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Implementation of Zero Defect Manufacturing using quality prediction: a spot welding case study from Bosch

Foivos Psarommatis[a,b]*, Baifan Zhou[c,a], Evgeny Kharlamov[d,a]

[a]*University of Oslo, SIRIUS, Centre for Scalable Data Access, Gaustadalleen 23B, 0373, Oslo, Norway*
[b]*Research Center on Production Engineering and Management (CIGIP), Universitat Politècnica de València*
[c]*Department of Computer Science, Oslo Metropolitan University, Oslo, Norway*
[d]*Bosch Center for Artifician Intelligence, Renningen, Germany*

Abstract

Product quality is a vital aspect in the operation of manufacturing systems, manufacturers need to implement at least one quality assurance method to assure the desired quality. The most recent approach for quality assurance is named Zero Defect Manufacturing (ZDM). The scope of the current paper is the implementation of ZDM approach in the automotive industry and specifically for the spot-welding process. Using a machine learning method that is utilizing linear regression and LSTM and consuming data from the production such as sensors and other engineering data to predict the quality of future spot welds. Using this quality prediction there is a root cause analysis to identify why the spot weld will fail and the appropriate prevention actions are proposed. The next step is the training and validation of the machine learning model and the calculation of the accuracy of the model. Once the accuracy of the model is validated a series of simulations, using a dynamic scheduling tool, are performed in order to calculate a series of KPIs to evaluate the impact of the proposed method to the production.

Keywords: *Zero Defect Manufacturing; ZDM; Machine learning; Quality prediction; Prevention; LSTM; Simulation Industry 4.0*

* Corresponding author. Tel.: +41 78 666 6309
E-mail address: foivosp@ifi.uio.no

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1. Introduction

The contemporary manufacturing landscape has changed, the product life cycle has been significantly reduced and the mass production paradigm has been replaced by mass customization or personalization paradigms [1]. These facts imposed lower batches of customized or personalized products which by extent created new challenges to the manufacturers, with the biggest one to be production quality [2,3]. Furthermore, there is a growing focus on sustainable production, which necessitates that manufacturing firms continuously produce goods of higher quality and greater complexity at lower costs, while also limiting the use (and particularly waste) of resources across entire industrial ecosystems [4]. Deming (1982) proposed that putting quality first is the secret to dominating the market, because higher quality results in lower costs (owing to less rework, fewer errors, and fewer delays), as well as greater utilization of tools and materials [5].

The effects of poor product quality can impact many different levels, ranging from immediate financial losses to the environmental effects of wasting resources [6]. The negative effects of poor quality can also be seen on a social level as well, where a company's reputation is harmed by its low-quality goods and disgruntled customers [7]. A minimum of one quality improvement (QI) approach must be used to produce high-quality products with little performance loss [6,8]. Traditional QI methods like six sigma (SS), lean manufacturing (LM), theory of constraints (TOC), and total quality management (TQM) for more than three decades and do not consider the recent technical breakthroughs, all within the framework of Industry 4.0 [6,9].

Using Industry 4.0 technologies a new quality assurance approach has been created named Zero Defect Manufacturing (ZDM) [8], which transcends traditional quality assurance strategies. It attempts to completely eradicate defects through defect prediction and prevention in addition to the detection and repair of defected products [8,9]. With the advent of digitization and Industry 4.0 in the 2010s, ZDM began gaining more momentum on the quality management agenda as a technologically demanding concept, holding the promise of a brand-new generation of digitally improved quality management. These technologies include in-line data gathering solutions, data storage and communication standards, data analytics tools, and digital manufacturing technologies [10,11].

The automotive industry, which is the focus of our study, is no exception to the trend of Industry 4.0. Specifically, in the manufacturing of car bodies, welding processes such as Resistance Spot Welding (RSW) play a crucial role in joining car body parts together. RSW generates welding spots by passing high levels of electrical current through two electrodes and the metal worksheets in between [12], resulting in a substantial amount of diverse data. In fact, RSW processes are fully automated and can involve up to 6000 spots in each car, with each spot accompanied by thousands of sensor measurements, welding configurations, status information, quality indicators, and more [13]. Consequently, millions of data records are generated solely from RSW in a single car. The failure of a single spot can disrupt the entire car production line, leading to delays and costly repairs. Thus, effective monitoring and quality control of welding spots significantly impact production efficiency and costs. However, reliably assessing spot quality without destructing welded cars is highly difficult and directly measuring quality poses significant challenges [14,15].

