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Welding Process Monitoring Applications and Industry 4.0

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Abstract— With the fourth industrial revolution in progress, traditional manufacturing processes are being transformed. Fusion welding is no exception from this transformation. The centuries-old manual craft is being reshaped by cyber-physical systems, turning into a digitized process governed by industrial informatics. By implementing process monitoring in welding applications invaluable data are collected that can be utilized in the new, futuristic smart factories of Industry 4.0.

In this article two purposes are being served. The first is to present the status quo alongside the future trends of welding process monitoring on industrial implementation. The second is to present the results of an ongoing investigation of robotic Gas Tungsten Arc Welding (GTAW) monitoring for defect detection and characterization. Deviations from the optimal values in three welding conditions (surface integrity, shielding gas flow rate and surface contamination) were introduced during stainless steel 316L beads-on-plates welding. Acquired data during the welding process were used to extract features in order to identify correlations between the disturbances and the monitored signals.

I. Introduction

Welding process monitoring can be defined as the simultaneous measuring and monitoring of weld conditions and additional factors which contribute to the quality of a weld [1]. To understand the principles and explore the possibilities of real-time process monitoring in welding, the welding process needs to be considered as a complex and uncertain system [2]. The adjustable welding parameters (also referred to as control variables) are the inputs of the system, whereas the properties of the generated weld and the heat affected zone (HAZ) are the outputs. What defines the output, apart from the input parameters, are the pre-determined constants and processes that comprise the system, in this case the welding conditions. Welding conditions are parameters such as the chemical composition of the metals and the groove geometry, which are expected to remain constant throughout the process. On the contrary, inputs of the system such as current, voltage, heat input and travel speed are expected to vary throughout the process based on the desired output. However, controlling the welding conditions to their nominal values may not always be feasible, therefore fluctuations and variations from their expected values will occur. These disturbances of the system's conditions result in alterations of the output, and subsequently undesired properties of the weld.

The uncertainty of the process' outcome highlights the need for monitoring of the process, either by directly detecting the disturbances of the welding conditions or their effect on the system's output. The online monitoring of a welding process is an active area of research, mainly attributed to the complex physics underlying the process and the lack of commercial efficient and reliable solutions [3].

Studies performed in this area are revolving around the physical phenomena that are involved in the arc welding processes, particularly those related to the plasma arc and its effects on the weld pool properties. Proposed solutions in the field spread from numerical simulations of the arc to vision systems with advanced image analysis. Acoustic sensing, ultrasonic emission analysis and electromagnetic emission analysis can also be used. Recent development growth in the field of artificial intelligence sees welding monitoring applications investigated by intelligent systems based on machine learning and fuzzy logic [4].

Monitoring Classifications

The sensor technologies used in research related to process monitoring are divided into four main categories: arc sensors, optical sensors, infrared sensors and ultrasonic sensors. Additionally to these categories, research has been conducted in the fields of x-ray radiography, plasma emissions spectroscopy and acoustic emissions. Each sensor category has its own benefits and disadvantages relating to the type of the welding method and process monitoring application. For example, optical and infrared sensors are susceptible to plasma radiation, but they reveal features (e.g. cooling rate temperature gradient and melt pool 3D geometry) that other methods are unable to provide.

Independently of the sensor categorization, welding monitoring methods can also be classified at different levels according to the nature of the monitoring which relates to the type of measurements. At the lowest level (Level 1), inputs of the system are monitored, to ensure their correct values throughout the different stages of the process. On the mid-level (Level 2) the welding conditions (constants) of the process are monitored to ensure their nominal values are maintained at a constant (or within accepted levels of variation). On the upper level (Level 3) the variables that are affected by welding conditions and controlled by the welding parameters are monitored. These intermediate parameters (e.g. temperature gradient) are not the final output of the process but have a closer relationship with the result than individual welding parameters and conditions [5].

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Welding monitoring systems can also be classified in three levels based on the system's ability to detect, identify and correct disturbances occurring in the process. On the lowest level (Level 1΄) the system is able to detect disturbances that occur in real-time. At the mid-level (Level 2΄), the system has the ability not only to detect the disturbances but also to identify their origin, highlighting the malfunction in the process. At the highest level (Level 3΄) the system is equipped with a feedback mechanism that intervenes in the process correcting the disturbances [6].

