APPLICATION OF SELF-ORGANIZING MAPS IN ANALYSIS OF WAVE SOLDERING PROCESS

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Abstract

This paper presents an overview of a data analysis method based on self-organizing maps (SOM), a well-known unsupervised neural network learning algorithm, which was applied to a lead-free wave soldering process. The aim of the study was to determine whether the neural network modeling method could be a useful and time-saving way to analyze data from a discrete manufacturing process, such as wave soldering, which is a widely used technique in the electronics industry to solder components on printed circuit boards. The data variables were mostly various process parameters, but also some solder defect numbers were present in the data as a measure of the product quality. The data analysis procedure went as follows. At first, the process data were modeled using the SOM algorithm. Next, the neuron reference vectors of the formed map were clustered to reveal the desired dominating elements of each territory of the map. At the final stage, the clusters were utilized as sub-models to indicate variable dependencies in these sub-models. The results show that the method presented here can be a good way to analyze this type of process data, because interesting interactions between certain process parameters and solder defects were found by means of this data-driven modeling method.

Keywords: Neural Networks, Self-Organizing Maps, Wave Soldering, Process Analysis.

Presenting Author's biography

Mika Liukkonen, born in Jyväskylä, Finland, August 22, 1979, graduated from the University of Oulu, Finland, as M.S. (eng.) in 2007. His main research interest includes process engineering, process modeling, industrial data processing, and data mining. He is currently preparing the Ph. D. degree in process informatics.

1 Introduction

Today, new environmental regulations [1,2] are forcing the electronics industry to reduce and even cease the usage of hazardous products, such as lead-bearing materials and substances containing volatile organic compounds (VOC). The implementation of lead-free and low VOC processes sets new requirements for process optimization also in the case of wave soldering, because the earlier process conditions determined for lead-containing manufacturing materials may not be applicable to the lead-free process as such. In addition, even switching from one lead-free solder alloy to another may lead to changes in the product quality if the process parameters are kept the same [3]. Hence, it can be considered an advantage if the manufacturing processes in the electronics industry can be optimized by data-driven modeling because that way the amount of testing and other experimental activities can be reduced. Additionally, a good computational model helps in reducing the costs of learning through trial and error, which makes the whole manufacturing process more efficient.

In current industrial processes, there is a general trend of a growing demand for methods that could be used to analyze different process parameters and their relationships fast and conveniently. Firstly, the demand for new analysis and modeling methods can arise, as already mentioned, from the need for optimizing the processes by using new materials and substances approved by new legislation. These kinds of materials and media are, in the case of electronics manufacturing, lead-free solders and solder pastes, lead-free components and other materials, and water-based or low VOC fluxes. The main problem is that switching to a new material can lead to an obligatory change in certain process parameters, because otherwise the quality of the products may drop. For example, in the case of using a lead-free solder in wave soldering, the suitable process window for process parameters is observed to be narrower than in a comparable tin-lead process [4].

The second reason for seeking new analysis and modeling methods is that, because large amounts of numerical data and other information are available in current industrial processes, any novel method that makes it easier to reveal interactions between different process parameters can be considered an improvement. This is because the already existing information can be then exploited more efficiently. Thirdly, the tightening requirements for process optimization and for increasing the production rates without affecting too much the quality of the products set their own demands on production planning in different manufacturing processes. A general method that could be used to reach the optimal process efficiency by defining the ideal process parameters unambiguously would be a valuable and powerful tool.

In electronics production, the traditional methods used in process improvement through data analysis have been mathematical data-driven methods such as statistical data processing methods or analytical and simulative methods [5]. For example the process optimization has often been performed using linear programming, dynamic programming or simulation-based methods. However, the use of advanced data-driven modeling methods, such as neural networks, in process analysis has been, so far, quite restricted in the field of electronics industry. Interesting questions are whether neural network modeling could be used successfully in the analysis of an electronics manufacturing process, and whether this kind of approach could lead to fruitful results more easily and faster than traditional analysis methods?