Machine learning (ML) has been attracting much attention as a powerful tool for data-driven analysis, enabling automated pattern recognition in various domains [16,17]. In manufacturing, ML offers significant potential for data-driven quality monitoring, process optimization, and defect detection by leveraging the large volume of data collected during manufacturing processes. With ML algorithms, it becomes possible to build data-driven models from complex welding data, facilitating preventive maintenance and informed decision-making in welding processes [18]. ML algorithms can effectively handle a number of inherent challenges of welding data, such as high-dimensional inputs, temporal dependencies, and non-linear relationships, enabling the discovery of hidden patterns and correlations. Existing works on quality monitoring used classic ML or deep learning [20]; most of them used laboratory data and had limited data amount [24]. This work uses both classic ML and deep learning and with a detailed comparison between these methods, with a relatively large number of production data.

The purpose of the current paper is to develop a data-driven method to predict welding quality before the actual welding process takes place. Machine learning pipelines have been developed to predict the quality of the spot welds and suggesting a prevention method to prevent the potential quality issue. The performance of the proposed virtual metrology model was validated using data from a real industrial case coming from a European industry (Bosch).

2. State of the art

2.1. Zero defect manufacturing and defects prediction

Manufacturing systems are characterized by a high number of uncertainty, therefore defects are an inevitable phenomena, that can significantly disrupt the production and the success of a manufacturing company [19]. ZDM consists out of four strategies Detect, Predict, Repair, and Prevent, along with the links that go with each one, as explained by Psarommatis et al. (2020) [8]. The four ZDM strategies can be classified into two different triggers and actions. To identify a quality issue, use the Detect and Predict trigger procedures. Notably, the triggering ZDM approaches must be applied to every product. While Detect is divided into physical and virtual detection of a defect that has already occurred [11], Predict is tasked with predicting when a defect will appear in the near future. Using only those two triggering strategies won't increase the production's efficiency [8,9]. As a result, if information from the triggering ZDM strategies is received, the other two ZDM strategies, Repair and Prevent, are available as potential actions. Therefore, while using ZDM approaches, one triggering strategy and one action strategy must always be used in tandem. The Detect-Repair, Detect-Prevent, and Predict-Prevent ZDM method pairs are the outcome [8,9].

2.2. Machine learning methods for quality estimation

We discuss related work of machine learning in welding quality monitoring in several aspects. Question definition: here the essential aspect is which quality indicator is used as the target feature. Most previous works have studied estimation of the spot diameter [20], as this is the suggestion by international standards. Many works studied estimation of tensile shear strength [21], and other less common quality indicators like load, gaps, penetration [22], pitting potential [23]. Data collection: most previous work have a rather limited amount of data labelled with quality features due to the costly data collection process [13]. The typical data amount in literature is less than 500, [24]. There could be three major data sources: (1) simulation data [13], (2) laboratory data [25]; (3) production data. Most previous work have (1) and (2) as data sources. Feature processing and ML modelling: most of the methods used for machine learning modelling can be classified as classical machine learning methods [26], like Linear Regression (LR) [27], Polynomial Regression (PolyR) [28]. A few work used deep learning methods, such as [29]. This work uses both classic ML and deep learning, and compares their performance on different welding machines from production.

