STRATEGIES FOR WELDING PROCESS CONTROL USING SOM SENSORS AND GENERIC MODEL PARAMETER ESTIMATION

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Abstract. *The control of spot welding processes (enforcement of given state variable values) by means of some driving force, is not easily possible, since the state variables are not directly measurable quantities. The usual solution approach to this problem class is by construction of a so-called observer based on an analytical process dynamic model and a statistical model of process and measurement noise. The observer gives an optimum estimate of the state variable values based on a measured history of accessible observable values. For spot welding, where the necessary model is not available, we propose two different approaches, depending on available a priori process knowledge: 1) A SOM sensor, which estimates the deviation (distance and direction) of the process from its optimum, giving the input of a controller to determine the driving force. 2) A process parameter estimator, which uses a generic process model to characterise the process state by the estimated parameter values, which can be easily interpreted and correlated to process disturbances to be compensated. The SOM sensor is derived from a process sample containing a set of feature vectors (covering almost all process states) calculated from the process observables. A two dimensional, discrete Kohonen map is trained with a representative process sample to optimally reflect the topology of the original feature space. It is therefore well suited to observe the process evolution by visualisation of the winner neuron motion in the SOM. The resulting path can be analysed in order to detect drift or to obtain control relevant information. The generic model parameter estimator is used as a substitute to the process observer. The generic model is derived to roughly reflect the behaviour of the welding resistance. It is fitted to an actual measured welding resistance curve, giving a set of parameter values, which characterise the process of the weld. For the proof of concept a spot welding process consisting of several thousand welds over the whole lifetime of the welding machine electrodes is analysed as a sample application with the objective to reveal the quality loss related to electrode wear.*

Keywords: *welding, quality monitoring, diagnosis, control, neural networks.*

1. Introduction

The classical approach to solve the control problem in cases, where the state variables are not directly accessible but only observables can be measured, is to use a state observer, which is used to estimate the values of the state variables (Fig. 1). For this purpose a model of the dynamic of the process under consideration is needed. The model should reflect all aspects of the process including systematic disturbances like degradation of system components in order to give a correct estimate of the state variable. To arrive at a comparison between estimated state and the measured real process observable one has to set up a second model, the measurement model, which defines how the state variables transform to the observable variables. The difference between the real and estimated observable values is fed back by the observer to the process model in order to correct the state estimate.

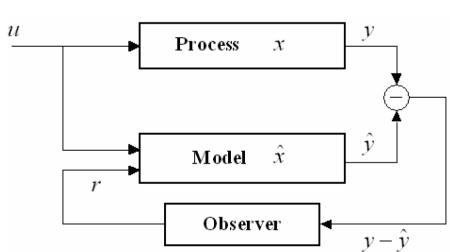

Figure 1. Observer used to estimate state from measurement

The most common observer is the Kalman observer (Gelb, 1986). It consists of a Kalman filter (Grewal and Andrews, 2001) that is responsible for the quantity estimation, a measurement model and a feedback loop with a Kalman matrix for the optimisation of the value estimated which is used as input in a process control (Fig. 2). The requirements of such system are:

- Dynamic process model for the estimation of the state variable quantities;
- Model of the measurement system;

- Systematic disturbances (process or measurement) must be previously identified and included in the models or eliminated from the system;

Process and measurement noise distribution functions must be known.

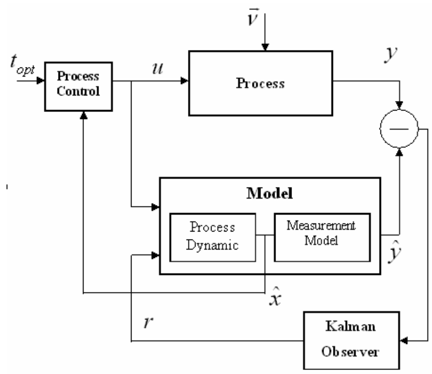

Figure 2. Closed loop control with Kalman observer to estimate state from measurement

Many applications of the Kalman observer can be found in recent literature. In vision-based control of motion it is used for predicting the target position (Chroust, Zimmer and Vincze, 2001), in autonomous unmanned vehicle it is used to estimate a submarine position as shown in (Walchko, Novick and Nechyba, 2003), another application of the Kalman Observer is to receive in a sensorless way the actual values of the rotor position, the rotor velocity, and the rotor flux of an induction motor. This practical example is based on a field orientated control method, where the necessary control variables position, speed, and rotor flux are estimated with a Kalman observer (Bejerk, 1996).