Adoption barriers

Despite the fact that welding monitoring technologies have demonstrated sufficient abilities in defect detection, these technologies have not been widely commercialized with the current state of adoption by industry in low levels. This situation is mainly attributed to the variety and complexity of the welding processes, which opposes to the specific application suitability of the monitoring methods [7]. Additional barriers and obstacles that monitoring systems developers need to overcome include the high initial costs, fragile and sensitive equipment operating in harsh industrial environments (e.g. contact-requiring sensors in high temperatures, fumes and spatter), arc radiation interference, restricted access in the welding area and weight limitations preventing the attachment of bulky components on the welding torch [8].

Under the context of Industry 4.0 to be explored in Section II, the aforementioned barriers are expected to be removed giving rise to a truly digitized welding process dominated by data analytics and industrial informatics. In Section III the experimental setup and results of an ongoing welding investigation for predictive quality control will be presented.

II. Industry 4.0

Industry 4.0, a term deriving from the German Industrie 4.0 conceived in 2011 at the Hannover Fair, is the context that has been the driving force behind the ongoing forth industrial revolution. It refers to the applications of Cyber-Physical Systems (CPS) in the fields of manufacturing and production [9]. The goal of Industry 4.0 is to pave the way towards the "factory of the future", turning organizations into truly digital enterprises utilizing industrial informatics and the networking of the Industrial Internet of Things (IIoT) in both their vertical and horizontal value chains.

Red Queen Hypothesis

In Lewis Carroll's 1871 book "Through the Looking-Glass", the Red Queen provides an explanation to Alice regarding the nature of the glass-land, which came to be known as the Red Queen Hypothesis [10]. "Now, here, you see, it takes all the running you can do, to keep in the same place" [11]. In an evolutionary race between prey and predators the ability to move fast and adapt to a dynamically changing environment ensures the survival of a species. Fast-forwarding to the 21st century, this hypothesis is applied in the field of manufacturing where companies who can quickly adapt to the fast-moving digital industrial ecosystem will stay competitive, whereas companies lose their customers when they can't anticipate demands for connected products and services [12].

In the "2016 Global Industry 4.0 Survey", responses were collected from over 2,000 participants from nine major industrial sectors and twenty four countries [13]. The results revealed that Industry 4.0 is no longer considered as a future trend revolving around a "buzzword", but companies have moved from talk to action. 33% of the participants classified their companies' current level of digitization and integration as high level, whereas 72% expect a high level of digitization in five years. To achieve that level, the companies are heavily investing in Industry 4.0. Global industrial products companies are investing US$907 billion per year through to 2020, with an average of 5% investment as a percentage of their annual revenue. 55% of the participants expect return of investment within two years. These investments are not only towards digital technologies (e.g. sensors and connectivity solutions) and software applications (e.g. modelling software, manufacturing execution systems), but also on training of their employees, since digital skills was found to be the biggest challenge in Industry 4.0 implementation.

In order to expand on the Industry 4.0 applications in welding manufacturing processes, the context of the design principles need to be analyzed, providing insight on how the future of welding will be shaped. While there are various definitions of what is Industry 4.0, all of them seem to agree on the following four design principles: interconnection, information transparency, decentralized decisions, and technical assistance [14].

A. Interconnection

Through the industrial adaption of the Internet of Things (IoT), the IIoT aims to connect people, machines, and products through communication technologies. Modules of standardized wireless communication devices (RFID, Bluetooth, Wi-Fi, etc) are being embedded, attached or connected on sensors, machines and equipment to allow real-time smooth exchange of information. Modularity and flexible adaptability is of high importance especially where manufacturing data are exchanged cross-disciplinarily along the product life-cycle (see B. Information Transparency). These characteristics are required not only on physical equipment but also on the software, where an adaptable code results in automatic re-configuration with less errors and transition time.

Interconnection in Welding

- Recent developments on applied interconnection in welding applications are focusing on human/machine communication that enables the remote control of welding parameters. Wireless foot-pedals and controls with operational frequencies in the industrial, scientific and medical (ISM) radio bands are already available in the market, where applications of voice-activated controls embedded on the helmet are taken into consideration [15].
- Wireless Bluetooth 4.0 communication (also in the ISM radio bands) between the helmet and the power source is also an option explored. Signals for the arc status are used to control the auto-darkening shades of the helmet's visor, ensuring the safety of the welder [16].
- Modern welding power sources are expected to be have the ability to connect to computers and the internet. Subsequently, sufficient documentation of each welding

station is provided with details of the usage, arc status and values of welding parameters, enabling remote asset utilization management [17, 18].

