Chapter

AI for Improving the Overall Equipment Efficiency in Manufacturing Industry

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Abstract

Industry 4.0 has emerged as the perfect scenario for boosting the application of novel artificial intelligence (AI) and machine learning (ML) solutions to industrial process monitoring and optimization. One of the key elements on this new industrial revolution is the hatching of massive process monitoring data, enabled by the cyber-physical systems (CPS) distributed along the manufacturing processes, the proliferation of hybrid Internet of Things (IoT) architectures supported by polyglot data repositories, and big (small) data analytics capabilities. Industry 4.0 paradigm is data-driven, where the smart exploitation of data is providing a large set of competitive advantages impacting productivity, quality, and efficiency key performance indicators (KPIs). Overall equipment efficiency (OEE) has emerged as the target KPI for most manufacturing industries due to the fact that considers three key indicators: availability, quality, and performance. This chapter describes how different AI and ML solutions can enable a big step forward in industrial process control, focusing on OEE impact illustrated by means of real use cases and research project results.

Keywords: machine learning, supervised learning, unsupervised learning, classification, regression, ensembles, artificial intelligence, data mining, data-driven, industry 4.0, smart manufacturing, cyber-physical systems, predictive analytics

1. Introduction

Industry 4.0 has emerged as the perfect scenario for boosting the application of novel artificial intelligence (AI) and machine learning (ML) approaches to industrial process monitoring and optimization. Artificial intelligence is a set of techniques and methodologies aimed at allowing machines, especially computer systems, to simulate human intelligence processes. Machine learning is a subset of artificial intelligence, which provides a set of methodologies and strategies to allow systems for improvement. ML relies in automatic learning procedures, which generate knowledge from previous experiences (data).

One of the key elements on this new industrial revolution, aligned with the disruptive capabilities that AI and ML provide, is the hatching of massive process monitoring data, enabled by the cyber-physical systems (CPS) distributed along the manufacturing processes, the proliferation of hybrid IoT architectures supported by polyglot data repositories, and big (small) data analytics capabilities. Industry 4.0 paradigm is data-driven, and the smart exploitation of this data can provide a large set of competitive advantages impacting productivity, quality, and efficiency key performance indicators (KPIs), which are of utmost importance in the current competitive scenario. Moreover, the manufacturing companies are evolving to low volume with high personalization manufacturing environments [1, 2], where their competitiveness depends on the industries' facilities, considering asset and resource availability, but also in the optimal execution of production processes [3].

Therefore, there is an opportunity on improving the performance of manufacturing processes taking as input those new streams of information; going through analytical processes; creating new supporting models, tools, and services; and benchmarking their recommendations and outcomes against classical approaches. To that end, the overall equipment effectiveness (OEE) is aimed at measuring types of production losses and indicating areas of process improvement [4, 5], ideal to be used as a benchmarking KPI, and one of the main indicators used in manufacturing execution systems (MES) [6, 7].

In the recent years, research projects are aiming to develop novel stand-alone solutions covering the entire monitoring and control value chain: from the CPS for retrieving the data, to wireless communication protocols, big data storage for traceability and advanced artificial intelligence techniques for production control, optimization, and maintenance.

The use of artificial intelligence algorithms is enabling a big step forward in industrial process control and monitoring: from statistical process control (SPC) and statistical quality control (SQC) methodologies, which require a high prior knowledge of the process, to AI optimized process boundaries that provide valuable insights of the monitored process. Industrial applications of AI have its particular requirements. Not only prediction and forecasting capabilities are desired but also increasing the process knowledge with the right selection of AI algorithms, providing a competitive edge over traditional approaches.

AI provides the right set of tools for automatic quality prediction and full part traceability, process optimization, and preventive maintenance. These sets of benefits are directly impacting into productivity KPIs such as OEE and breakdowns, among others.

This chapter will describe the application of different AI and ML algorithms, including classifiers, regressors, or ensembles such as random forest trees, gradient boosting, or support vector machines, to some real-case industrial scenarios, such as quality prediction or process characterization for plastic injection molding or iron foundry, predictive maintenance for industrial water treatment processes, and means of leveraging production data (quality control, time series, batch data, etc.) at different granularity levels and its impact to OEE: from soft real-time to batch analysis and how this can be translated to valuable production insights.

2. Overall equipment effectiveness as KPI

As introduced before, the current scenario for manufacturing industries can be summarized as high demanding, very competitive, with dynamic market demand, and last but not least, hyperconnected and digital. Low-volume and more personalized parts or product work orders are replacing old high-volume ones without personalization, and this implies that effectiveness may not only focus on specific process optimization but also, for example, on improving changeover setup times, reducing scrap, or improving quality. Therefore, there is a clear need on improving and optimizing all manufacturing processes to overcome this demanding situation with effective response, also considering the efficient adaptation and usage of production lines. Traditional approaches tended to focus on throughput and utilization rate, but nowadays this is insufficient. The main reason relies on the importance of unconsidered context information, or even small details, which are making a difference.

The overall equipment effectiveness indicates how good the equipment is being used. OEE has emerged as the target KPI for most manufacturing industries due to the fact that considers three key indicators:

- Availability: Percentage of time that an equipment can operate
- Quality: Percentage of good produced parts
- Performance: Percentage of maximum operation speed used

But before going deep into OEE calculation, we must first understand in which phases of the manufacturing process AI can impact, so that we can relate all together. To that end, please refer to **Figure 1**, where OEE components are summarized, and **Figure 2**, where a standard manufacturing process is compared with an AI-powered one.