The benefits of the neural network modeling method, or an artificial neural network, ANN, are its flexible modeling abilities and its ability to reveal nonlinear and complex dependencies. For instance, it has been proposed that adaptive neural network methods are more efficient than traditional ones when the functional relations between data elements are nonlinear [6]. Moreover, many studies have indicated already that ANNs can be useful and efficient methods for modeling biological and industrial type of data [6,7,8,9,10,11]. However, the applications have been so far principally in the field of dynamical processes, such as energy producing, whereas there have been quite few neural network applications in the field of electronics industry. Thus, studying the suitability of ANN-methods to more discrete manufacturing processes, such as wave soldering, requires some further attention.

In this study, the aim was to determine whether the neural network modeling method could be a useful and time-saving way to analyze a batch-like industrial process, where materials and process substances are combined to make separate and individual, but still similar, products. The wave soldering process, which is one of the techniques used to solder components on printed circuit boards, is ideal for this kind of study, because the process has quite many adjustable factors that can easily have an effect on product quality or, more accurately, on the occurrence of some solder and other defect types.

The returns of this study show that the applied neural network method could be utilized to reveal interesting multidimensional dependencies between some wave soldering process parameters. The results indicate that the method makes it quite easy to find relations in large data sets faster than conventional data processing and analysis methods. As a result, because the detection of relations is made easier, it is possible to reduce the amount of resources spent on learning through trial and error, which releases these resources to some other, perhaps more productive, work. In addition, if the optimal process conditions could be confined more easily and faster, large cost reductions could be achieved.

2 Wave soldering process and data

2.1 Process

Wave soldering is a mechanized soldering technique that allows components and lead wires to be attached to a printed circuit board (PCB) as it is transported over a wave of molten solder [12]. In a typical setup the PCB, on which components have been placed, is transported through a wave soldering machine by using an automatic conveyor. The sides of the board are attached to the conveyor system, so that the underside of the board is exposed to the processing stages.

The wave solder process consists of three main stages as shown in Fig. 1. (1) At the first stage, the surface of the PCB assembly, with components already been adjusted to it, moving along the conveyor is wetted by the fluxing system containing the flux pump and the necessary devices to deliver the flux. The main purpose of fluxing is to improve the wetting of the surfaces and to protect the metal parts from oxidation during soldering. (2) The second stage is for pre-heating the PCB usually in several zones that can include, for instance, convection, tubular resistance or infrared types of heating elements. Pre-heating activates the flux, reduces the thermal shock resulting from thermal expansion and, in addition, removes the possible moisture and undesired substances from the surface of the PCB. (3) At the last stage, the components are soldered to the board using the solder wave at the third stage, where the wave-like molten solder is pumped through a slit to the underside of the board. A smaller and more intensive chip wave can also be used in addition to the main solder wave to get the solder into the narrowest spaces between the components.

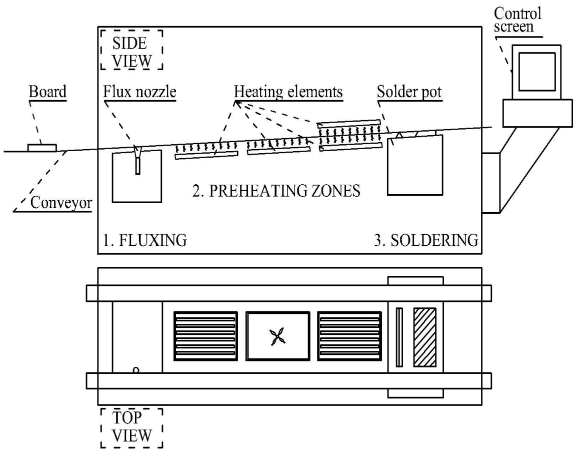

Fig. 1 The wave soldering process

2.2 Data

The acquired process data consisted of process information gathered from some test measurements, in which PCBs were put through the wave soldering process using a lead-free solder, more accurately an SAC (Sn-Ag-Cu) solder. In the case of the modeling data, only water or low VOC -based fluxes were used in the fluxing phase of the soldering process. The size of the used data matrix was 418x40 (418 rows, 40 variables in columns). The data variables were mostly various process parameters, but also some solder defects as a measure of the product quality were present. The variables used in the modeling and the numbers of model inputs for each variable can be viewed in Tab. 1.