2.3. Spot welding

Resistance Spot Welding (RSW) is extensively utilized in the automotive industry, particularly in car chassis production. In this welding process, two electrode caps are attached to the ends of the welding electrodes (Fig. 1) [13,30], and they exert pressure on two or three workpieces. An electric current is then passed from one electrode, through the workpieces, to the other electrode. This current flow generates significant heat due to the resistance encountered and due to the pressure from the cups and the near melted metal the attached pieces are welded together, forming a weld nugget that connects the workpieces. It is important to note that the electrode caps, which directly contact the workpieces, experience rapid wear due to the high thermal-electric mechanical loads and oxidation. Therefore, regular maintenance is required for these caps. After a fixed number of welding spots, a thin layer of the cap is removed to restore its surface condition, a process known as Dressing. Once a certain number of dressings have been performed, the electrode cap becomes too short and needs to be completely replaced, which is referred to as Cap Change. The welding process is regulated by an *Adaptive Control System*, which not only controls the process but also serves as a data storage system. Its primary objective is to ensure that the electric current flowing through the electrodes and worksheets adheres to a predetermined profile known as the reference current curve. Furthermore, the welding program contains additional information, such as the welding position on the car part, worksheet characteristics (thickness, material, surface coating), and adhesive properties. Precise measurement of the nugget diameter poses challenges. Destructive methods, which involve tearing the welded chassis apart, are expensive and provide only partial quality control. Nondestructive methods, such as ultrasonic wave and X-ray techniques, are also costly, time-consuming, and yield imprecise results [31,32].

3. Proposed methodology for ZDM implementation

The proposed solution is comprised of two parts: (i) the machine learning (ML) pipelines that will consume data from the production, such as sensor data or process data, to predict the quality of a future spot weld; and (ii) the creation of an automated procedure for identifying the source of the potential future defect and suggest the correct prevention action to avoid the defect in the first place, and therefore achieve ZDM with zero waste. Fig. 1 illustrates the overall flowchart of the proposed solution. Since the actual physical measurement of the weld nugget is not possible with non-destructive means, in order to be cost and time efficient, a virtual metrology model was developed in order to estimate the quality of a spot weld after it has been made [11]. The estimated quality is named Q-Value is a comprehensive metric derived from process curves, incorporating statistical, geometric, and other features that leverage domain knowledge. This data in combination with the different sources of data will be used for the training of the proposed ML method. The different data streams that will be used in the current study are shown in Table 1.

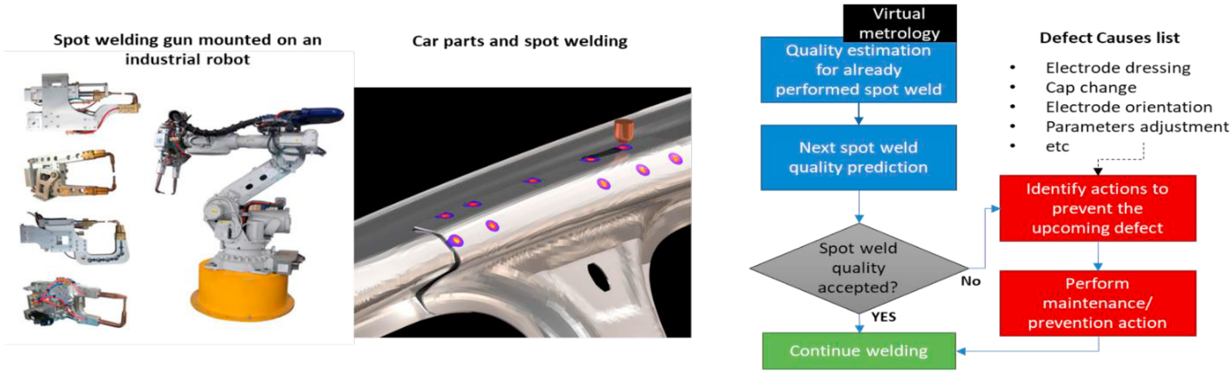

Fig. 1. Spot welding explanation and proposed solution flowchart

Table 1. Data streams for predicting spot weld quality

Group No.	1	2	3	4
Sensors	reference current (I_{ref})	reference voltage (U_ref)	reference resistance (R_ref)	reference pulse width modulation (PWM_ref)
Count Features	WearCount	DressCount	CapCount	
Status	System Component Statuses	Monitor Statuses	Control Statuses	
Quality Indicators	Process Stability	HasSpatter	Q-Value	
Process Curve Means	which are the average values of the process curves during their welding stages, calculated by the welding software system			
Program Numbers (ProgNo)	are nominal numbers of the welding programs, each prescribing a set of welding configurations			