B. Information Transparency

With digitization at the core of the forth industrial revolution, data acquired from sensors in the manufacturing plant are fused with models created from software to create virtual copies of the physical world. Digital copies of manufactured products are created by the combination of pre-production fabrication guidelines, environmental and machine condition monitoring data, data from process monitoring during production and results from post-production of in-line metrology and quality assurance tests. These copies are then stored in databases both locally and in the cloud, with access to the respected parties involved, ensuring a digital trust between them. In order for this digital ecosystem to function properly, safety measures regarding cyber-security need to be taken. Clear guidelines on data integrity and digital security need to be applied not only for the data acquired during manufacturing but also for the communication data between the parties involved and the intellectual property surrounding the manufactured products.

Information Transparency in Welding

- Data collected from the variety of sensors involved in welding process monitoring are fused with the data collected from the power sources to create detailed performance documentation for each weld. These data, as described above, need to be securely stored with access only to respected stake-holders. Therefore not only strong foundations of digital trust are established between the manufacturer and the customer but also their reliability and reputation is ensured in case faulty products require further investigations. In areas where post-production testing is a requirement, the test-results can be linked and stored alongside with the collected process data.

C. Decentralized Decisions

The aforementioned design principles on interconnection and information transparency empower CPS with the ability to make decisions locally, without the need for approval from higher levels of hierarchy. Validation data required for the decision making can be provided between the interconnected parts, avoiding causing delays and bottleneck effects in a production line.

Decentralized Decisions in Welding

- The most important feature of real-time welding process monitoring systems is their ability to detect, identify and classify disturbances, parameter variations, process interruptions and malfunctions as they occur. With decentralized decisions, modern welding systems are expected to have the authority not only to automatically readjust parameters and alter conditions but also to intervene with process interruptions when deemed necessary. To achieve such high level of automation, the monitoring systems should be equipped with advanced data analytics recruiting machine learning and predictive models, while maintaining fast data transferring and high processing power. As the number of monitoring parameters is increasing and the predictive models become more complex, more processing power will be required, hence the need for intelligent sensors with embedded processors.
- In cases where complex geometries of welded products proscribe the use of a feedback mechanism, or in cases where the system's response time forbids a Level 3´ monitoring system, the analyzed data can be used in post-weld evaluation to ensure the weld quality. This solution reduces the cost both in terms of time spent from waiting the results of a Non-Destructive Testing (NDT), as well as in terms of money to perform the NDT.

D. Technical Assistance

The term technical assistance in Industry 4.0 refers to the ability of CPS to support human actions in a production line. This assistance can be in the form of physical support, where difficult and hazardous tasks are performed by robotic systems, or in the form of comprehensive representation of complex datasets via visualized information. The former protects the manual worker from work-related hazards and the latter ensures faster reactions and better decision making.

Technical Assistance in Welding

Robotic welding has been around from the very beginning of the third industrial revolution. Since the 1960s when industrial robots were introduced, the welding processes have grown to be the most common applications on industrial robots worldwide [19]. Apart from reducing processing time, improving productivity and obtaining high quality welds, among the benefits of the robotic welding there is also the reduction of exposure of human welders to the hazardous welding environment [20]. Risks emerging from arc radiation exposure, fumes, extreme temperatures and prolonged sitting positions have been reduced, and the concept of technical assistance has been incorporated for years in the welding industry. There are however cases where robotic welding cannot be applied, as in products with complex geometries limiting robotic movement and access. Manual welding isn't predicted to be completely replaced in the near future, raising the need for technical assistance to be provided in additional ways.

- Advances in monitoring technologies have been applied to welding wearables, attaching sensors and display screens on welding helmet. Arc sensors detect and register arc initiations and welding durations, projecting information to the welder about total arc time [15]. This development can also be used in predictive maintenance, calculating the electrode replacement based on the operational time recorded.
- Another way of visualizing information to the welder can be by applying augmented reality technologies in the welding helmet. This innovating technology will transform manual tasks and with significant options for applications in welding. Apart from the projection of welding parameters and conditions on the welder's field of view, process monitoring systems can visualize corrections to ensure quality. Vision systems and arc sensors used for torch position identification can be utilized to "show" the welder the correct positioning while infrared thermography can be utilized to project to the welder isothermal images marking potential defects.

- Under the concept of "Virtual Welding" the welding process and the welders are modelled in the virtual world. This digitization allows programmers to check the robot movement for correct torch positioning, avoiding unnecessary rejects that lead to wastes. Additionally it helps human welders in training, allowing them to practice virtual welds holding dummy welding torches, avoiding exposure to hazards and eliminating materials and consumables wastes. Both augmented reality and virtual reality training modules are already available [21, 22].