Some common points in these applications can be identified. Sudden state changes are not well predictable by the Kalman observer, which possibly reacts with strong oscillations. Non-linear systems with uncertainties in modelling produce large estimation inaccuracies that perhaps can be compensated by the control strategy but has as result a relatively lower performance. Implementing a Kalman Observer is a very complex problem, and it requires a precise model to be calculated in real time. The observer equations must be calculated, which normally means many matrix multiplications and a matrix inversion. In many situations neither a process model is available nor the distribution of the process noise can be assumed to be normal. In these cases a statistical approach has to be developed.

Resistance spot welding is a process very commonly used in the industry that consists of the joining of two or more metal parts together in a localized area, based on the heat produced according to Joule's Law (Q = RI2t).

The parts to be joined are pushed against each other by a tong-like arrangement of two opposing electrodes. High current is passed through the parts via the electrodes and since heating (Q) is produced mainly at the interface between the parts due to the electrical current, a molten pool is created in this location by the net heating energy flowing in. After switching off the current, this molten material cools down and a solid weld nugget is produced. The complete process consists of a repeating sequence of the production of such welding spots, where all spots should have the same good quality without respect to disturbances.

For this kind of process no complete physical model (also taking into account disturbances like material unevenness, electrode wear and others) is available and even the measurement of necessary model parameters is not possible on-line. For example, these parameters are the temperature between the welded metal parts, the pressure over time applied by the electrodes and the conditions of the surface of the welded metal parts. Therefore no observer approach is applicable to this kind of process.

Only two quantities are accessible and can be measured during the welding process: the voltage and the current signals for each welding spot. The only material characteristic that can be extracted for each individual spot from the accessible voltage and current signals is the electrical resistance. The latter forms the basis for deriving process features. The desired state value would be (depending on the application) the value of a certain quality measure like the resulting spot diameter or the maximum shear force the spot can withstand.

For such an application, a controller is to be developed. It should be able to control a process with very short welding times (10-40 ms), compensating electrode wear and external disturbances. In this way, the controller should compensate the resulting process drift and keep the quality of the controlled process always in an optimum range.

2. Proposed methods

With resistance spot welding, the processes are highly non-linear with many external influences that can not be modelled and also the noise distribution parameters can not be measured or reasonably be estimated. The only material dependent quantity, which can be determined in-line from the observable current and voltage curves, is the resistance curve evolving from a welding spot formation. For these situations, in special for process drift detection, in this paper the substitution of the Kalman observer by a statistical image of the process using a SOM is proposed (Fig. 3). For this purpose no a priori knowledge about the process is necessary. Only relevant features have to be extracted from the resistance curve to form a feature vector, which is input to the SOM. The SOM characterises the vector with a map position. This position has a difference vector with the optimum position in the map, which was assigned by a map calibration procedure before. The difference can then be used as input to a closed-loop controller to adjust the welding parameters and visualised to monitor the process. In spot welding processes, we have qualitative knowledge of how the process of a weld formation normally takes place and how this affects the resulting resistance curve. From this knowledge, we propose a generic process model, describing qualitatively the evolution of the resistance curve (the model curve). The model is governed by a set of parameters describing the influence of material properties and external boundary conditions. The model curve is fitted to a measured resistance curve by adjusting the parameters for the smallest deviation. These parameters are now features describing the present weld, which can be interpreted due to their meaning in the model or correlated to certain external influence (like electrode wear). The welding parameters can then be adjusted to compensate a detected disturbance cause.