From the engineering perspective, this work formulates the problem as predicting the future quality with historical data. The question comes that the quality of how many spots in the future should we predict. We aim at predicting the quality of the NEXT spot in the future, for two reasons: (1) it should be the most reliable prediction compared to spots in further future, because the available historical data for predicting the spot quality of the NEXT spot in the future (namely the first spot in the future) are all ground truth data, and if we predict the spot quality in the second spot in the future, then the prediction error is likely to accumulate; (2) it is sufficient to predict the quality of the NEXT spot in the future, since we only need to make sure every next spot has good quality, and undertake measures if the next spot is predicted to be have bad quality. In this way, we ensure of future spots have good quality in a recurrent way.

The scope of the machine learning model is to find a *function* between the available information (Table 1) and the quality (Q-Value) of the next welding operation Q_{k+1}, shown in Eq. 1, where $X_1, \ldots, X_{k-1}, X_k$ are data tuples (including single features and time series) of historical welding operations (from time step 1 to k) and known features of the next welding operation in the future (SF^*_{k+1}, e.g., welding program)

$$Q_{k+1} = f(X_1, \dots, X_{k-1}, X_k, SF^*_{k+1}) \tag{1}$$

3.1. Quality prediction method

In this section, we delve into the machine learning methods explored for quality monitoring. We begin by addressing strategies for effectively managing the two structures present in the data and combining features across different time levels. Additionally, we discuss feature selection and the process of machine learning modeling. Given that the data is organized into at least two levels, namely the welding level and welding operation level, feature engineering is performed accordingly on different time levels. This hierarchical feature extraction approach forms the foundation of the machine learning pipeline.

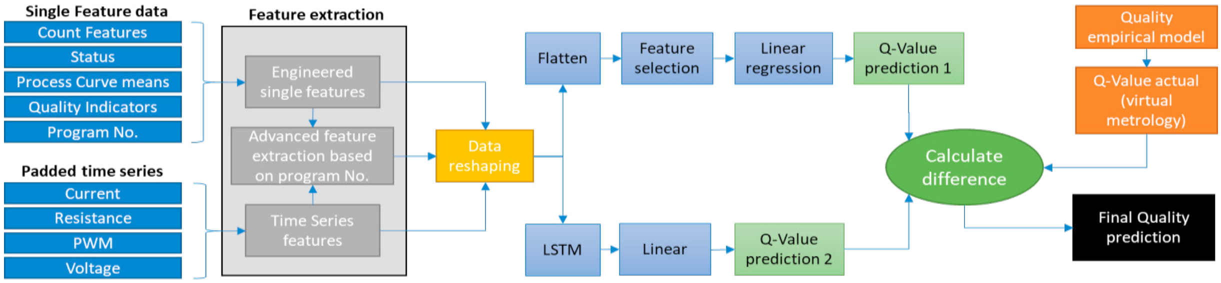

Fig. 2. Quality prediction model

3.2. Feature engineering (FE) on the time series and single features

Feature engineering is conducted at different time levels (Fig. 2). First, features are extracted from the padded time series. These extracted features can be viewed as vectors containing compressed information derived from the time series (TS) data. Following the TS feature extraction, shows the transition into features at the welding operation level since they remain unchanged across the welding time but vary across different welding operations. These time series feature extracted (TSFE) can be combined with single features, resulting in consecutive combined features that form time series at the welding operation level. These combined features can undergo further feature extraction modules, enabling hierarchical feature extraction.

Strategies aimed at feature engineering for individual features are devised based on the domain knowledge and the underlying meaning of the features. The objective is to transform the representations of raw features to enhance machine learning modeling. These engineered single features (EngSF) include three generated features. The WearDiff quantifies the difference between the WearCount of two consecutive data tuples, providing insight into the extent of the wear effect. Typically, the value is ONE for continuous data, while in cases where some data tuples are missing, the value accurately reflects the wearing effect. Additionally, after each fresh dressing, the value becomes a large negative number. The NewDress assumes a value of ONE following each dressing operation, while it is ZERO for other welding operations. The NewCap takes on a value of ONE following each Cap Change, and ZERO for all other welding operations. Moreover, the EngSF and time series features are combined and processed by advanced feature extraction that group features of previous welding spots with welding program No, resulting in EngF_Prog.

