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Data-Driven Framework for Electrode Wear Prediction in Resistance Spot Welding

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Abstract. Smart Manufacturing (SM) can be defined as the extensive application of computer-integrated manufacturing and advanced intelligence systems to enable rapid manufacturing of new products, dynamic response to product demand, and real-time optimization of manufacturing production and supply-chain networks. For this reason, SM is now attracting a huge interest in both academic and industrial communities and will probably drive the manufacturing evolution in the next decade. In SM, data play a key role. They can support decisional systems and human operators by helping them to improve production and process control, to monitor continuous production flows, to prevent or detect equipment failures at an early stage, to minimize inefficiencies through the overall supply chain, and so on. In fact, data can be exploited by combining a wide variety of advanced technologies to give machines the ability to learn, adapt, make decisions, and display new behaviours. In this regard, the aim of the study concerns the proposal of a data-driven framework to predict the electrode wear in Resistance Spot Welding process. Electrode wear is the most important factor that introduce high variability and uncertainty in the quality of spot welds. Using an equipped medium-frequency welding machine, various data such as thermal maps of the spot surfaces by passive thermography, electrode surface diameters, electrodes-workpiece contact conditions, process variables, and electrode displacement curves can be collected. These data can be provided as input to a Machine Learning algorithm to predict electrode wear over time, thus ensuring a reliable spot weld process and joint quality.

Keywords: Resistance Spot Welding, Electrode Wear Prediction, Industry 4.0, Data-Driven Prediction.

1 Introduction

Product Lifecycle Management (PLM) can be thought of as a tool for the creation, organization, and dissemination of product-related knowledge across the entire company. In such a context, maintenance activity plays a crucial role [1]. Indeed,

nowadays, the functionality of maintenance is no longer limited to the operative phase of the production systems. It is an important part of PLM in terms of providing the desired availability of components or systems, minimizing the wastes, lowering the materials usage and the energy consumption to satisfy both the sustainability and efficiency requirements [2].

The impact of maintenance activity in the manufacturing world takes from 15% to 60% of the overall production costs [3]. This highlights the need for companies to improve the available tools to maintain their systems. It would ensure to reduce the overall cost of the entire production and, thus, of the product.

Maintenance is a broad field where many approaches can be adopted but, it turns out three main macro strategies can be used by the enterprise [4]: corrective maintenance, preventive maintenance, and predictive maintenance.

The first type is a Failure-Based strategy, and it requires the waiting for the fault occurrence to perform maintenance interventions. Corrective maintenance can only be implemented for systems or components not critical for both economic and functional standpoint [5].

Preventive maintenance can use a Time-Based or Use-Based criterion and it aims to avoid the failure of a machine with a predetermined scheduled maintenance activity. In this way, sometimes faults can be avoided, and machine parts can be replaced or repaired before that significant damage is accumulated. Such strategy is adequate whenever the time to failure of a component or system is adequately ascertainable [2]. However, often modern manufacturing processes operate in environments characterized by high dynamicity and uncertainty, so, their operating conditions can be variables and difficultly predictable. This makes the preventive maintenance strategy unusable in contexts where a just-in-time philosophy is required.

The latter philosophy allows the factory to minimize the downtimes of machines and to replace or repair the components at the opportune moment before the achievement of their critical conditions.

A tempting methodology toward such direction is to monitor some condition indicators of the machine health and predict the maintenance intervention on the ground of the inspections carried out. This is a Condition-Based technique that enables a Predictive Maintenance strategy. It can be interpreted as an industrial prognosis process assessing the remaining useful life of the system based on the status of the monitored condition indicators [5-6].

The decreasing cost in sensor equipment and computing resources is making possible the advent of Industry 4.0, with Big Data and Industrial Internet of Things enabling the possibility to extend the predictive analysis for the whole production sector, and not only for the most critical ones [7].

Welding processes have always been widely used in manufacturing and, in the Industry 4.0 era, it becomes crucial to exploit the information directly from the process itself both for performance improvement and life-cycle evaluations in the whole industrial supply chains [8].

Control the weld quality in Resistance Spot Welding (RSW) process requires the knowledge of the weld nugget size and/or the weld strength, but a direct measure of the weld nugget size is not possible because it remains between the two sheets. Therefore,

joint quality has normally been assessed through destructive tests. This has fostered the research activity toward the implementation of many indirect measurement methods for the evaluation of the joint quality, many of them exploiting process signal curves and non-destructive analysis.