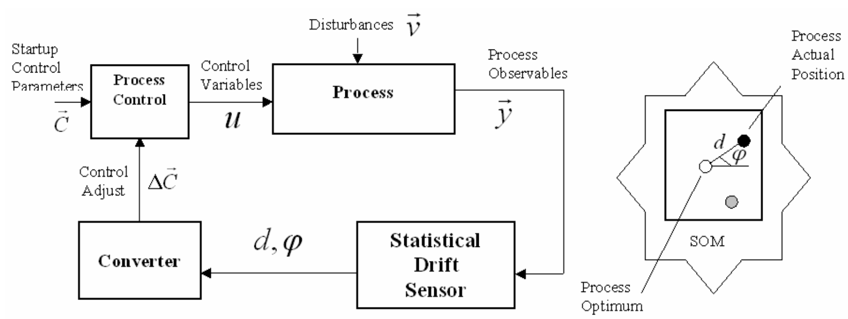

Figure 3. Control with SOM drift detector

3. State sensing with SOM sensors

The process observable variables form the input vector $\vec{y}$ for the SOM. From a sample of the high dimensional input vectors $\vec{y}$, representative of the complete state set of the process, the SOM forms a two dimensional image (map) of the process states. By calibration, a map area can be marked, where the process can be identified as optimum. If the actual position of the process in the map (actual relative process state) is in an area of the image apart from the optimum area, a process optimisation can be made on the basis of distance (d) and angle (φ) between these two areas. Both values (d,φ) are defined as the output of the statistical drift sensor. This difference information should now be converted to the same quantity as used in the process control. The vector $\Delta\vec{C}$ represents the correction increment of control parameter vector and can be used directly as input to the process controller.

From the mapping of the high dimensional space of $\vec{y}$ in a two dimensional space it is also possible to:

- form and analyse the process path by tracking the process and
- visualise the process state and its temporal evolution.

Both information can be used to modify the start-up control parameters $\vec{C}$.

3.1. Application of SOM sensors to resistance spot welding

The possible control variables in this process are the level of the welding current and the welding time given that in this application the electrode force is fixed. As the welding time is permitted to vary only in a very small range in order to maintain the machine’s cycle time of 400 parts per minute, it is also kept fix. Therefore the only really controllable variable in this process is the welding current level.

The figure 4 shows the proposed spot welding control system in which the Kalman observer and the model are replaced by a SOM drift sensor connected to a converter.

3.2. The SOM drift sensor

The SOM drift sensor is composed of four components: A pre-processing unit to obtain noise filtered curves of the electrical resistance over time („resistance curve“), a feature extractor for a first reduction of the dimensionality, the SOM to finally reduce the process state space to a discrete two-dimensional map and the drift detector to derive the difference from the optimum process state.

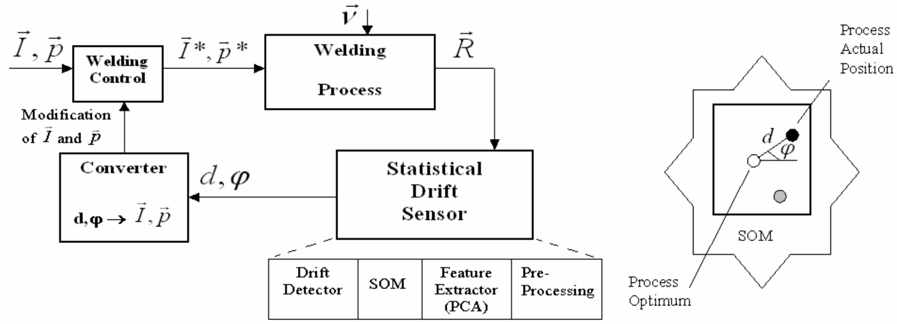

Figure 4. Spot welding control system with SOM drift sensor

- Pre-processing: In the application area of short-time weldings the middle frequency technology is state-of-the-art. Therefore the resistance curve has to be calculated from the phase-corrected current and voltage signals. A non-linear filter is used for the removing of high-level noise from these raw signals, smoothing the curves without eliminating relevant information.
- Feature Extraction: The resistance curves from the pre-processing step are sampled with approximately 600 points. In order to arrive at a reasonable number of features with respect to the training and response time of the SOM, the linear sub-space, which approximates the sample in the best manner, is found via principal component analysis (PCA). The effect is:
  · Reduction of the training time and the response time of the SOM during operation,
  · Elimination of irrelevant information,
  · Saving memory with the operational system.

The resulting features are then the projection coefficients onto the first principal components (linear sub-space basis vectors with highest variance), which are calculated as the Eigenvectors with the highest Eigenvalues of the co-variance matrix of the sample vector set. Only five such coefficients are sufficient to represent a resistance curve with originally 600 samples.

- Self-organising Map: Self-organising maps (in our case we use Kohonen maps) are a special kind of neural networks, which consist of one layer of „active neurons"(Zell, 1994). They are mainly used for data analysis and data classification. The basic property of a SOM within the context of our drift sensor is the mapping of the high-dimensional feature space onto an only two dimensional discrete map (grid). Each cell (also called neuron) of the grid is assigned a representative feature vector. These representatives (called weight vectors) are formed during the training from a representative feature vector sample of the process in a way that the neighbourhood relations of the feature vectors are optimally retained in the map.