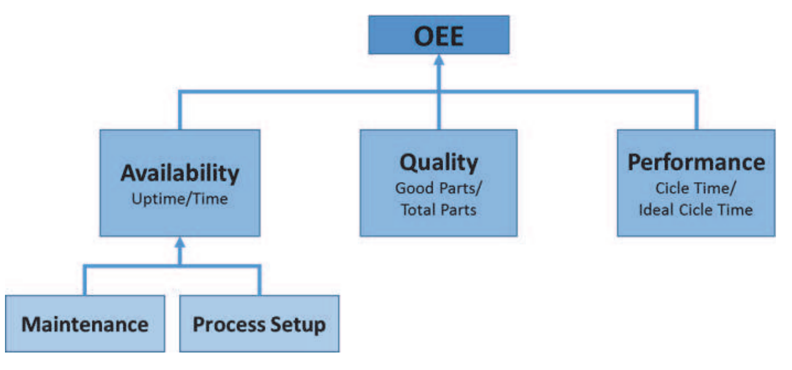

Figure 1.
OEE components and focus.

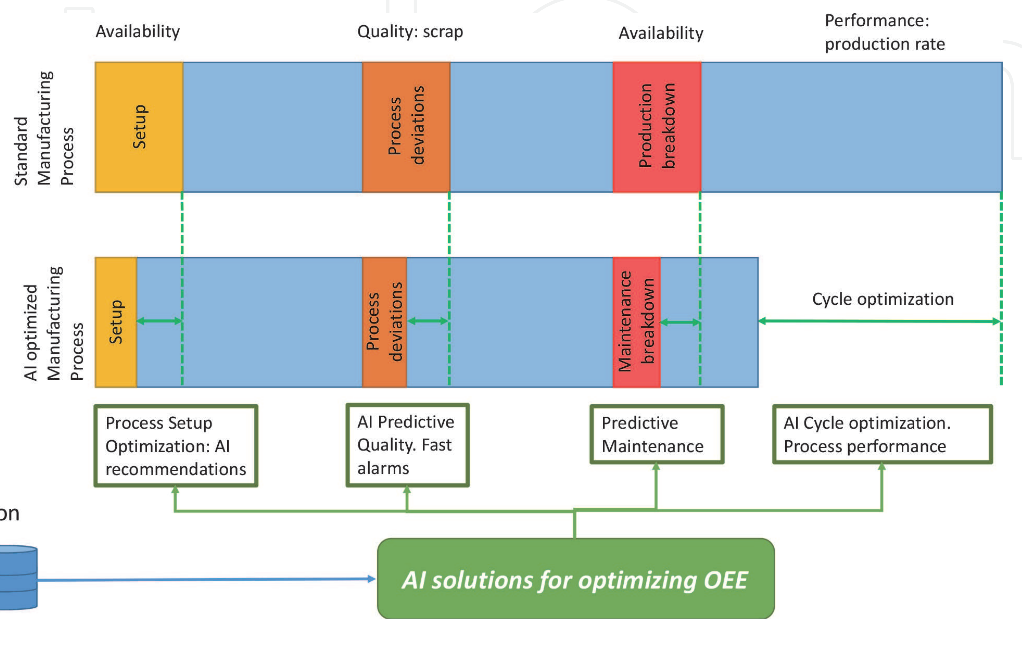

Figure 2.
OEE optimization using AI.

Focusing on **Figure 2**, let us introduce some simple examples of how AI impacts in the manufacturing process:

- Setup: We can improve the time needed to set up or adapt the environment, lines, and tools when a new incoming work order arrives, considering results from previous similar experiences. As we are able to do it in less time, and in a more effective way, we are impacting to the availability of the assets, and consequently, improving the OEE.

- Process deviations: In a similar way, AI allows for quality prediction relying on process parameters, which combined with real-time tuning of execution parameters, results in better quality outcomes, and scrap reduction, again, improving OEE.

- Maintenance: Predictive maintenance allows us to plan and provision with the needed spare parts so that impact in production is minimized. With this management we improve availability, and therefore, OEE is also improved.

In the text below, we define how the literature calculates the OEE, while in the following sections, we'll provide some real examples in which the OEE performance indicator has improved thanks to AI.

According to [8], the overall equipment effectiveness can be calculated as follows:

$$OEE = Availability * Performance\ rate * Quality\ rate. \tag{1}$$

where

- Availability

$$Availability = \frac{(available\ time - unplanned\ downtime)}{available\ time} \tag{2}$$

$$Availability\ time = \text{total available time–planned downtime} \tag{3}$$

Planned downtime: excess capacity, planned breaks, planned maintenance, communication break, and team meetings

- Unplanned downtime: breakdowns, setup and adjustment, late material delivery, operator availability

- Quality rate

$$Quality\ rate = \frac{(total\ produced\ parts - defective\ parts)}{total\ produced\ parts} \tag{4}$$