III. Experimental Setup and Results

As welding process monitoring is advancing in the context of Industry 4.0, the need for complex data analytics is emerging. In order for a system to be able to detect and characterize disturbances, machine learning algorithms are recruited to "teach" a monitoring system how to do it. In this section the experimental setup to detect disturbances utilizing time-domain features of acquired signals is described. The aim of this research is to evaluate the extracted features as potential detectors and identifiers of weld disturbances in real-time process monitoring.

The present welding trials were performed on robotic Gas Tungsten Arc Welding (GTAW), using an ABB IRB 2400/16 robotic arm (Figure 1) connected with a VBCie IE175i Heat Management System power source. The welding system was used to deliver linear beads-on-plates welds on stainless steel 316L plates. The welding parameters of the experiment are presented on Table I. The data acquisition system (DAQ) was composed of a Tektronix DPO 2022B Digital Oscilloscope connected to a custom-built sensor box developed by the University of Sheffield. Measurements of both voltage and current were acquired.

Three welding conditions were recruited to introduce undesired disturbances to the welding process, in order to simulate potential disturbances that could occur in a welding workshop. Surface integrity was disturbed by machined notches on the plates, to simulate improper surface preparation and material handling. Shielding gas flow disturbances introduced by flow rate reduction from a brass ball valve were used to simulate potential regulator failures and accidental hose step-on. Amounts of grease applied on the welding path simulated surface contamination. All three disturbances were introduced in three levels (0, 1 and 2) resulting in 27

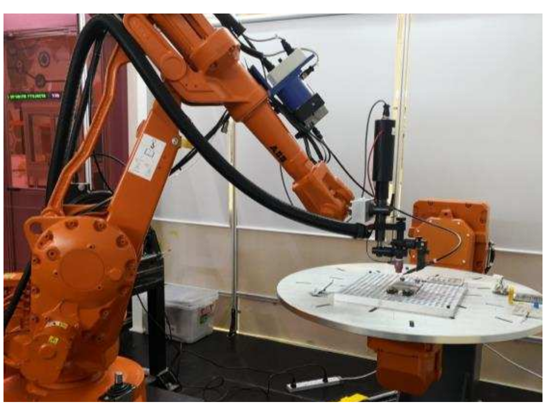

Figure 1: The robotic arm with a GTAW torch attached

combinations of welding conditions and subsequently 27 welds. Level 0 represents the optimal condition in which the system is expected to perform normal. This translates into no contamination, no notch or in the nominal value of the shielding gas flow rate. Level 1 represents "small" disturbance, which was simulated by 0.1 ml of grease, a V-shaped notch of 0.2 mm depth and 0.4 mm width, or a gas flow reduced by 15%. Level 2 represents "bigger" disturbance, simulated by 0.2ml of grease, a V-shaped notch of 0.6 mm depth and 1.2 mm width, or a gas flow reduced by 75%.

TABLE I. Experiment Welding Parameters

Parameter	Value
Current and polarity	Direct Current - Electrode Negative
Welding current	128 A
Shielding gas	Pure Argon
Shielding gas flow rate	17 L/min
Feeding wire	Inconel 718, 0.889 mm
Wire feeder speed	4.4 mm/s
Torch travel Speed	3.3 mm/s

The acquired data were analyzed in order to extract time-domain features including the first four statistical moments (mean, variance, skewness and kurtosis). A total of 15 features were extracted for each acquired signal (Table II) [23].

TABLE II. Definitions of Time-domain features

Feature	Definition
Mean (average amplitude)	$p_1 = \frac{1}{k}\sum_{i=1}^{k} s(i)$
Variance (standard deviation)	$p_2 = \left(\frac{\sum_{i=1}^{k}(s(i)-p_1)^2}{k-1}\right)^{1/2}$
Root-mean-square amplitude (RMS)	$p_3 = \left(\frac{1}{k}\sum_{i=1}^{k} s(i)^2\right)^{1/2}$
Square of mean of rooted absolute amplitude (SMRA)	$p_4 = \left(\frac{1}{k}\sum_{i=1}^{k}\sqrt{\lvert s(i)\rvert}\right)^2$
Peak value	$p_5 = max\lvert s(i)\rvert$
Skewness coefficient	$p_6 = \frac{\sum_{i=1}^{k}(s(i)-p_1)^3}{(k-1)p_2^3}$
Kurtosis coefficient	$p_7 = \frac{\sum_{i=1}^{k}(s(i)-p_1)^4}{(k-1)p_2^4}$
Peak factor (crest factor)	$p_8 = \frac{p_5}{p_3}$
Margin factor	$p_9 = \frac{p_5}{p_4}$
Waveform factor	$p_{10} = \frac{p_3}{\frac{1}{k}\sum_{i=1}^{k}\lvert s(i)\rvert}$
Impulse factor	$p_{11} = \frac{p_5}{\frac{1}{k}\sum_{i=1}^{k}\lvert s(i)\rvert}$
Min amplitude	$p_{12} = min(s(i))$
Max amplitude	$p_{13} = max(s(i))$
Max - Min	$p_{14} = p_{13} - p_{12}$
Peak - Mean	$p_{15} = p_5 - p_1$