For the training of the SOM no a priori knowledge is required. After the training, each new feature vector is only characterized by the grid location of the most similar representative (the winner neuron) in the map. The grid positions of different such winner neurons define a 2-D difference vector, which can be used to measure a distance and a deviation direction of the actual process state from the process optimum, once the map area of the optimum is identified. Later on, a subsequent converter can use the difference measures to calculate increments of the welding parameters, which are fed into the welding controller in order to push the process back to the optimum state.

Once the welding signals have been pre-processed and the PCA coefficients have been calculated for all sample resistance curves, the following three steps are executed to set up the SOM: training, calibration of the SOM with respect to the process optimum and process observation.

3.2.1. Training

Before the SOM can be used as a sensor, it has to learn the process topology. For this purpose a process representative learning sample data set consisting of a set of PCA coefficient vectors (training vectors $\vec{X} = [x_1, .., x_n]^T$, n=number of PCA coefficients) is used. The representatives (weight vectors $\vec{w}_j = [w_{1j}, \ldots, w_{nj}]^T$, j: cell index) of each cell are initialised with random numbers. When training the SOM, in one training step a training vector $\vec{X}$ is compared with all weight vectors $\vec{w}_j$ to determine the most similar weight vector (winner). As difference measure we choose the mean square difference of the vector components. After the winner neuron has been found, all weight vectors are adjusted by adding a proportion of the difference from the training vector, weighted by a learning function, which depends on the map distance of the corresponding neuron from the winner neuron. Usually a Gaussian or a step function of the radius from the winner neuron position is used. This is repeated for all training vectors (14,900 in our case) in one training epoch. In the subsequent epochs, the variance of the Gaussian or the threshold of the step function as well as the proportionality factor is reduced and the procedure repeated, until the learning rate decreases to zero.

In order to define the training procedure, two steps are necessary:

1. Generation of the training data set;
2. Determination of the optimum learning parameters.

Due to the fact that the state variables (the quality measure in our case) can not be monitored and a process representative sample is necessary, assumptions about the process underlying the training data set have to be made and verified, if possible.

The training data set must contain more data close to the process optimum than marginal data. The process optimum is defined as an ideal quality value, which is neither too low nor too high. With a too high quality the tools might wear too fast or the energy is not used most efficiently.

In a regular industrial production process these assumptions are justified on the average over the lifetime of the production tools used, if there is no interference by adjusting process parameters.

A common issue during the unsupervised training of a SOM is to find the ideal training, topology and initialisation parameters. There is no way to directly make sure the correctness of the produced SOM.

In order to determine the optimum learning parameters and obtain an accurate SOM, variables that are process-relevant and measurable should be selected. These variables should have also a direct effect on the not measurable actual process state x and can be considered to be their substitute in the context of SOM assessment. A representative dataset $T=\vec{t}_1 \ldots \vec{t}_n$ (n number of measurements) for the process under consideration is then determined. An initial training parameter set is defined as well as its range of variation. For each defined combination of training parameters the SOM is validated with the variables introduced above in order to find the best one.

The validation process consists of finding a winner neuron for each vector of the dataset T. The value of the chosen relevant variable is associated to it. For each neuron, a histogram is created with all associated values belonging to it. The associated value with highest frequency in the histogram will define the class of the neuron.

In an ideal trained SOM, the sum of the histogram's highest frequency of each neuron (called here score) should be equal to the size of the training dataset, this means that vectors with the same relevant variable value will be associated to the same neuron (belong to the same class) and a neuron will embrace only vectors with the same relevant variable value. In a real case this rarely will happen due to the reduced dimension of the SOM, the size of the dataset T and the number of classes present in it. Therefore the combination of training parameters that achieve the highest score will be considered the optimum learning parameter combination due to the best separability of classes.

$$s = \sum_{i=0}^{n} h_{winner} ,$$

where: h_{winner} = Maximum value of the histogram, s = Score for the SOM and n = Number of neurons in the list

The ideal score s is the number of training vectors. This method of varying the training parameters and obtain for each combination a score has been called "Scoreboard".

3.2.2. Calibration of the SOM with respect to the process optimum

Under the assumption made for the training data set, the label „process optimum" defines the region of the map where most of the hits (winner neuron occurrence) can be found. In complement to that, a histogram for the whole SOM is created. During the tests clearly a region showed up where a small group of neurons forms a hit frequency maximum. After labelling the „process optimum" region, the distance and angle for each other neuron or region in the map can be calculated (see Fig. 5 - left).