Wan et al. [9] used some features extracted from the voltage curve during welding to feed Neural Networks and predict the failure load of the joints. The same researchers [10] used the signal of the dynamic resistance of the sheet stack to estimate the nugget size and the failure load. Zhao et al. [11] extracted many features from the electric power signals to predict the nugget size. Some studies [12,13] have predicted weld quality by using the electrode displacement signal. Alghannam et al. [14] have proposed an interesting image-based approach combined with fuzzy logic to predict joint quality. Many efforts for the prediction of weld quality in RSW process have also been made through thermographic techniques. Some examples can be found in the literature [15–22].

Although there are many studies in the literature relying on the processing of one signal type and, hence, on one sensor only, the multi-sensor fusion monitoring is regarded to be a more effective technique since it combines different sensor signals to understand in more detail and different aspects of the welding process [8-23]. Moreover, there is a lack of predictive techniques pertaining the electrode wear, which is one of the primary factors affecting the quality of the weld spot.

By implementing a suitable IoT infrastructure on the machine and by carrying out a proper experimental plan, it is possible to collect different kind of data and build a data-driven framework capable to predict the electrode wear during the process.

The aim of this work is to propose a data-driven methodology for the electrode wear prediction in Resistance Spot Welding (RSW) process.

Next section describes the RSW process presenting the monitorable process signals and the electrode wear phenomenon. Section 3 discusses both the proposed experimental procedure and the data processing activity needed to build the predictive model. Section 4 concludes the paper by outlining the possible advantages attainable by such framework and the future developments.

2 RSW process

Resistance Spot Welding (RSW) is a joining technique widely used in the automotive industry. In the RSW process, two electrodes are pressed first against the sheets to weld for a certain amount of time (squeeze time). Then, a high current flows through the electrodes and the sheet stack for a prefixed time (weld time). The heat generated by the Joule effect provides the thermal energy to locally melt the sheets and form a nugget, which is the junction. Fig. 1 shows a schematization of the RSW process.

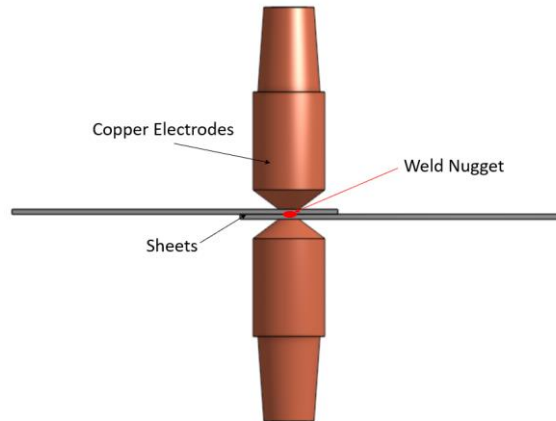


Fig. 1. Schematization of RSW process

The mechanical strength of a RSW joint depends strongly on the nugget size, which is the main key indicator of the joint quality. To achieve the desired nugget size, the first step is the correct setup of the spot weld cycle, schematically displayed in Fig. 2. This requires the setting of the following process parameters.

- Squeeze time, Weld time, Hold time.
- Weld current.
- Electrode pressure.

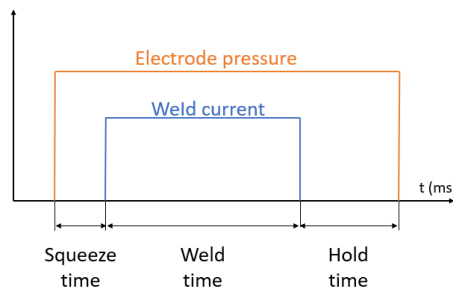


Fig. 2. Schematization of a spot weld cycle

However, the proper setting of the process parameters does not ensure a defect-free joint. Other phenomena such as shunting, edge proximity, initial sheet gaps and electrode wear can be sources of weld defects and hence, responsible for poor joint quality [24]. The first three causes can be avoided with a correct joint design, whereas electrode wear plays a critical role.

2.1 Electrode wear

In many manufacturing plants, 60% of the defective spot welds are due to worn electrodes [25]. Typically, a modern body car contains from 4000 to 7000 spot welds [12]. Having an accurate control of the electrode wear can ensure the required quality level by the joint and, thus, it would allow to reduce the number of weld spots needed to assembly a body car.