- Performance

$$Performance = \frac{(total\ production\ parts/operating\ time)}{idle\ run\ rate} \tag{5}$$

$$Operating\ time = Available\ time - unplanned\ downtime. \tag{6}$$

$$Idle\ run\ rate = number\ of\ parts\ per\ minute. \tag{7}$$

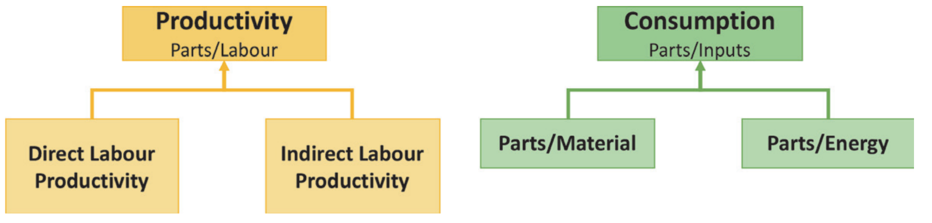

Figure 3.
Productivity indicators.

Other productivity indicators can also be very helpful when evaluating a manufacturing process and benchmarking how AI and ML solutions can provide tangible benefits (**Figure 3**).

Productivity indicators:

- Good produced parts/operator
- Good produced parts/total produced parts (scrap, setup, testing, etc.)

Consumption indicators:

- Material consumption (MC): weight of material consumed per time unit

$$MC\left(\frac{kg}{h}\right) = \frac{part\ weight\ g}{cycle\ time\ \ sec} * \frac{3600\ \ sec}{1\ hr} * \frac{1\ kg}{1000\ g} \tag{8}$$

- Specific energy consumption

The specific energy consumption (SEC) can be defined in terms of the amount of power (P) input into the system, divided by the process rate ($\dot{m}$):

$$SEC = \frac{P}{\dot{m}} \tag{9}$$

3. Artificial intelligence for availability

While guarantying high OEE, availability is key. OEE considers availability loss, which considers any event that stops the production plan for a significant amount of time, including unplanned and planned stops. An availability of 100% means the process is always running during planned production time.

There are other considerations which should be included in the availability computation, such as the changeover times. Changeovers are a source of setup and adjustment time, which is one of the main time loss reasons, and thus represent a valuable opportunity for improvement. Changeover times are most commonly improved (reduced) through the application of single-minute exchange of dies (SMED), which relies on performing as many changeover steps as possible while the equipment is running. In fact, these days equipment manufacturers tend to provide an availability rate in the specifications of their equipment, considering, among others, these changeovers.

But what can AI do for us? If we think in data processing and analytical capacities that can be run over information coming from equipment, we rapidly think in predictive maintenance to anticipate problems or virtual sensors to simulate, when feasible, some defective or malfunctioning sensors. Let us see some examples of this in the following subsections.

3.1 Virtual sensors

Virtual sensors (VS) are implemented with software to emulate real-world or even newly artificially defined sensors and are commonly used to (i) compute extra parameters derived from real sensors that are impossible to be measured, contributing to a better understanding of the whole environment, and (ii) simulate real sensor outputs. In the scope of this chapter, the second functionality becomes useful to mitigate system stops due to equipment failure or even planned maintenance, increase the availability of complex systems, and therefore improve the OEE.

For example, in a water treatment facility, where a lot of processes are continuously and simultaneously working to improve the quality of water, the decisions taken to manage the global system depends directly on the observations obtained by the sensors that are deployed along the premises. When any of those sensors is not working, the system cannot operate correctly because sometimes those input values are of utmost importance to determine which decision is correct.

In this case, a VS can be used to simulate and replace that lost sensor during the downtime. For this purpose, the VS is implemented through machine learning algorithms and is based on different inputs or sensors that are operating in the different parts of the water treatment cycle in the system.

Following this procedure, we showcase a VS simulating a measurement of one of the water quality parameters in a water treatment facility. In this case, this measurement is of utmost importance in the system because, depending on its observations, the processes adapt their execution parameters to fit the required quality requirements.

Therefore, we must overcome three main challenges, the combination of which increases considerably the complexity of the problem to be solved using AI/ML algorithms:

- The complexity of the processes: In water treatment facilities, physical and biological processes are combined to clean the water and achieve the expected levels of quality.

- The delayed responses: The water flow may be slow, so a change in the input state will not be immediately reflected in the rest of the system.

- The bad quality of the signals: In this kind of environments, where the sensors are in direct contact with dirty water, the observations usually contain anomalous values.

We start implementing the needed filters and preprocessing steps to clean and improve the data, but usually this is not enough, and ML algorithms cannot achieve the desired performance. Consequently, extra efforts are needed to obtain better models.

This example is a regression problem, where the target is a continuous value, and the predictors are composed of current and past values from other sensors which are part of the same process.

During the first iterations of the analysis, one of the main tasks was to select the optimal past values of each observation/sensor to be used as predictors. This process was done through the analysis of the importance of the variables once a model has been trained, selecting the N last values with the most importance. Also different frequencies of lags were tested using the same approach.

It is important to note that the target variable was not used to make next predictions, avoiding accumulated errors and allowing an infinite horizon of predictions, since the only requirement was the observations of the other sensors.

Different ML algorithms were tested and compared, and **Figure 4** showcases the three ML models that have better performance:

- XGBoost: Extreme gradient boosting. Optimized distributed gradient boosting library. Gradient boosting is a ML technique which produces a prediction model in the form of an ensemble of weak prediction models. It builds the model in a stage-wise fashion, training the weak models sequentially, each trying to correct its predecessor, and it generalizes them by allowing optimization of an arbitrary differentiable loss function [9].