3.2.3. Process observation

The first tests with a trained SOM showed a very noisy behaviour of the winner neuron position in the map, which reflects the process noise. A Kalman filter might again be the appropriate measure if latency would be a serious problem. In our case the noise correlation times are short compared to the time constant of the system and a much simpler sliding average filter was implemented, where the filtered position x_f and y_f is calculated from the actual and past s-1 positions x and y by:

$$x_f = \frac{1}{s}\sum_{i=0}^{s-1} x_{(p-i)} \text{ and } y_f = \frac{1}{s}\sum_{i=0}^{s-1} y_{(p-i)} .$$

After filtering with s=10 a clear path of the process becomes visible, where the process (marked by the winner neuron) only moves to neighbouring neurons at a time. This is illustrated in figure 5 - right, where winner neurons are coloured according to their sample number (proportional to process time).

Only the last hit was retained in the map colouring. The counter-clockwise motion of the process can be clearly seen. The observed path from high distance from the optimum in the beginning to a first „island of stability", then to the process optimum (where the process lasts for the longest period) and then again to high distance at the end is in good agreement with quality observations of the producers.

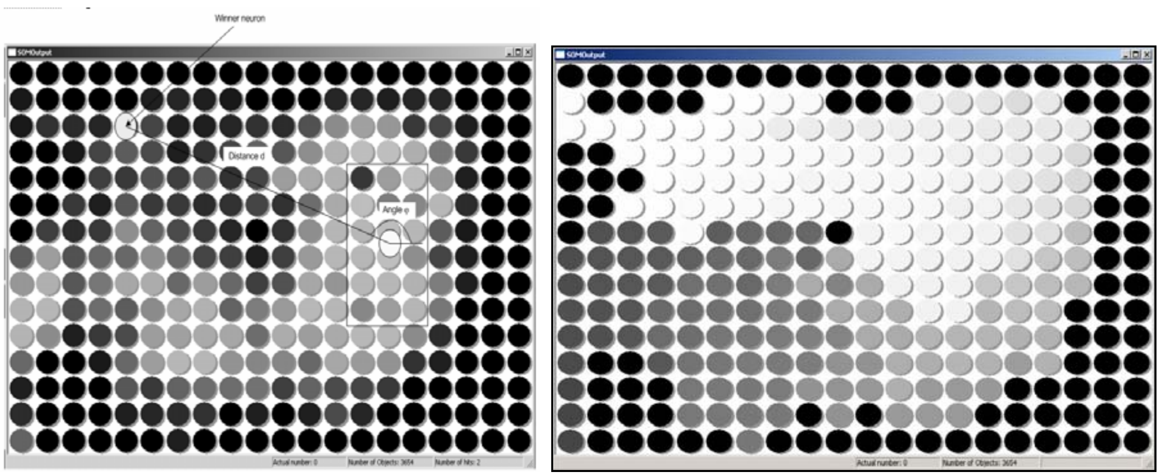

Figure 5. left: SOM with process optimum area (rectangle, center: white circle), one winner neuron
right: Process motion through the map (dark gray=start, middle gray= middle, white=end)

4. Creating a generic process model

Even if there is a lack of models describing precisely resistance spot welding processes, we have certain qualitative knowledge about the system behaviour. This knowledge is used to go beyond the purely statistical approach presented so far to gain more detailed information about the process and to derive better features. We present a framework based on generic models derived from physical considerations in order to obtain a process state sensing from observable process signals. These generic models reflect the fundamental properties of the described signal-generating process. In contrast to implicit model building methods like Principal Component Analysis (frequently used in pattern recognition) where the model is represented by the retained eigenvectors of the sample covariance matrix, the generic model does not itself depend on a specific statistical sample but on first principles.

A best fit of the model against an actual signal will only reflect those signal properties expressed by the model and yield a set of corresponding model parameter values. All signal components orthogonal to the model will be discounted. The model parameters are used as features concentrating the relevant information of the signals (compression). The signals reconstructed from the parameter values can be considered to be relevance filtered.

Process conditions can be detected and quantified by using the relations between the estimated (physically interpretable) model parameter values and respective process conditions. The relations may be set up either from principal considerations (based on process knowledge) or by calibration with measured condition characteristic values.

The framework for a process state sensing using a generic model is shown in the Fig. 10.