As the number of welds increases, the electrode damage by wear due to different and complex electrical, chemical, mechanical and thermal phenomena, which also interact one another. Overall, three main different types of wear mechanisms occur on the electrode surfaces: radial wear, axial wear, and pitting. The radial wear causes an enlargement of the electrode tip diameter. The axial wear reduces the electrode length. Pitting concerns the erosion of the electrode surface [26].

When the electrode tip diameter enlarges, and the contact surface oxidizes, the current density decreases. This leads to a reduction of the nugget size, and, hence, to a lower joint quality.

2.2 Process signals in RSW

RSW machine can be equipped with different sensors to measure during the welding the voltage between the electrodes (V), the electrode force (F), the electrical energy (E), the electric resistance of the sheet stack (R) and the electrode displacement (D). Furthermore, a thermal imaging camera can be also used for the detection of the temperature field (T) in a point of the sheet surface close to the working area, as shown, illustratively, in Fig. 3.

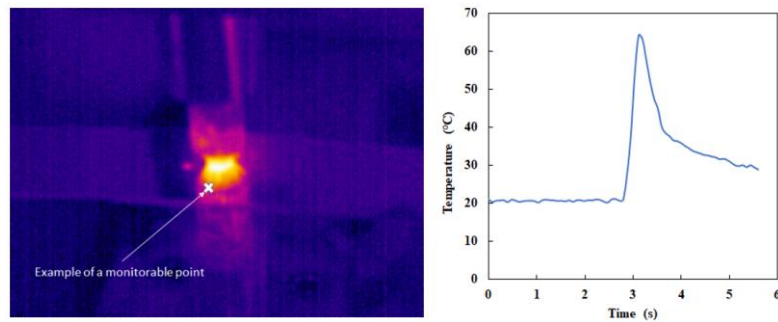


Fig. 3. Example of an infrared camera record with the associated transient thermal curve in RSW

The process signals and the infrared camera records can be processed to extract a set of explanatory features (predictor variables) to map wear parameters of the electrode (target variables), as described in the following section.

3 Proposed Methodology

The scope of this section is to describe a data-driven methodology to predict the electrode degradation through a multi-sensor fusion monitoring of the RSW process. The basic idea is to monitor different process signals from hundreds and successive RSW spots and relate them, after a data analysis, to electrode wear indicators.

3.1 Experimental procedure for data acquisition

The first step requires a proper experimental plan to collect the following data.

- Process signals over time to extract predictor variables (Electrode wear welds).
- Electrode wear indicators to get target variables (Carbon imprint tests).
- Mechanical strength of the joints to establish the service life of the electrodes (Shear tension tests).

The experimental plan consists of replicating the same welding cycle hundreds of times until the end of the electrode life with an optimal setting of joining parameters.

The process signals can be extracted automatically from any weld carried out in the experimental procedure without adding costs or time-consuming activities. Conversely, electrode wear measures and mechanical strength of the joints need of proper tests. For this reason, the latter are not performed at each weld, but with an established temporal frequency.

Electrode wear welds

With the aim of deteriorating the electrode over time by acquiring the corresponding welding signals, hundreds of welds on a sheet stack made of two overlapped sheets can be executed, as shown in Fig. 4. For this scope, the AWS D9.8 standard [27] can be adopted. It defines the position of the several spots on the sheets: the minimum distance of the spots from the edge of the sheets (edge distance), the minimum distance among adjacent spots (pitch), and the correct sequence for the execution of the weld spots to avoid excessive heating of the sheets during the welding, which would alter the electrode condition (i.e., excessive electrode heating).

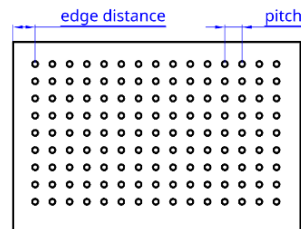


Fig. 4. Example of weld spots distribution on two overlapped sheets

Carbon imprint tests

The AWS D8.9 standard [27] defines a simple and reliable method to evaluate electrode wear through a carbon imprint test. In this test, a layer of white paper and a layer of black carbon paper cover one sheet. Then, a weld cycle is carried out without passage of current. In this way, the electrode face imprint remains visible on the white paper. Based on the electrode impression, some considerations on the electrode wear can be made. A schematization of this test is shown in Fig. 5.