- KNN: K-nearest neighbors. Nonparametric algorithm. Predictions are computed based on the mean of the labels of its nearest neighbors [10].

- RF: Random forests. Ensemble of decision trees, where each tree is usually built from a sample drawn with replacement (bagging method) from the training set. If the sample is obtained without resampling, the method is called pasting. When splitting each node during the construction of a tree, the best split is found either from all input features or a random subset of size *max_features* (RF algorithm hyperparameter) [11].

In order to compare the performance between model results, we are using the following metrics:

- Mean squared error (MSE) measures average squared error of our predictions, calculating the square difference between the predictions and the target and then the average of those values:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2 \tag{10}$$

- Mean absolute error (MAE) is calculated as an average of absolute differences between the target values and the predictions:

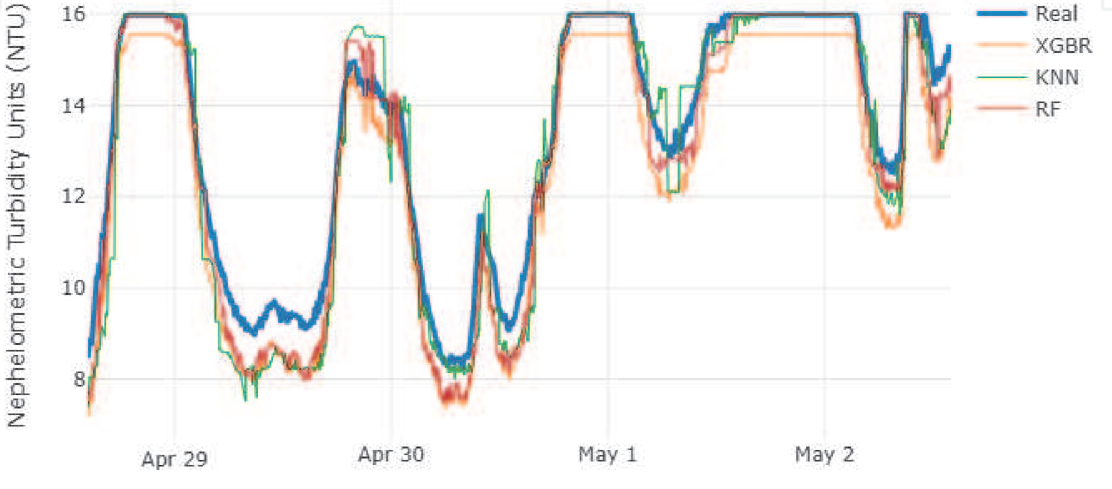

Figure 4.
Initial predictions.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \tag{11}$$

- Explained variance score (EVS) measures the proportion to which a mathematical model accounts for the variation (represented as σ^2, s^2, or Var (X)) of a given data set:

$$EVS = 1 - \frac{Var\{y_i - \hat{y}_i\}}{Var\{y_i\}} \tag{12}$$

The best performance is achieved by random forests followed by KNN (MSE, 0.69; MAE, 0.43; EVS, 0.86) and XGBoost (MSE, 0.81; MAE, 0.85; EVS, 0.98). In all the cases, grid search [12] has been used to tune the hyperparameters.

The scorings seem to be acceptable, but analyzing one by one the predicted values (**Figure 5**), unusual behaviors appear in the predictions. So, in order to try to improve the outputs, an ensemble model is implemented combining the previous algorithms and following the stacking methodology (**Figure 6**, [13]), where a new ML algorithm (called blender or meta learner), in this case a ridge regressor [14], takes the previous predictions as inputs and makes the final prediction, usually better. The blender has been trained following the hold-out set approach.

Basically, the main idea is to, instead of taking the best model and use it to make predictions, try to combine the predictions of completely different ML algorithms, which are based on really different approaches and are good to operate in specific conditions, into a new ensemble which combines the best of each one, is able to operate in all the cases, and reduces the global error.

This process improves significantly the predictions (**Figures 7** and **8**), achieving the following scores, MSE, 0.27; MAE, 0.40; EVS, 0.98, and resulting in a ML model that is able to simulate the real sensor during downtimes, allowing the system to continue working normally.

3.2 Maintenance

We define predictive maintenance as the set of techniques used to determine the condition of equipment, allowing for a better and more personalized maintenance