Tab. 1 Data variables

VARIABLE	Data inputs
PCB PROPERTIES	
PCB surface finish: 5 materials	5
PCB material: FR-4 or CEM	1
Number of layers	1
FLUXING	
Liquid base of flux: water or low VOC	2
Acid number of flux [mg KOH/g]	1
Solid content of flux [%]	1
Flux: 10 fluxes	10
Flux pump frequency [Hz]	1
COMMON FEATURES OF PROCESS	
Nitrogen on/off	1
Track speed [cm/min]	1
PRE-HEATING	
Zone 1 Resistance heater temperature [°C]	1
Zone 2 Convection heater temperature [°C]	1
Zone 3 IR Lamps [%]	1
Top Zone 3 IR Lamps [%]	1
SOLDERING	
Chipwave pump [rpm]	1
Chipwave on/off	1
Solderwave pump [rpm]	1
Solder temperature[°C]	1
Back plate [mm]	1
Cooling on/off	1
DEFECTS PER BOARD	
Poor through-hole wetting	1
Solder bridges	1
Balled solders	1
Solder balls	1
Solder flags	1
Degree of flux residue amount [0, 2]	1

3 Modeling methods

3.1 SOM

Kohonen's self-organizing map [6] is a well-known unsupervised learning algorithm, and its common purpose is to facilitate data analysis by mapping n-dimensional input vectors to the neurons for example in a two-dimensional lattice. In this lattice, the input vectors with common features result in the same or neighboring neurons. This preserves the topological order of the original input data. The map reflects variations in the statistics of the data sets and selects common features, which approximate to the distribution of the data points. Each neuron is associated with an n-dimensional reference vector, which provides a link between the output and input spaces and thus describes the common properties of the neuron. This lattice type of array of neurons, which is called the map, can be illustrated as a rectangular, hexagonal, or even irregular organization. Nevertheless, the hexagonal organization is used most often, as it best presents the connections between the neighboring neurons. The size of the map, as defined by the number of neurons, can be varied depending on the application; the more neurons, the more details appear.

The SOM analysis includes an unsupervised learning process. At first, random values for the initial reference vectors are sampled from an even distribution, whereby the limits are determined by the input data. As the learning proceeds, the input data vector is mapped onto a given neuron (best matching unit, BMU) based on a minimal n-dimensional distance between the input vector and the reference vectors of the neurons. The nearest neighbors of the central activated neuron are also activated according to a network-topology-dependent neighborhood function, a Gaussian distribution. The common procedure is to utilize an initially wide function, which is subsequently reduced in width during learning to the level of individual neurons. After this procedure, the reference vectors of activated neurons will become updated. The procedure features a local smoothing effect on the reference vectors of neighboring neurons leading eventually to a global ordering [13].

3.2 Clustering

The K-means method is a well-known non-hierarchical cluster algorithm [14]. The basic version of the K-means is started by randomly selecting K cluster centers, assigning each data point to the cluster whose mean value is closest in the Euclidean-distances-sense. Then, the mean vectors of the points assigned to each cluster are computed and used as new centers in an iterative approach.

3.3 Methods in practice

The raw data were coded into inputs for the self-organizing map. All input values were variance scaled. The SOM having 225 neurons in a 15x15 hexagonal arrangement was constructed. The linear initialization and batch training algorithms were used in the training of the map. A Gaussian function was used as the neighborhood function. The map was taught with 10 epochs and the initial neighborhood had the value of 6. The SOM Toolbox [15] was used in the analysis under a Matlab-software [16] platform.

The K-means algorithm was applied to the clustering of the trained map or, more precisely, to the clustering of the reference vectors. By clustering the map the interactions can be detected more easily, and the clusters can then be treated as sub-models of the main model, which was formed by the SOM-algorithm. After training and clustering, the desired reference vector elements of clustered neurons were visualized in a two-dimensional space to reveal the possible interactions between data variables.

4 Results

The map was obtained by training a self-organizing network using the soldering data as inputs. The map is shown in Fig. 2. The SOM was then clustered according to the ten known flux types by using the K-means algorithm. These clusters are also illustrated in Fig. 2.