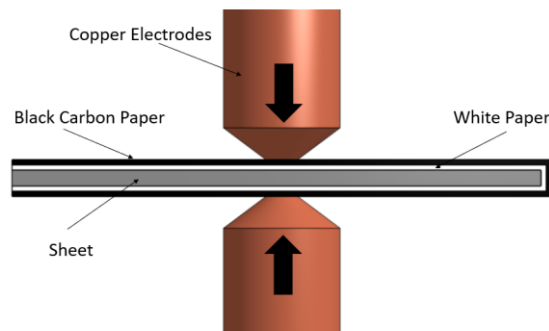


Fig. 5. Schematization of the carbon imprint test

Shear tension tests

Mechanical tests are needed to acquire and monitor the strength of the joint with the increase of the number of welds and hence with electrode wear. The mechanical strength of spot welds falls over time because of the electrode wear, which mainly reduces the nugget size. Therefore, the mechanical strength can be used as a factor to define the critical level of electrode wear. For instance, when the mechanical strength of weld spots reduces of 20% with respect to the initial value, the electrode can be considered worn and to be replaced [27, 28]. However, other threshold values can also be used. The most common mechanical test for spot welds is the shear tension test, as illustrated in Fig. 6. The weld strength can be defined as the maximum force, F_{max} , reached during the test according to the [27].



Fig. 6. Schematization of the shear tension test

Firstly, the mechanical strength of the weld spots needs to be evaluated at the beginning of the experimental plan, when the electrode is still new. Then, the shear tests are performed every time a couple of sheets is completely welded, as shown in Fig. 4. At least three repetitions for each shear tension test should be carried out.

In the proposed methodology, the maximum load F_{\max} is only used as parameter to establish the end-of-life of the electrode. When an electrode is considered worn, the experimentation can be repeated with a similar electrode, but different settings of the process parameters in order to enlarge the observation domain.

Figure 7 summarizes the experimental procedure adopted in this study to obtain data for electrode wear prediction.

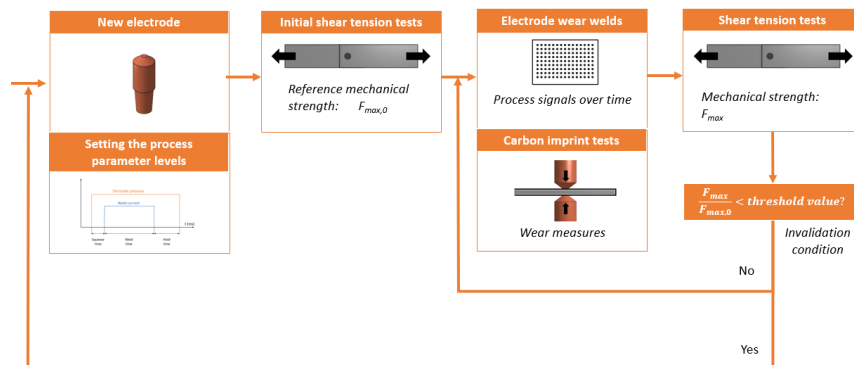


Fig. 7. Experimental framework for data acquisition

It should be noted that carbon imprint tests are carried out with an established frequency. The latter can be equal to the frequency of the mechanical tests, even if a higher acquisition frequency of the electrode imprints would enhance the accuracy of the methodology.

Once the experimental procedure is ended, the electrode imprints can be processed to obtain wear indicators (target variables of the framework), and the weld signals can be manipulated to get explanatory features (predictors of the framework). Next section discusses how to perform such data processing activity.

3.2 Data processing

Data processing activity can be thought as a transformation of industrial raw data into predictor and target variables suitable for feeding a Machine Learning (ML) algorithm.

Target Variables

In this study, the target variables are the electrode wear indicators, which come from the carbon imprint tests. The raw data, constituted by the electrode face imprints on white paper (Fig. 8), need to be converted into image format to be processed. A simple scanner machine can be used for this task.

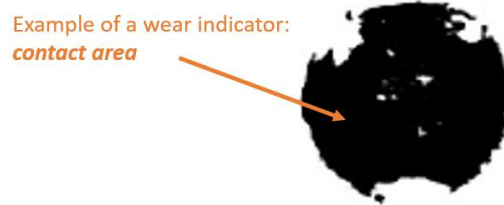


Fig. 8. Example of an electrode face imprint and identification of a target variable

Then, an image processing tool can be adopted to extract the geometrical features characterizing the electrode wear and use them as wear indicators. In the following, some suggestions are presented inspired by the work of Peng et al. [28].