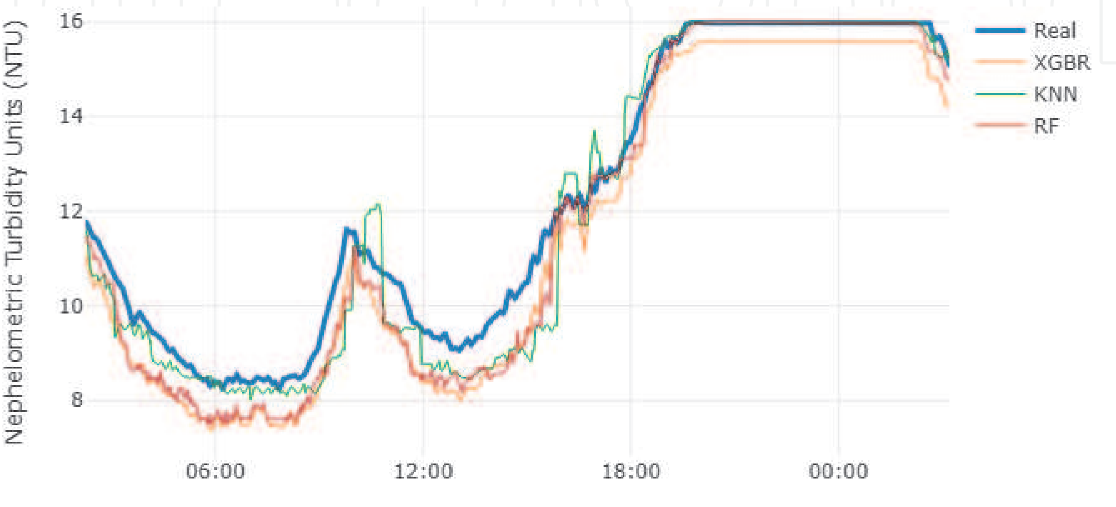

Figure 5.
Initial predictions detail.

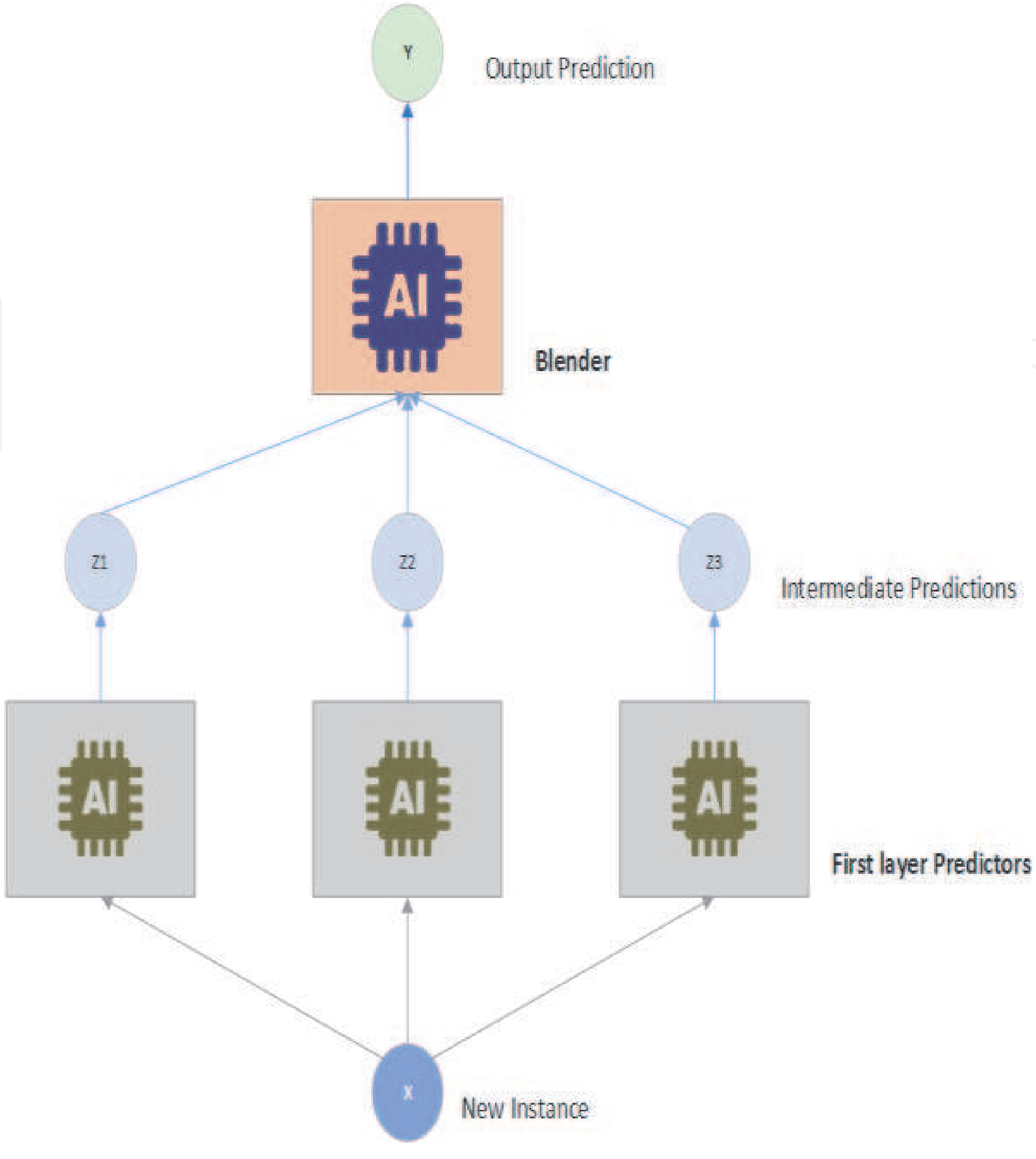

Figure 6.
Blending predictor schema.