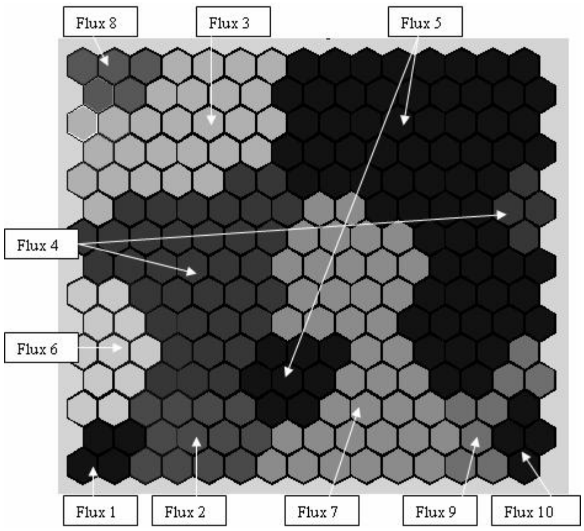

Fig. 2 SOM using the data of a soldering process

As a result of the flux-specific inspection, interesting multidimensional correlations between certain process variables were found after clustering the modeled wave soldering process data. Two examples of these correlations are illustrated here. In Fig. 3 and Fig. 4, the neurons of the trained SOM map are presented according to the selected variable components of their reference vectors. For example, the number of balled solders is presented as a function of the solder wave in Fig. 3. A tremendous variation between the behaviors of different flux types can be clearly observed. In the case of flux 3, the appearance of balled solders decreases with the growth of the solder wave intensity. In contrast, in the case of flux 2 the number of balled solders on the PCB increases linearly with the solder wave.

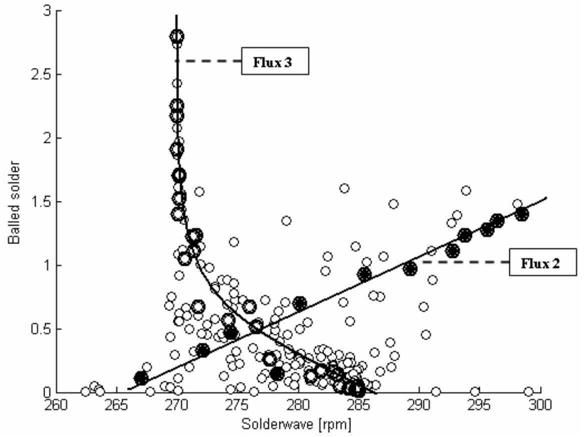

Fig. 3 The number of balled solders presented as a function of the solder wave [rpm] by using the reference vectors of neurons.

In Fig. 4, the differing behavior between three separate fluxes can be seen. For all these three fluxes, the number of solder bridges decreases as the power of the solder wave pump is increased. However, the overall patterns and locations of the flux plots are essentially dissimilar to each other, and they can be easily seen as separate models.

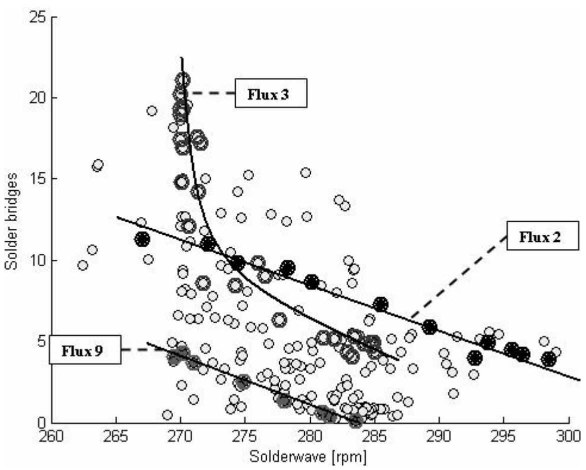

Fig. 4 The number of solder bridges presented as a function of the solder wave [rpm] by using the reference vectors of neurons.

5 Discussion

The aim of the study was to discover whether the neural network modeling method could be a useful and time-saving way to analyze a batch-like industrial process, such as wave soldering. The findings indicate that the approach described in this paper is a useful way to model the wave soldering process data that were under examination. By using the selected method, interesting relations were found quite fast and easily, the relations which would have been much more difficult to find using traditional data processing methods.