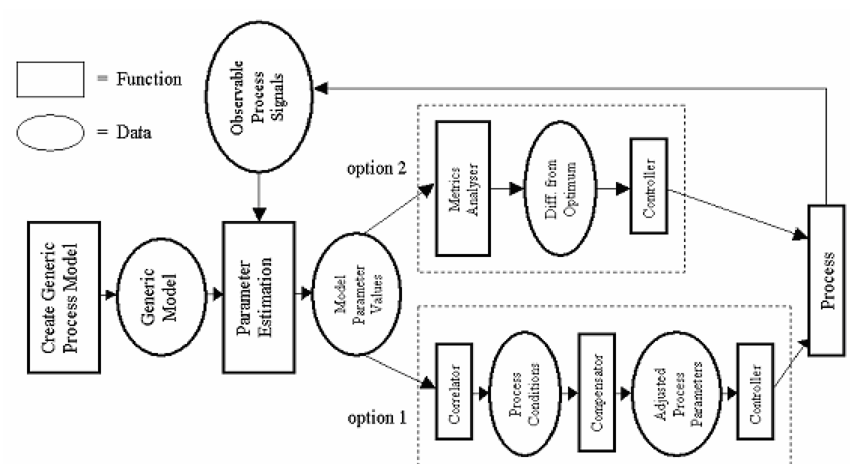

Figure 6. Framework for a process state sensing using a generic model

The first step is to create a generic model that reflects the fundamental properties of the process. The actual process signal is obtained and the generic model is fitted to this signal varying its parameters. The best fit delivers the values of model parameters that represent the actual state of the process.

Now in the proposed framework there are two options to use these parameters to control the system (these two options can also be combined). The first option is to correlate the model parameters and the process conditions. In this way it is possible to deliver the actual process conditions to a compensator that according with these conditions will adjust the process parameters of a controller in order to bring the process to an optimum state. The second option is to directly set up a metrics of the parameters using for instance a Self-Organizing Map (SOM) as described in the first section of the paper with the model parameters as features. The difference from the process optimum in the SOM can be used as feedback in a controller also trying to have the process always in an optimum state.

4.1. Generic model of spot welding resistance curves

We consider the electrical resistance R as a combination of contact, bulk and electrode resistance values, affected by physical properties and laws. In this way, the changes in R will follow these properties and laws invariant to the control strategy. The generic model was created to describe the main variations of the electrical resistance during the welding process and in this way to be used to fit a measured resistance curve, finding a relation between the model parameters and the process state. Assuming symmetry of the arrangement *R(t)* will be defined:

$$R(t) = 2 \cdot R_B(t) + R_C(t) + 2 \cdot R_{ELM}(t) \qquad \text{(Eq. 1)}$$

The electrical resistance R is the sum of the electrical resistance of the bulk material (R_B), the electrical resistance of the interface between the sheets (contact resistance R_C) and the electrical resistance of the interface between the sheet and the electrode plus the electrical resistance of the electrode itself (R_{ELM}). We consider each of these parameters independently and discuss them separately.

In a first approximation, the average temperature in the weld region is assumed to behave roughly like an exponential over time, approaching the melting temperature, dissipating energy via heat flux and phase transformation.

The electrical resistance of the bulk material depends on the electrical resistivity of a material (ρ), which follows mainly the temperature variation.

Another electrical resistance component is the electrical resistance of the electrode and the electrical resistance of the interface between electrode and sheets. These resistances will be considered as one resistance called R_{ELM}. In a first moment of the welding process the electrode will have certain contact area with the sheets. When the material is softening due to increase of the temperature, the electrodes will fit better and may also sink in the sheets and the contact area will increase. In this way the resistance between the electrodes and the sheets will be reduced since the current has a bigger surface to flow. This sinking in is also directly related to the force applied in the electrodes.

The electrical resistance of the interface between the sheets is called contact resistance R_C. R_C is mostly responsible for the heat produced and necessary for the welding process. In the beginning this resistance is relatively high and will decrease due to the fitting of the surface of the two sheets by material softening. This is basically influenced by the force applied in the electrodes and the surface of the material used.

After this, R_C will continue to slowly decrease until certain value is reached. This will happen because the temperature will increase, the sheets will become soft and consequently will fit better to each other. After the start of the melting, this resistance tends to a small increase due the electrical resistance in the liquids is normally higher than in the solids but this effect will not be considered in this model.

The details of these parameters and their equations and parameters can be found in Sampaio *et al.*, 2004.

After defining all these partial resistances, the electrical resistance of the whole process can be calculated.

