.4579	369.2758				256.713

Different MISO NN models must be designed with different structures. For all these models the initial number of hidden nodes is setup to twenty.

The inputs number depends of the order of the sequence. The first MISO model must determine its output by using the same thirty eight inputs of the MIMO model. The second one shall have one additional input (the output of the first MISO model). The third one shall have two additional inputs (the outputs of the two preceding MISO models).

The table 2 presents the RMSE values obtained for the learning and the validation datasets for the different MISO NN models designed. The first line indicates if the considered model is the first, the second or the third of the sequence. The second line indicates which the supplementary inputs if available are.

First, it can be noticed that the use of one or two supplementary inputs improve the accuracy for the three outputs. As example, the RMSE value for the validation dataset for load factor is reduced with a reduction from 0.4336 to 0.2856 (34% improvement) when product number is used as supplementary input. The same observation may be performed for the two other outputs.

So it is necessary to determine the optimal sequence of MISO models. To do that, the decrease in terms of percent of RMSE (compared with the results obtained with the MIMO model) is studied and the sequence which minimizes the sum of the three "RMSE decreased in terms of percent" values for the three outputs (on the validation dataset) is selected. With this criterion, two sequences gives very similar results:

- First: products number (5%); second: basis weight (6%); third: load factor (36%).
- First: products number (5%); second: load factor (35%); third: basis weight (4%).

For the sequel, we choose arbitrarily the first sequence and the results obtained for the three MISO models of the sequence are highlighted in table 2. This is these results which must be compared to those obtained with the MIMO models

presented table 1. These results show a slight improvement for two outputs (5% for products number and 6% for basis weight) which is not very significant. However, the improvement obtained for the third output (load factor) is relevant and reaches 36%.

It can be noticed that the choice of the sequence is important to obtain the best results, but all sequences allows to improve substantially the results compared to those obtained with the MIMO model. In our case, the worst sequence is:

- First: load factor (2%);
- Second: products number (4%);
- Third: basis weight (31%).

The choice of the sequence may also be performed by using expert knowledge.

The three selected MISO models have been pruned in order to find the optimal structure of the model and to limit the overfitting risk. A second advantage is, that it allows to determine if a causal link occurs between the considered setup parameter (output) and the defects types (some of the inputs).

For the setup parameter "products number" the pruning algorithm has preserved only one defect type: "grain on face". This fact implies that the optimal tuning of this parameter has no impact on the twenty nine other defects types.

For the second setup parameter: "basis weight", only three defects types are discarded: "grain on back", "scratch" and "sanding defect". So, the optimal setting of this parameter may have an impact on the twenty seven other defects types.

For the third setup parameter: "load factor", seven defects types are discarded: "grain on back", "stain under the paint"; "scratch", "paint refusal"; "priming defect", "sanding defect", "silicone mark".

It can be noticed that some types of defects are impacted by none of the setup parameters: "grain on back", "scratch" and "sanding defect". This is due to the fact that these types of defects don't find their origin in the considered workstation. Scratch defects are mainly caused by handling problem. Sanding defect are certainly produced during the preceding sanding step. Grain on back are performed during a

preceding step of lacquering.

It can be noticed that some defects types which probably don't find their origin in the considered workstation are not pruned in the second MISO model: "priming defect" or "silicone mark". This fact is probably due to the pruning algorithm accuracy.

5 CONCLUSIONS

An on line quality monitoring approach based on neural network models is proposed here. The main goal of this proposed approach is to determine quickly and simply the optimal tuning of setup parameters considering the actual operating point and the product routing. This quality monitoring is based on inverse approach NN models which try to determine the tuning of setup parameters by using both, non controllable parameters collected upstream of the workstation, and quality defects occurrence collected downstream of the workstation.

Two approaches may be used to perform the design of the inverse model. The simplest is to use a multi-inputs multi-outputs model able to set up all the controllable parameters simultaneously. The second one is to use a sequence of different multi-inputs single-output models able each to set up only one parameter. These two approaches are tested and compared. The results have shown that the second approach allows to improve the accuracy of the complete system.

Moreover, the using of a pruning algorithm next the learning allows to determine if a causal link occurs between some defects types and the considered setup parameter.

In some extreme environmental conditions, it is possible that none setup is able to avoid defects production for certain product routing. In this case, one drawback of the proposed approach is that our system will give a setup, possibly the best one, but which will be insufficient. Our future works will focus on the detection of these particular conditions in order to be able to propose to the operator to delay the machining of the considered products.

REFERENCES

Cybenko, G., 1989. Approximation by superposition of a sigmoidal function. *Math. Control Systems Signals*, 2, 4, 303-314.
Hajimani, M., Dashti, Z.A.S., Gholami, M., Jafari, M., Shoorehdeli, M.A., 2014. Neural adaptive controller

for magnetic levitation system, *Iranian Conf. on Intelligent Systems ICIS'14*, Bam, Iran.
Ishikawa, K., 1986. *Guide to quality control*. Asian Productivity Organization.
Liu, G., Chen, L., Zhao, W., Jiang, Y., Qu, L., 2013. Internal Model control of permanent Magnet synchronous motor using support vector machine generalized inverse, *IEEE Trans. on Industrial Informatics*, 9, 2, 890-898.
Nguyen, D., Widrow, B., 1990. Improving the learning speed of 2-layer neural networks by choosing initial values of the adaptative weights. *Proc. of the Int. Joint Conference on Neural Networks IJCNN'90*, 3, 21-26.
Noyel, M., Thomas, P., Charpentier, P., Thomas, A., Brault, T., 2013a. Implantation of an on-line quality process monitoring. *5th Int. Conf. on Industrial Engineering and Systems Management IESM'13a*, Rabat, Maroc.
Noyel, M., Thomas, P., Charpentier, P., Thomas, A., Beauprêtre, B., 2013b. Improving production process performance thanks to neuronal analysis. *11th IFAC Workshop on Intelligent Manufacturing Systems IMS'13*, Sao Paulo, Brazil.
Taguchi, G., 1989. *Quality engineering in production systems*, NY, MacGraw-Hill.
Thomas, P., Bloch, G., Sirou, F., Eustache, V., 1999. Neural modeling of an induction furnace using robust learning criteria. *J. of Integrated Computer Aided Engineering*, 6, 1, 5-23.
Thomas, P., Noyel, M., Suhner, M.C., Charpentier, P. and Thomas, A., 2013. Neural Networks ensemble for quality monitoring, *5th Int. Joint Conf. on Computational Intelligence IJCCI'13*, Vilamoura, Portugal, 515-522.
Thomas, P., Suhner, M.C., 2015. A new multilayer perceptron pruning algorithm for classification and regression applications. *Neural Processing Letters*, 42, 2, 437-458
Vollmann, T.E., Berry, W.L. and Whybark, C.D., 1984. *Manufacturing Planning and Control Systems*, Dow Jones-Irwin.
Widrow, B., Bilello, M., 1993. Adaptive inverse control, *Proc. of the Int. Symp. on Intelligent Control*, Chicago, Illinois, USA.
Yildirim, S., 2004. Adaptive robust neural controller for robots. *Robotics and Autonomous Systems*, 46, 3, 175-184.