It has been suggested that the wave soldering process parameters can be optimized using statistical methods, namely variance analysis, Pareto diagrams, and finally, regression analysis after eliminating any insignificant effects [5]. By using the statistical method, the optimal values for certain soldering parameters, such as chip wave, flux quantity and surge plate height, could be found to obtain a minimum number of solder bridges and wetting defects [5]. However, this kind of approach demands a very careful design of experiments and much testing work, and, on the other hand, does not work properly if there are a lot of missing values present in the input data. In addition, if the data set to be analyzed is large and includes many variables, applying the statistical methods may become quite laborious.

At the beginning of this study it was suggested by process experts that, in the case of solder bridges, the most important wave soldering parameters affecting the bridging problem would be track speed, chip and main solder wave intensities, and the back plate height, all of which have an influence on the contact time for the board and the solder. Additionally, the experts suggested the flux type and quantity, and the flux properties, such as the solid content and the acid number of the flux, to have a minor influence on the bridging phenomenon. Furthermore, it is estimated [17] that merely the contact time itself may contribute over 30 % to the bridging in lead-free wave soldering, the effect of preheat temperature being ca. 30 %, whereas the flux quantity may contribute less than 10 % to the formation of solder bridges.

In the case of these data, though, the effect of flux quantity, i.e. the flux pump frequency, to the bridging problem was not very clear. Instead, the solder wave seems to have an impact on the formation of solder bridges, but this influence is clear only when the flux type is taken into account also, which can be observed in Fig. 4. By using any of the three fluxes presented in Fig. 4, the increase in the solder wave intensity seems to have a positive effect on the soldering quality, if only the bridging problem is considered. A new problem arises if the optimization of the process has to be done by considering several defect types at a time. As can be easily noticed in Fig. 3, increasing the solder wave intensity may also have a bad effect on product quality, so compromises must be made if optimizing is wanted to be done all-inclusively.

Nonetheless, it must be borne in mind that the presented results must be considered to be tentative, and more research should be made on the subject. It is still possible that there is an unknown factor that has been contributing to the differing behavior between separate fluxes. One reason for this could be that the test arrangements for gathering the data were not planned properly considering the SOM-method used in the analysis stage. It must be taken into account that the model can not reveal any features that are not already present in some form in the modeling data.

Preferably, the purpose of the method used is to refine the raw data to a form that can be interpreted more easily.

Hence, if the data space, defined by the data points in it, is lacking observation points in some crucial areas, the defined overall process conditions could easily favor some flux types over others and somewhat distort the results. Thus, hasty conclusions should not be drawn concerning, for example, putting the flux types into some order based on their tendencies to defect formation. On the other hand, the flux type is rarely switched to another one in a real industrial process unless some external factor makes the switch obligatory. This is because replacing the flux with a totally new one often leads to a new optimization routine concerning the whole process. Of course, it might be useful, in general, to consider more deeply whether more time should be put to determine which flux is finally selected to the process concerned.

At this stage, the question that might be raised is, why use so complicated modeling methods, such as neural networks, in the analysis? Why not just pick one flux type at a time and analyze its process data, for instance, with some conventional statistical method? There are two aspects that defend the use of the neural network method presented in this paper. Firstly, if the data to be analyzed involve a lot of missing values, the conventional methods would be difficult and very time-consuming to apply. Instead, by using the batch algorithm -based SOM method presented here, this problem does not appear, because the possible missing values in the data are simply ignored while counting the reference vector values. Secondly, if the data set to be analyzed is very large, it could be a very time-consuming operation and demand a lot of resources to separate the desired subsets from it before the actual analysis stage. Thus, by using the method presented here, considerable cost savings could be reached because the resources used in the analysis could be used in some other productive work. The method even makes it possible to analyze the process and detect the dependencies online, which could be useful in some industrial cases.

It has been suggested [6] that the main applications of the SOM method are in visualizing complex data for example in a two-dimensional space, and in creating abstractions based on the data. Dividing the data vectors to classes, i.e. the neurons, and counting their generalized descriptions, i.e. the reference vectors, can reveal process features that can be otherwise very difficult to observe. Additionally, the SOM is a nonlinear method, quite simple to modify and use, and the fact that the missing values of the data do not have to be substituted separately is a considerable advantage in cases where the data to be handled are more or less incomplete. Under these circumstances, the method presented here is a valuable alternative among the other modeling methods.