3.3. Feature selection

Due to feature engineering, the number of features expands significantly. Each of the 4 time series contributes 8 features, resulting in a total of 32 features. Additionally, 3 new features are derived from single features that describe temporal structures. Initially, there are 164 raw single features. After reshaping the previous l operations and flattening them into a table format, the number of engineered features can surpass 2000. For instance, assuming a value of l = 10, the number of engineered features before reshaping becomes 164+3+32 = 199. Furthermore, when accounting for EngF_Prog, the number of features doubles, resulting in (164+3+32) × 2 = 398, and ultimately 398 × 10 = 3980 features after reshaping and flattening (Fig. 2). To address this issue, this study proposes the utilization of step-wise forward feature selection to limit the number of features for modeling. This serves two purposes: 1) maintaining the prediction power of machine learning models, particularly when the number of data points is fewer than the number of features, and 2) achieving model transparency. Considering the time cost of feature selection, a wrapper method is employed for linear regression models, while for MLP and SVR, a pre-selection using linear regression is performed.

3.4. Machine learning modelling

We select two representative machine learning modelling methods, linear regression (LR) as the representative method for classic ML, and LSTM as the representative method for deep learning. After data reshaping, the reshaped features can be directly modelled by LSTM networks, corresponding to the FE-LSTM pipeline. They can also be flattened, and reduced by feature selection and modelled by LR, corresponding to the FE-LR pipeline.

We suggest Linear regression (LR) to begin with for solving every problem, according to the principle of Ockham's razor [33]. The performance of LR models provides a first estimation of problem complexity. Before performing LR, the data need to be flattened, because classic machine learning methods require the input features to be reshaped to a flat table-like data format (consisting of columns and rows similar to a SQL relational table), and normally assume these input features are independent from each other. In addition, we perform feature selection before ML modelling, because features with high correlations will negatively influence model performance of classic ML, and feature selection will also reveal the most important features for ML modelling, improving the model explainability.

As representative method of deep learning, we select LSTM [34], which is a widely used method for processing time series data due to its ability to capture long-term dependencies, retain memory, and robustly handle noisy and missing data. Unlike traditional recurrent neural networks, LSTM overcomes the vanishing gradient problem by incorporating a memory cell and gating mechanism, allowing it to learn and propagate information over extended sequences. The memory cell selectively remembers or forgets information, enabling the modeling of complex temporal patterns. These qualities have made LSTM a representative method in time series processing.

3.5. Performance metric

To calculate the predictive capabilities of the model the mean absolute percentage error (MAPE) as the performance metric (Eq. 2). MAPE [13] provides a percentage representation of the mean absolute error, which is easily comprehensible for process experts. Moreover, MAPE is relatively less affected by localized errors, where predictions for certain points deviate significantly from the true values. Alternative performance metrics, such as the mean absolute error (MAE), were deemed less intuitive by the process experts in our group and were therefore not included in the paper.

$$mape = \frac{1}{N}\sum_{n=1}^{N}\left(\left|\frac{y_n - \hat{y}_n}{y_n}\right|\right) \times 100\% \tag{2}$$

4. Bosch use case results

In the current section a specific industrial use case from Bosch will be used in order to validate our proposed ZDM solution. In section 4.1 the results from the training and use of the ML model and in section 4.2 the prevention method and its influence to the performance of the production will be presented.