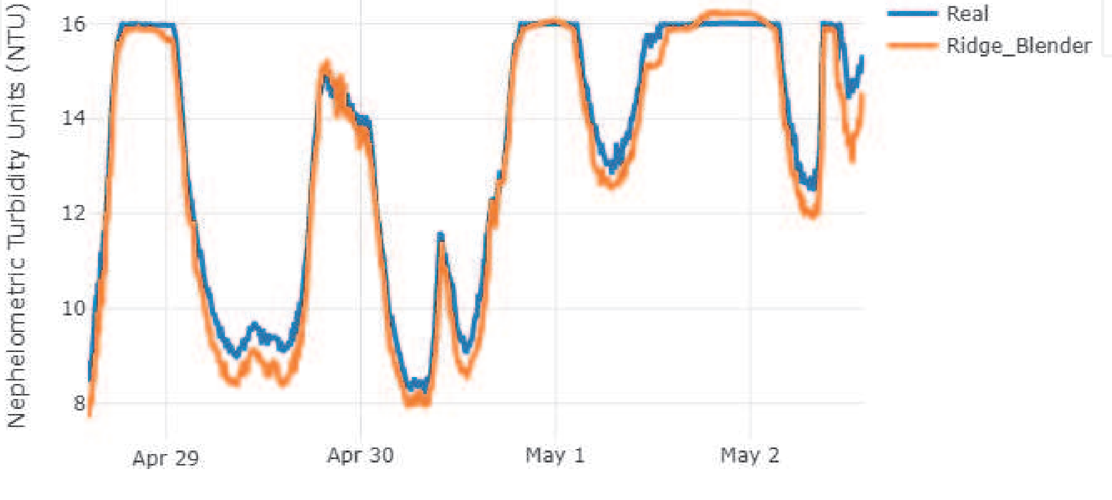

Figure 7.
Final virtual sensor predictions.

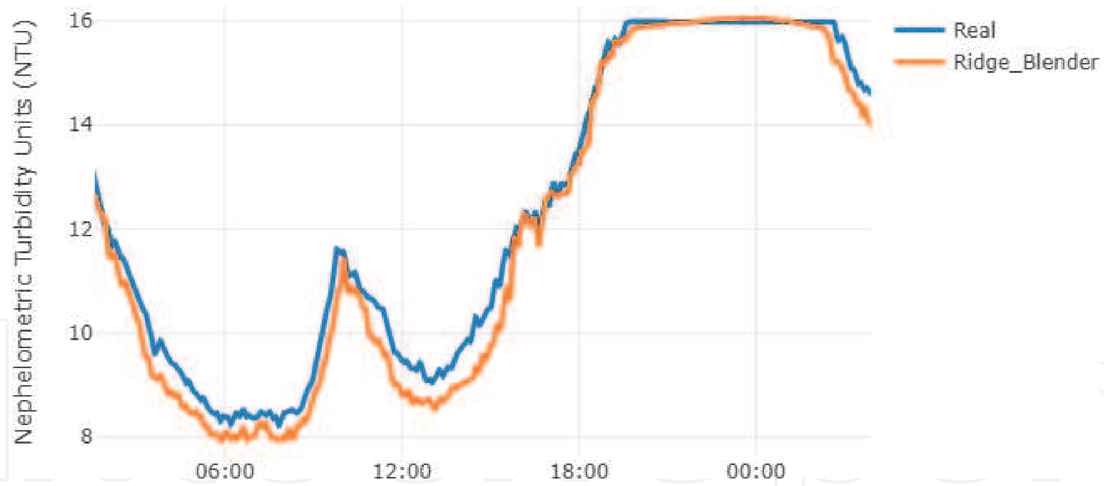

Figure 8.
Final virtual sensor predictions' detail.

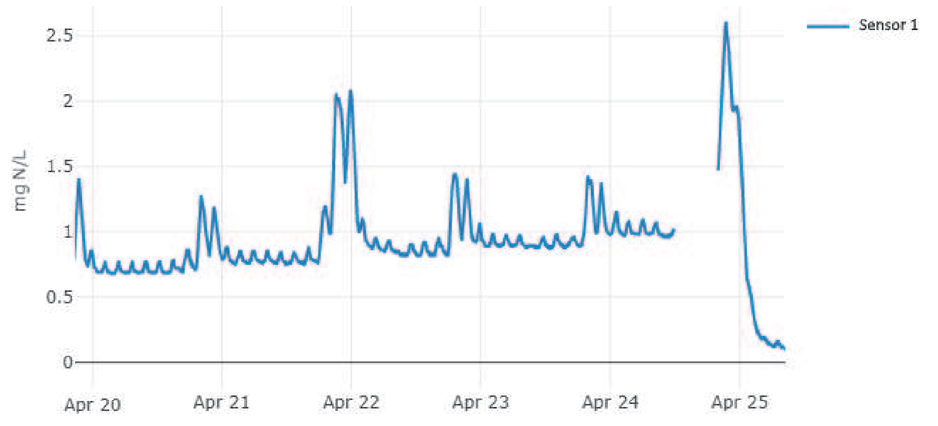

Figure 9.
Drift over the time.

plan. This plan depends on the performance, among other indicators, of the specific equipment (actual condition), instead of only relying on periodic maintenance routines, and this enables spare parts optimization, better maintenance actuations planning, and of course, OEE improvement due to its impact in availability, performance, or even quality.

Continuing on the water treatment facilities case introduced previously, one of the main problems faced in this environment is related to those sensors that are in direct contact with dirty water.