The method presented in this paper can be further illustrated as in Fig. 5. At the first stage, there is a data set from the process containing values for process parameters. Then, the SOM is generated using the data as model inputs. Next, the map is clustered according to desired elements of the data to reveal the dominating element of each territory of the map. At the final stage, the clustered map can be used to form sub-models that are able to reveal and visualize relations between selected variables in a convenient and user-friendly way. In one sense, the method can be seen as refining the raw data into a more illustrative form that can be visualized graphically.

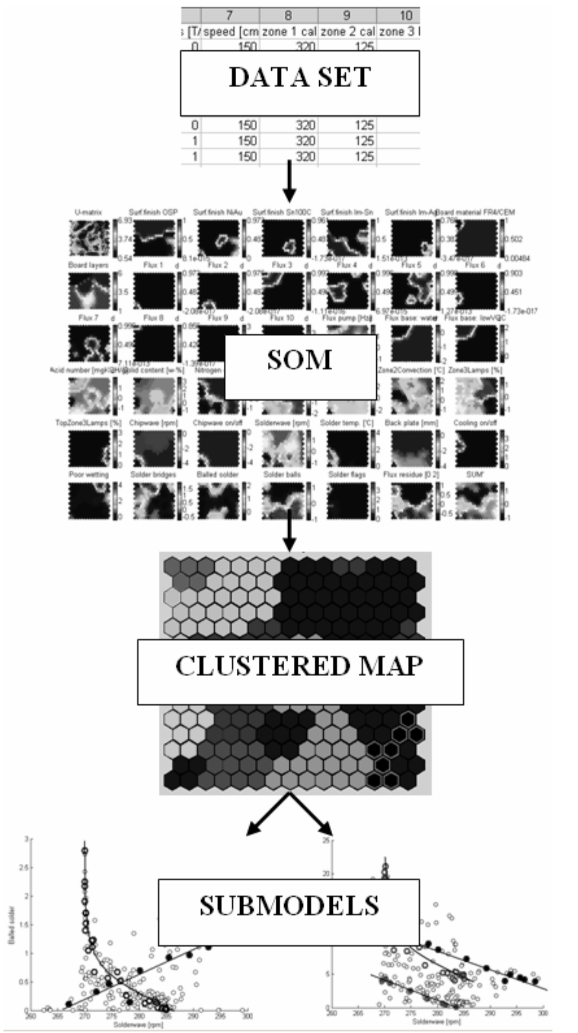

Fig. 5 Schematic presentation of the method used

As can be easily noticed by examining Fig. 3 and Fig. 4, the overall data point patterns in these figures seem rather confusing. It is not possible to detect any clear interaction between the solder wave intensity and the defect numbers without knowing the flux clusters that are also presented in these figures. On the whole, the reference vector values seem to be located haphazardly in the illustrated two-dimensional space. In contrast, after illustrating the flux clusters as sub-

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models, the interactions between solder wave and soldering quality are revealed. This leads to the fact that, in this case, creating and studying sub-models is the best way to reveal the interactions.

In electronics production, the process conditions determined for lead-containing manufacturing materials and VOC-containing substances may no longer be applicable or at least optimal. On the other hand, the correct adjustment of the wave solder process is, of course, important as such to produce soldered PCBs with high quality and to minimize ineffective process tuning. In this respect, the successful computerized modeling of the process has several advantages including the reduction of process costs; a more efficient process and reduced material loss are achieved as learning through trial and error is decreased. Additionally, the resources that were previously spent in time-consuming analysis work can be now released for some other beneficial purposes. The findings presented in this research seem very promising considering the successful use of the analysis method developed.

6 Conclusion

Because of the growing need for optimizing industrial processes due to, for example, material replacements in a process, developing new methods for process analysis is very important. The results presented in this paper show that the applied SOM-based neural network method is an efficient and fruitful way to model data acquired from the electronics industry. By means of this data-driven modeling method, some new findings were discovered concerning the dependencies between the process parameters and some solder defects.

However, further research is still needed to validate the method more widely in the field of electronics production processes. In addition to wave soldering, manufacturing electronics includes other important processes, such as paste printing, component placement, testing, and also other soldering methods. In analyzing the wave soldering process, though, the findings seem this far very encouraging considering the successful use of the analysis method developed.

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