- Diameter of the electrode imprint can be computed and normalized with respect to the nominal diameter when the electrode is still new.
- Eccentricity can be evaluated as the distance between the centroid of the electrode face imprint and the geometric centre of the electrode, normalized by the actual electrode diameter.
- Electrode pitting can be evaluated as the ratio between the eroded zone (i.e., the white area of the imprint) and the contact zone (i.e., the black area of the imprint).

These measurements can be used to characterize the electrode health state.

Predictor Variables

Predictor variables come from the manipulation of the process signals acquired during the experimental welding procedure. By following the scheme proposed by Traini et al. [29], a procedure to get predictor variables from the raw data of multiple sensors during a RSW process is described in the following paragraph.

Pre-processing

A pre-processing activity is needed to check the validity of data and get manipulable time series data. It can be summarized as data cleaning and validation phase, and usually, in an IoT infrastructure design context, it is assigned to the edge computing components of the system. The main functionalities of this step are:

- evaluation of the level of need to acquire data (deciding whether to carry out a process inspection)
- general validation of the data relating to a single weld (welding process carried out correctly)
- validation of each individual measurement from different sources (data acquisition process carried out correctly)
- selection of the time window of interest (selection of the range of data relating exclusively to the period of machine operation).

For data validation, time-series anomaly detection techniques are used. The interquartile rule for outliers can be an effective method [29].

The electrode force signal can be exploited for the identification of the machine activity period in RSW. As shown in the previous sections, the weld spot cycle starts with the squeeze time and ends with the hold time.

Feature extraction

At this point, information can be mined from the time series data through feature extraction techniques. In this way, computational costs can be saved in the future learning activity of the algorithm. Time-domain statistics can be extracted from every kind of process signal. Depending on the type of the sensor measurement, several features like the mean, the maximum, the minimum, the increasing time, the decreasing time, the increasing rate, the decreasing rate, the amplitude increase, the amplitude decrease, the variance, the skewness, the Euclidean distance between subsequent curves, and so on, can be extracted. The same reasoning can be applied in the frequency domain to enrich the dataset with valuable information.

Feature normalization

Once features are extracted from time series, they need to be normalized to deal with their magnitude. Feature normalization activity yields to get data roughly in the same range by improving the convergence of the future algorithm. Min-max normalization and standardization are two suitable techniques.

Feature selection

Finally, a feature selection activity is useful to further reduce data dimensionality by only keeping the most explanatory ones. For this purpose, many techniques can be used to build an effective feature selection strategy, such as correlation-based analysis between predictor variables themselves, correlation-based analysis between predictor variables and target variables, hypothesis testing, monotonicity and prognosability analysis [29].

3.3 Predictive Algorithm

The task of the predictive algorithm is to take in inputs the predictor variables and make predictions of the target variables. Even if these tasks can be performed by any supervised statistical model, given the huge amount of data generated by the different sensors equipped on the machine, ML algorithms with high degrees of freedom are preferred in order to use the information contained in hundreds of features, as the size of the available processing sample increases. For this purpose, different ML algorithms can be used and tested against each other to choose the most accurate one. It is important to split the whole dataset obtained by the data processing phase into training set, validation set, and test set. The training set is used to train the ML algorithms, the validation set is used to tune the hyperparameters of the models, while the test set generalizes the overall performance of the chosen algorithm.

According to Biggio et al. [30], regarding of traditional ML algorithms, three sub-categories of models frequently employed in prognostics activities can be identified: Neural Networks (NNs), Support Vector Machines (SVMs), and Decision Trees (DTs).

NNs are models inspired by the neural connections in the human brain. NNs are organized in layers where each of them includes several computational units, called neurons. Each neuron firstly computes a weighted sum of its input, and then apply a non-linear function, called activation function [31]. In this way, starting from the data feeding the Input Layer, going through the Hidden Layers, until to reach the Output Layer, complex relationships between inputs and outputs variables can be mapped. For this reason, NNs are suitable when the predictor variables have a non-linear relationship with the target variables. The architecture of the specific NN (number of neurons and number of layers) depends mostly on the task to be executed and by computational resource.

SVMs is a supervised classification algorithm. It can be thought as a large margin classifier because its decision boundary has the property that it is as far away as possible from the nearest data of each class. It turns out to be a linear classifier, but this condition does not often deal with the real-world scenario. So, a kernel can be used in cases where it is needed to address the non-linearity of a data, such as Gaussian Kernel. Typically, in problems where a high-dimensionality of features is involved, SVMs show good performance, even if the computational cost of the kernel matrix can be prohibitive [30].