Over the time, a continuous and incremental drift appears in the observations of the sensors, thereby generating incorrect measurements. Since these measurements are the base of the system which takes operational decisions, the sequent of the taken actions will be incorrect, resulting in an unnecessary waste of resources or, even worse, an immediate stop of the system to repair and calibrate the sensors.

This pattern can be easily identified in **Figure 9**, having an incremental drift over the time until day 25, when the sensor was stopped during some hours for maintenance. Once the sensor is turned on again, the real value of the observations is shown, approximately 0.

Before the proposed approach, trying to prevent these problems, a set of preventive maintenances was defined, which consisted of manually taking measurements to compare them in the laboratory with the values of the sensors. Despite this, these actions were not enough, and the drift usually appeared before the scheduled maintenance, making necessary a better approach: a predictive maintenance-based approach.

There are different ways to implement a ML predictive maintenance solution. For example, it is possible to predict the remaining useful life of an equipment, which is a regression problem. But in this case, it has been defined as a binary classification problem, where the goal is to, given an observation (and the previous values), predict if there will be an anomaly in the following 24 hours (estimated minimum range of time to define a maintenance).

In the presented problem, the term anomaly refers to a sensor deviation or a drift in the observations measured by it, due to the contact with dirty water, making necessary a maintenance action in this specific sensor to clean or even replace it if it is necessary.

As in other classification problems, the basic requirement is labeled data, in this case, labeled anomalies. This was the main problem, there was a lot of historical data, but the anomalies were not labeled so the first step consisted of an anomaly detection problem.

Through unsupervised anomaly detection algorithms, such as:

- Isolation forest: Isolation forest algorithm isolates observations by randomly selecting a feature and then randomly selecting a split value between the maximum and minimum values of the selected feature. Since recursive partitioning can be represented by a tree structure, the number of splittings required to isolate a sample is equivalent to the path length from the root node to the terminating node. This path length, averaged over a forest of such random trees, is a measure of normality [15].

- Local outlier factor: Local outlier factor algorithm computes a score reflecting the degree of abnormality of the observations. It measures the local density deviation of a given data point with respect to its neighbors. The idea is to detect the samples that have a substantially lower density than their neighbors [16].

And thanks to an intensive data preprocessing steps such as data segmentation or feature engineering (which made the task easier to detect this specific anomaly), the historical dataset was labeled. Finally, a simple clustering algorithm was run to discard different anomalies.

The result of the anomaly detection analysis is shown in **Figure 10**, where sensor 1 is measuring a value different than 0 (anomaly), and therefore the system tries to force a response increasing excessively the resource measured by sensor 2.

Finally, we face the predictive maintenance classification problem, where the key was the definition of the target variable: a binary column indicating whether in

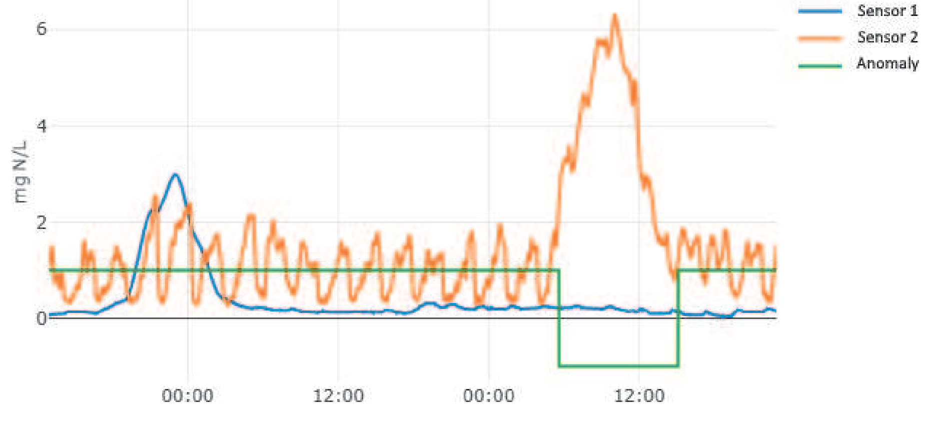

Figure 10.
Anomaly detection results.