4.2. Parameter estimation and process data

For the determination of the generic model parameter values a fitting algorithm is needed. Due to their non-linear dependence on the parameters this has to be non-linear. Nonlinear models cannot be estimated using simple matrix techniques. Instead, an iterative approach is required.

The Levenberg-Marquardt method (LV) is a standard iterative method for non-linear curve fitting. It is useful for finding solutions to complex fitting problems (Press *et al.*, 1996).

In this investigation the stopping and search method for the iterations was modified according with the model characteristics. A precision value, an increase (multiplication) factor, a decrease (division) factor and the chi-square value are the basis for the stopping condition.

4.3. Sensing process influences by means of generic parameter estimation

The data used to assess the method was obtained from a welding process of the company Stanzbiegetechnik (SBT). In this process two thin materials, a contact (0,85mm) and a base material (0,18mm), are welded. Due to the special material properties, a welding help (spikes on the base material produced by molding) is used in order to increase the contact resistance between the two materials. There is a very good cooling in the electrodes in the way that their temperature is kept about 16°C. There is also a very short welding time of about 25ms.

The voltage and current signals were measured and recorded during each welding test and from those the resistance curves were derived. During the tests some conditions of the process were changed like the level of the applied current and the applied force and also the “welding help” was not used in some tests in order to simulate real variations that can occur during the welding production.

The process consisted of the production of 30,000 welded parts and was started with a reference current value that is an optimum value used by the SBT Company for the process in consideration. During the process, the current value was adjusted for groups of welds to five other levels. Initially reduced consecutively by 5,4%, 13,5%, 24,3% and 35,1% from the reference, subsequently increased by 5,4% from the reference and in the end returned to the reference value. In each level some samples were drawn and their resistance curve obtained. Afterwards the model parameters were estimated for each curve.

4.4.Current Influence

The model has five fixed parameters: α (temperature coefficient of resistance), T_{melt} (melting temperature), T_0 (initial temperature), K_T (temperature factor), R_{0B} (initial electrical resistance of the bulk material) and also five adjustable (free) parameter: R_{0C} (initial electrical resistance of the interface between the sheets), R_{0ELM} (initial electrical resistance of the electrode and interface between electrode and sheets), K_C (factor of the variation of the contact resistance), $K_{C\text{-}Soft}$ (material softening factor) and K_{ELM} (electrode-material factor) (see Sampaio *et al.*, 2004). Analyzing now the five free model parameters individually, it is possible to observe how the current variation is reflected in each of them and in this way finding a relation between the estimated parameters and the actual process condition using this information as feedback to the process controller.

All parameters show a clear correlation with the current variation, for which K_C is shown as an example (Fig. 7).

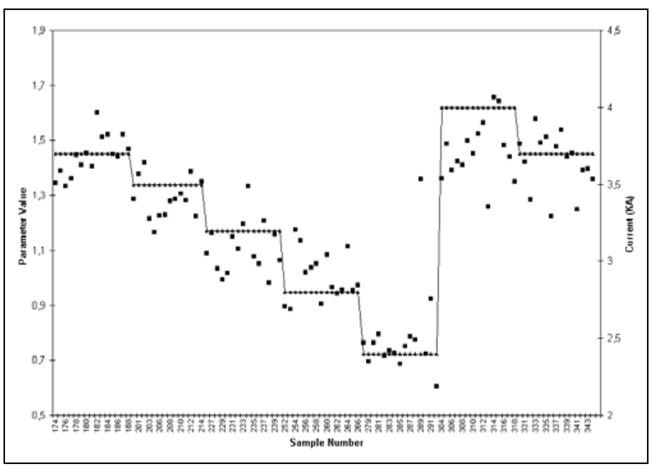

Figure 7. Parameter K_C and the current variation. Left ordinate is the model parameter value (single square points), on right ordinate the imposed current (polygons) and on the abscissa the experiment number

4.5. Force Influence

The process was started with a reference force value that is an optimum value used by the company SBT for the process in consideration. During the process, the force was adjusted to five other different levels. Initially increased consecutively by 6,3%, 9,5%, 12,7% and 15,8% from the reference, subsequently decreased by 6,3% from the reference and in the end returned to the reference value. Again with each level some samples were drawn and their resistance curves obtained. Following the steps for the current influence, afterwards the model parameters were estimated for each curve.

Analyzing again the five free model parameters individually, it is possible to observe how the force variation is reflected in each of them and in this way finding a relation between the estimated parameters and the state parameters of the process using this information as feedback to the process controller.