In order to evaluate the features as potential disturbance detectors - and subsequently disturbance identifiers - analysis was first performed on data corresponding to individual disturbances. Each recorded signal was segmented into 1562 parts and for each segment the time-domain features were calculated. By plotting together each group of similar disturbances (e.g. Figure 2), correlations were observed for

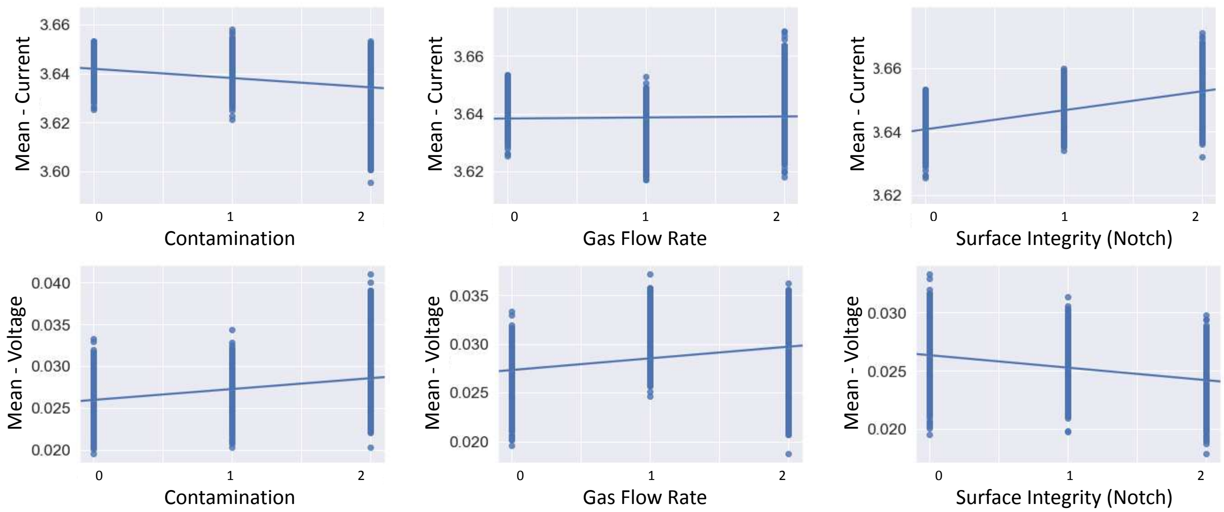

Figure 2: Current and voltage mean values for the following welding conditions:
(C = contamination, GF = gas flow, N = notch)
(Left: C:0-2, GF:0, N:0; Middle: C:0, GF: 0-2, N:0; Right: C:0, GF:0, N:0-2)

each feature. In Figure 2, the correlations of the first statistical moment (mean) on both current and voltage signals are seen for the welds where the disturbances were individually introduced to the welds. The voltage signal mean increased in the presence of grease and in the decrease of shielding gas flow rate, and decreased in the presence of surface marks. The current mean, decreased in the presence of contamination and increased in the presence of surface marks. While a higher value variation was recorded during shielding gas flow disturbances, not sufficient correlation was stablished on the mean values, mainly attributed to uneven quantification of the disturbance (manual brass-valve).