4.1. Quality prediction results and discussion

In this study, we implemented two pipelines [30], namely FE-LR and FE-LSTM, using Python and the MATLAB toolbox SciXMiner [35]. The evaluation was conducted in two regimes: *Base* and *Full*. In the *Base* regime, the optional part of the pipelines (as shown in Fig. 1) remains inactive. Consequently, feature engineering is only performed on padded time series (TS) at the welding time level. The resulting TSFE is then concatenated with raw single features

(RawSF) for modeling purposes. On the other hand, the *Full* regime activates the optional parts, performing feature engineering on both the welding time level and the welding operation level. These configurations result in a total of four models. The data splitting followed a standard approach, dividing it into training, validation, and test sets with a ratio of 0.8:0.1:0.1. After hyper-parameter selection, the best four machine learning models were retrained using the combined training and validation sets, and subsequently tested on the independent test set. The evaluation of these models was performed using the mean absolute percentage error (*mape*). To establish a baseline, a simple benchmark was employed, where the Q-Value of the previous welding spot (Q_{prev}) was used as the prediction for the next Q-Value $\hat{Q}_{next}$, that is $\hat{Q}_{next} = Q_{prev}$.

Table 2 provides a summary of the results obtained from the four models. It is worth noting that the benchmark performs well for Welding Machine 1 (WM1, with 1998 spots), which has only two welding programs, but exhibits poorer performance for Welding Machine 2 (WM2, with 4996 spots) with four programs. The performance of the feature engineering (FE) pipelines surpasses that of the benchmark, indicating the effectiveness of the feature engineering process. As expected, the model performance shows improvement from the Base mode to the Full mode, where a higher level of feature engineering is employed, resulting in enhanced performance. For WM1, the best-performing model is FE-LR with an error rate of 1.61%, while for WM2, the top-performing model is FE-LSTM with an error rate of 1.94%. Interestingly, FE-LR outperforms FE-LSTM for WM1, whereas the opposite is observed for WM2. This discrepancy may be attributed to the fact that WM1 has fewer complex data compared to WM2, leading to varying performance outcomes between the two models. The developed model is very robust and quick and requires less that one second to predict the quality of the next spot, something that makes it highly efficient and able to cope with the application of spot welding. In the cases where spots are in a range closer to 1 second then the process of welding is delayed, but this could happen rarely.

Table 2 Model performance tested on test sets of Welding Machine 1 (WM1) and Welding Machine 2 (WM2)

Data preprocessing and feature setting			**Modelling**	***mape* (WM1)**	***mape* (WM2)**
Benchmark: $\hat{Q}_{next} = Q_{prev}$				3.19%	7.74%
Base	Feature engineering:	RawSF, TSFE	LR	2.38%	2.50%
			LSTM	2.35%	2.27%
Full	Feature engineering:	RawSF, TSFE, EngSF, EngF_Prog	LR	1.61%	2.10%
			LSTM	2.04%	1.94%

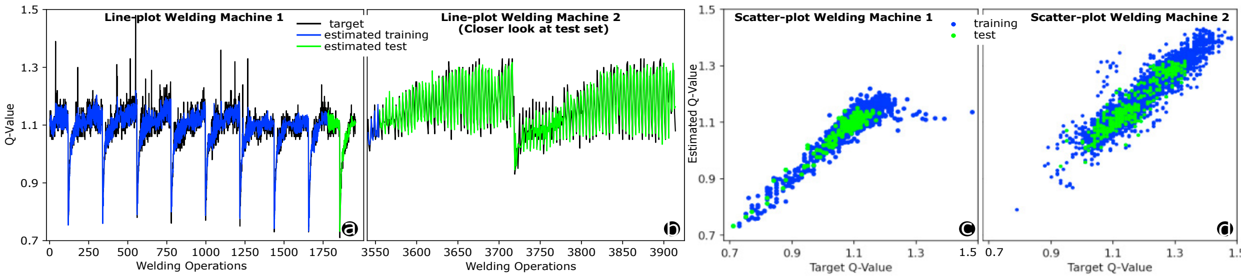

Fig. 3. Prediction results of Full FE-LR for WM1 in (a) line and (c) scatter plots and for WM2 in (b) line and (d) scatter plots

Fig. 3 presents the prediction results for FE-LR on both WM1 and WM2, utilizing line and scatter plots to illustrate the behavior of the model on different machines. In Figure 5a, it is evident that the model predictions for WM1 closely align with the target trend. However, we observe that the estimation for targets with high values in the training data is less accurate. This finding suggests that the model exhibits robustness and insensitivity to outliers. Furthermore, the test set area of WM2, revealing a close match between the predictions and the target values, indicating a strong performance of the model.