The parameters R_{0C}, R_{0ELM}, K_C and $K_{C\text{-}soft}$ show an anti-correlation with the force variation. R_{0ELM} is shown as an example in figure 8. The parameter K_{ELM} does not show a relation with the force variation.

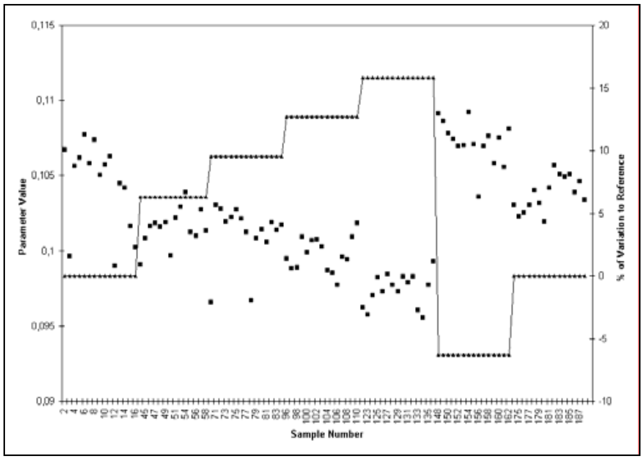

Figure 8. Parameter R_{0ELM} and the force variation. Left ordinate is the model parameter value (single square points), on right ordinate the imposed force (polygons) and on the abscissa the experiment number

4.6 Welding Help Missing

The third influence analyzed was the welding help. The process was started and always kept in a reference configuration that is an optimum configuration used by the SBT company for the process in consideration. During the process, some welds where chosen to be analyzed and their resistance curve obtained. They were the welds number 2 to 16, 174 to 188, 330 to 344, 360 to 374 (with these welds the welding help was missing), 420-434 and 2960 to 2970 respectively. Afterward the model parameters were estimated for each curve.

Analyzing again the five free model parameters individually, it is possible to observe how the welding help affect each of them. These parameters are very unstable in the weld experiments where the welding help was not used. In the parameter K_C, defining a threshold, it is possible to clearly identify the welds where the welding help was missing. Fig. 9 shows the variation of the parameter K_C during the process and by the samples where the welding help was missing.

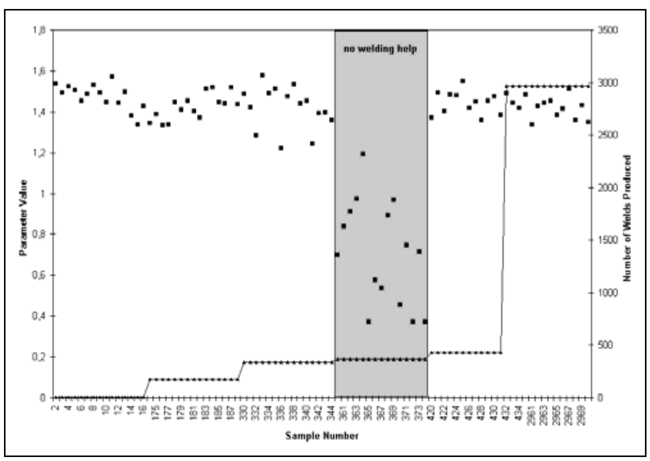

Figure 9. Parameter K_C and the welding help missing. Left ordinate is the model parameter value (single square points), on right ordinate the number of welds produced (polygons) and on the abscissa the experiment number

5. Conclusion

The lack of accessible state variables and of precise physical process models, which cover all effects encountered in resistance spot welding and could thus be used to create observers, prohibits the set-up of effective welding process controls. Two complementary approaches to overcome these difficulties have been presented.

A Self-Organising-Map sensor is proposed to generate input for process controllers, where the state variables are not available and an observer approach is not possible due to lack of appropriate models. A difference between process optimum and present state is derived from the process map, which is obtained by training with process samples and can be used as controller input. The approach was applied to a spot welding process. A general procedure for the training in such cases was set up and successfully applied. The process optimum map area was identified and the motion of the process in the map was visualized and found to be in accordance with quality observations of similar spot welding processes. On going work is to check the reusability of such maps and to close the control loop.

The second approach presented closes the gap between process observers and purely statistical methods like the SOM by the use of generic models.

A framework was set up and successfully applied to a resistance spot welding process where a clear and physically reasonable correlation between process conditions and estimated values of the generic model was found. The most crucial point with non-linear models is the parameter estimation, especially with short processing time. Major improvements are possible by further investigating robust parameter estimation and linearization methods.

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