DTs is a class of non-parametric supervised ML algorithms commonly employed for regression and classification problems [30]. A decision tree is a predictor applying a series of simple decision rules on the given point. This process can be outlined as a tree, where in the non-leaf nodes of the tree there are the conditions to be applied to go on. After descending the tree in the way prescribed by each node condition, the leaves of the tree contain the predictions of the algorithm [31].

Choosing a specific algorithm depends on many factors. The algorithm can be selected on the ground of a set of performance metrics for each candidate model, but there also other aspects to be considered, such as the specific task to be performed, the characteristics of data, the interpretability and transparency required. However, NNs are expected to be the most suitable candidate due to the high non-linearity of the welding processes [8].

The aforesaid classes of algorithms are only a suggestion to predict electrode wear in RSW, in fact other models can also be considered.

Once the algorithm has been trained, measurements of electrode wear are no longer needed since the algorithm is capable to predict the electrode wear only by acquiring the sensor signals during the process.

Since the level of the electrode wear, is usually identified with a set of indicators, the predictive algorithm must be based on a multivariate model that estimates different target variables (i.e., each wear indicator). Once the model(s) is chosen based on data-driven tests, the model is used continuously to monitor the status of the tool and provide the operator with a platform to support operational tool change decisions. To make models able to estimate the wear, a continuous sensors data collection is necessary, so to obtain an up-to-date wear profile that does not compromise production performance

by generating downtime. If investment costs for an IoT infrastructure capable of constantly monitoring every asset is unsustainable for a company, these methodologies can provide excellent results also by using data only from periodic machine inspections.

Figure 9 shows a schematization of the data processing activity discussed in this study.

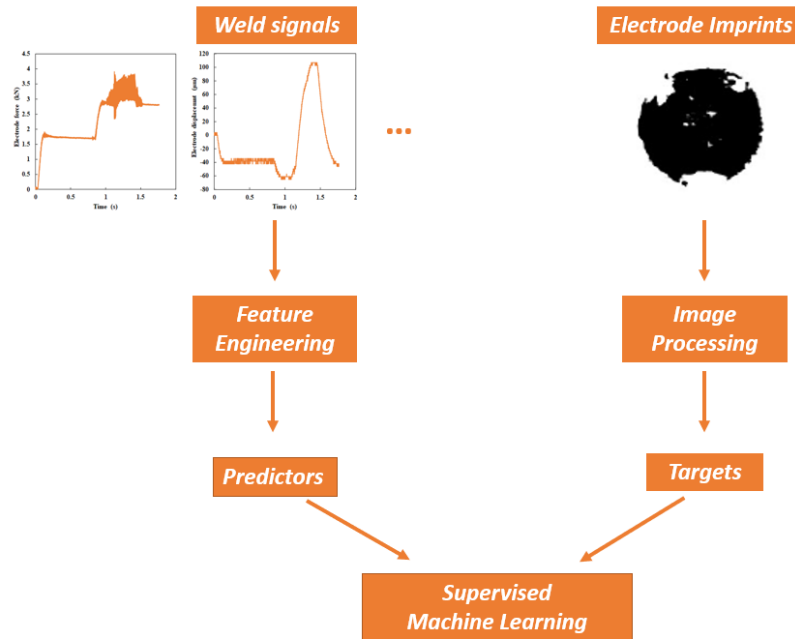


Fig. 9. Schematization of data processing activity

4 Conclusions and future developments

Many research works related to prediction of spot weld quality rely on measurements from single sensors. This means the predictive algorithm is only trained with a limited amount of information, so limited conditions can be detected. Moreover, most of predictive models focus on the predictions of joint quality, and not on electrode state prediction.

This paper proposes a methodology to build a Condition-Based Maintenance tool for RSW process according with the primary needs of Industry 4.0. The novelty of the proposed framework is to use multiple sensor measurements to make predictions. Once the algorithm has been set up, it could be potentially deployed directly on the machine and provide a helpful support to the welding operator for the maintenance activities. Indeed, the operator could monitor in real-time the predicted wear indicators by getting quantitative information for the decision-making process pertaining to the replacing or dressing of electrodes. Moreover, based on the quality level required by the company,

the critical level of electrode wear can be customised during the experimental procedure.

An accurate prediction of the electrode wear would lead to a just-in-time maintenance activity by fostering the lean production philosophy, reducing the number of defective joints, and avoiding premature electrode replacements.

Future research will be focused on testing the practical feasibility of the proposed methodology and in investigating the most suitable Machine Learning algorithm to be used.

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