Of the 15 different time-domain features that were extracted, some showed higher correlations than others in different conditions of disturbances. In current measurements

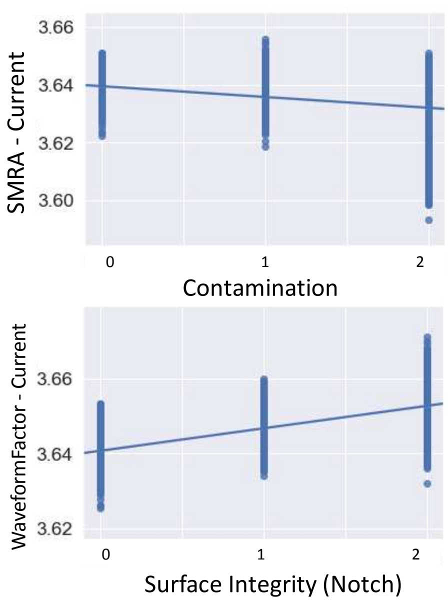

Figure 3: Examples of SMRA (top) and Waveform factor (bottom) of current signals for individually induced disturbances.

the features that presented the highest correlation level on all three disturbances were the "squared mean of rooted absolute amplitude (SMRA)" and the "waveform factor" (Figure 3). In voltage measurements higher correlations were found on the "peak mean" and "standard deviation (variance)" (Figure 4). The difference found in the correlation levels of different features attributed to different disturbances can be utilized in future machine learning algorithms in order to distinguish between the disturbances. Using similar datasets, a system incorporating neural networks can be trained to distinguish the disturbances and pinpoint the source of disturbance in a recorded signal.

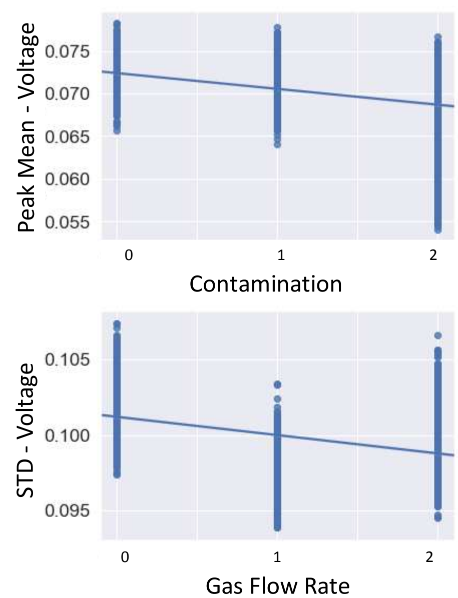

Figure 4: Examples of voltage peak mean (top) and standard deviation (bottom) values for individually induced disturbances.

Detection and characterization of the disturbances become more complicated when two or three types of disturbances are simultaneously introduced to the weld. From Figure 2 it is extracted that voltage in welds with simultaneous contamination and gas flow rate disturbances will show sufficient correlation levels. However, when these disturbances are occurring in the presence of a notch, it is expected that the correlation in the measurements will not be so clear since the effects of the different disturbances to the measurements are opposing to each other. As a result, when the time-domain features are collectively analyzed for all of the 27 welds simultaneously, the correlation levels are reduced compared to the individual disturbances (Figure 5).

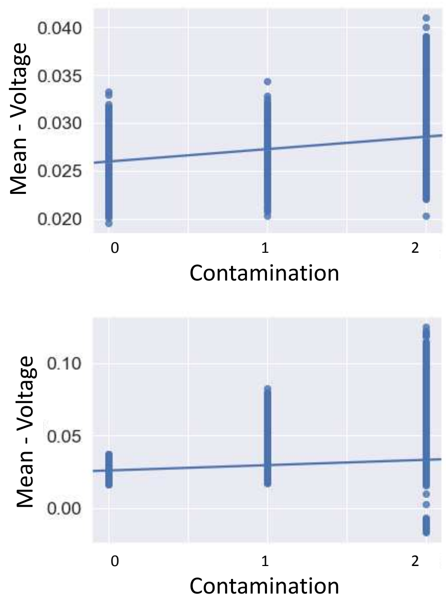

Figure 5: Voltage mean value vs. contamination
(Top: C:0-2, GF:0, N:0; Bottom: C:0-2, GF: 0-2, N:0-2)

IV. Conclusion

The industrial digitization under the context of Industry 4.0 is already being adopted by manufacturers of welding equipment. Interconnected cyber-physical systems are designed to generate invaluable industrial data through real-time process monitoring, with high implementation expected in the "factory of the future". It is therefore becoming essential the development of tools for analysis of data captured by monitoring systems. In order to detect and identify disturbances of the welding process that will result in failures, time-domain features for correlation analysis were recruited in the present work. Extracted from welding voltage and current signal measurements, the features have revealed significant correlations with induced disturbances, providing a potential tool to be used in identification, characterization and classification of welding process disturbances.

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