FE-LR offers the advantage of providing insights through the interpretation of selected features. The resulting LR models reveal that the most significant features are Q_{prev_prog}, WearDiff, I_{mean}, and R_{std}. These findings indicate several important observations: (1) A substantial amount of information regarding the quality of the next spot is encapsulated in the previous spot with the same program number. (2) The degree of wearing effect has a significant impact on the quality prediction. (3) Factors such as current and resistance hold greater importance in predicting quality compared to other features like PWM.

4.2. Defect prevention and production performance

In the current section a series of simulations will be performed in order to demonstrate the impact to the implementation of the proposed approach to the specific industrial use case. For the simulation a dynamic scheduling tool has been used, which complies to the ZDM principles and implements the detect, predict and prevent ZDM strategies [19,36–38]. The simulations was performed for the WM1 for the period of 1.5 months. In total eight key performance indicators (KPIs) were used to evaluate the performance of the different scenarios, those KPIs can be seen in Table 3 along with the simulation results. Three individual scenarios were simulated, the first one is a benchmark that stipulates the ideal scenario if there were no defects, the second is the current production procedure and the final is the production utilizing the developed prediction and prevention solution. Furthermore, there are four different causes of defects which represent most of the cases electrode needs dressing, cap needs change, electrode needs alignment and parameters tuning, with average corresponding application time 37, 15, 5, and 4 minutes accordingly. The values that have been used for the simulations are the average values, each spot requires 0.7s to be performed and [2,7] seconds for the robot to move to the next point. The nominal value of completed processes in the simulated period is 526 and on average each welding cycle requires 123.21 minutes. The weight of the car body at this stage is around 135.2kg and the energy each spot weld requires is 50kJ.

Table 3. Simulation results

KPIs/Scenarios	Ideal	Current (No prediction)	Proposed with prediction
Makespan (mins):	64808.46	70559.35	65973.81
Tardiness (mins):	8.46	3533.756	303.09
Process throughput (mins):	123.21	134.14	125.42
Production cost (€):	228220.88	263545.33	243712.34
Cost/unit (€):	433.88	523.19	478.87
Energy (kWh):	14596.61	16541.13	15074.51
Material waste (kg):	0	3561.99	730.85
Defect rate (%)	0	5%	0.9 %

The simulation results show a significant improvement to the performance of the production, compared to the current situation. In the end, the proposed solution manages to decrease the unit cost by 8.84% which is a significant reduction taking into account that we are discussion only one manufacturing stage. Furthermore, the defect rate from an average of 5% is reduced to 0.9%. In total, the following maintenance processes were performed 5 times: electrode dressing, 2 times cap change, 6 time electrode orientation change and 10 times parameters tuning. The results prove the potential that the implementation of ZDM has and the fact that our proposed approach significantly reduces the cost, time, waste and energy.

5. Concluding remarks

The current paper developed a viable solution for implementing ZDM approach. More specifically, machine learning pipelines were created using linear regression and LSTM in order to predict the quality of spot welds. The proposed solution was applied in a real use case in the automotive industry based on a Bosch scenario. The prediction model was trained and tested using real data from the production. The data streams that were used were from different sensor and other engineering data from the production. The developed ML model showed great fit to the data and was able to achieve 97.69% and 96.69% accuracy for WM1 and WM2 accordingly. Further to that, to test and evaluate the impact of the prevention actions to the actual production a series of simulations were performed with three scenarios, a benchmark, the current situation and the production using the proposed solution. The results clearly showed that the proposed solution significantly improves the performance of the system, which reflects to the cost pers process which is improved by 8.84%. The challenges for adopting the ZDM approach and more specifically predictive approaches are the data collection and lean modelling for the real time data analyses. Also, predicting quality defects creates a new problem, to respond fast in order to prevent the quality issue. This require high flexibility from the production line and the operators. Future research will focus on the development of similar quality prediction models for other manufacturing steps that shows also high defect rate and the quality inspection is either costly or time consuming.

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