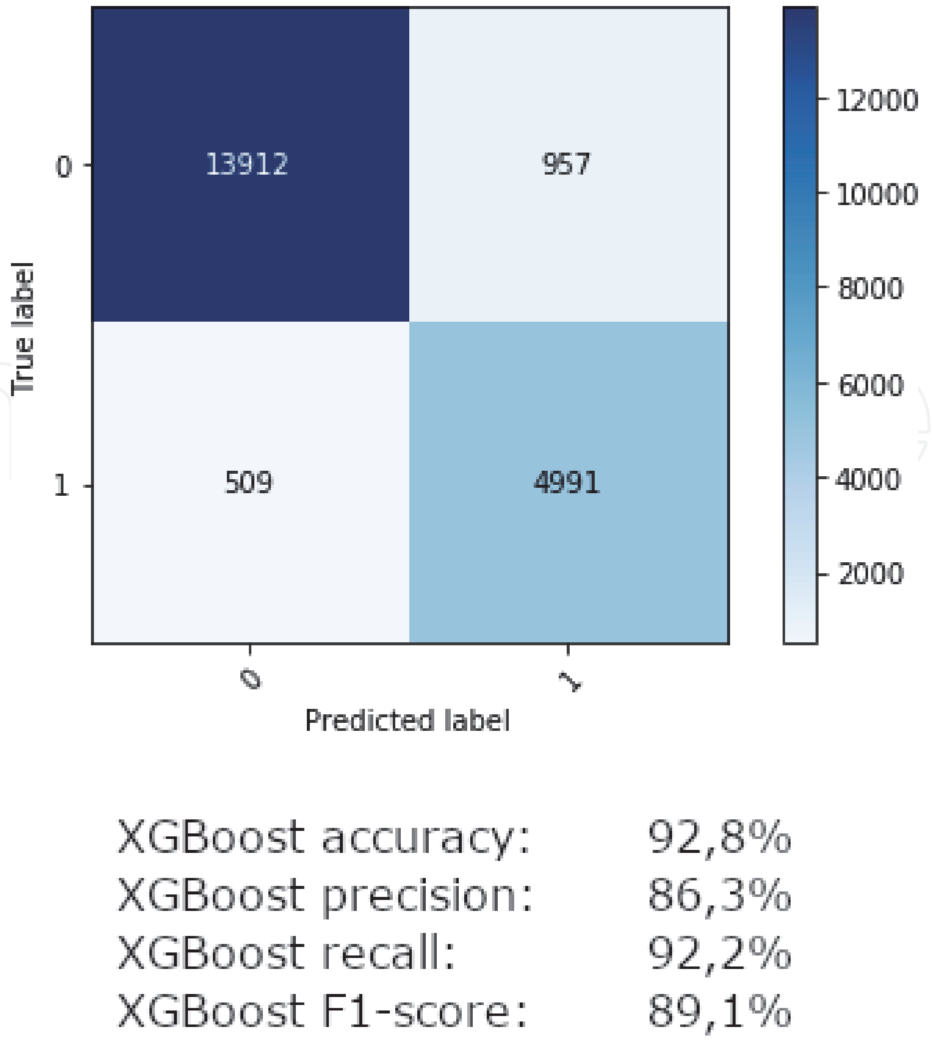

Figure 11.
Confusion matrix.

the next 24 hours an anomaly is detected or not. At this point, different ML classification algorithms were tested, and the best performance was achieved by XGBoost, obtaining the following classification results (**Figure 11**) in a test set.

In order to measure the algorithm performance in the classification task, we are using confusion matrix and the following metrics:

- Confusion matrix: In a ML classification problem, a confusion matrix is a specific table that simplifies the analysis of the performance of an algorithm. Each column of the matrix represents the instances in a predicted class, while each row represents the instance's real class (or vice versa) [17].

- Accuracy: Classification metric that computes the fraction of correct predictions:

$$\text{accuracy}(y, y') = \frac{1}{n_{\text{samples}}} \sum_{i=0}^{n_{\text{samples}}-1} 1(y'_i = y_i) \tag{13}$$

- Precision: Classification metric that computes the fraction of relevant instances among the retrieved instances. It is also called positive predictive value:

$$\text{precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \tag{14}$$

- Recall: Classification metric that computes the fraction of relevant instances that have been retrieved over the total amount of relevant instances. It is also called positive predictive value:

$$\text{recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \tag{15}$$

- F1-score: Classification metric that computes a weighted harmonic mean of the precision and recall. F1 score reaches its best value at 1 and worst score at 0.

$$\text{F1 score} = 2 * \frac{(\text{precision} * \text{recall})}{(\text{precision} + \text{recall})} \tag{16}$$

As depicted in **Figure 11**, the final version of the model provides good results while predicting anomalies with time enough to articulate the needed preventive actions. Not only the accuracy is important, but we would also like to remark that the false negative rate is low, that is, the algorithm performs very well in detecting anomalies, and only a few of them are undetected.

3.3 Process setup

Process setup, especially during changeover operations, can affect the availability indicator and thus represents an opportunity for manufacturing AI and ML based solutions. New production trends based on a high degree of flexibility, customization, and small batches require for an extra effort in terms of process setup and scheduling. For instance, in plastic injection molding quite often due to production flexibility and scheduling, a mold needs to be re-installed and set up for production again in order to deliver a new production batch to the final customer. This situation requires for a new tuning process involving an important waste of time, material, and energy. This situation opens the opportunity for developing supervised ML models to compare past production data with real-time data for recommending tuning parameters and reach in a shorter time frame the optimal process operation.

To this end, the real-time evolution of a key process parameter can be used as training of the manufacturing process setup or configuration. By comparing the actual real-time evolution within the manufacturing cycle versus the known optimal (acquired from previous production runs), a set of recommendations can be provided. This strategy can boost the process setup, providing recommendations to reach the optimal targeted key parameter cycle evolution, following an iterative method as depicted in **Figure 12**.

Following the plastic injection molding example, within the PREVIEW project [18], a set of experimental trials were performed in order to create the historical database that supports the AI system in charge of providing process tuning recommendations. Within the AI solution, different algorithms were tested for comparing new sensor data versus historical data to provide tuning recommendations. **Figure 13** shows a PREVIEW project result using random forest trees [19] to provide tuning recommendations when the injection speed parameter was changed to different operational points. As can be seen, for lower than optimal injection speeds, the AI system based on RF recommends increasing the injection speed, while for higher injection speeds recommends a reduction, driving always the parameter toward the optimal operational window that leads to optimal cavity pressure evolution within the manufacturing cycle.

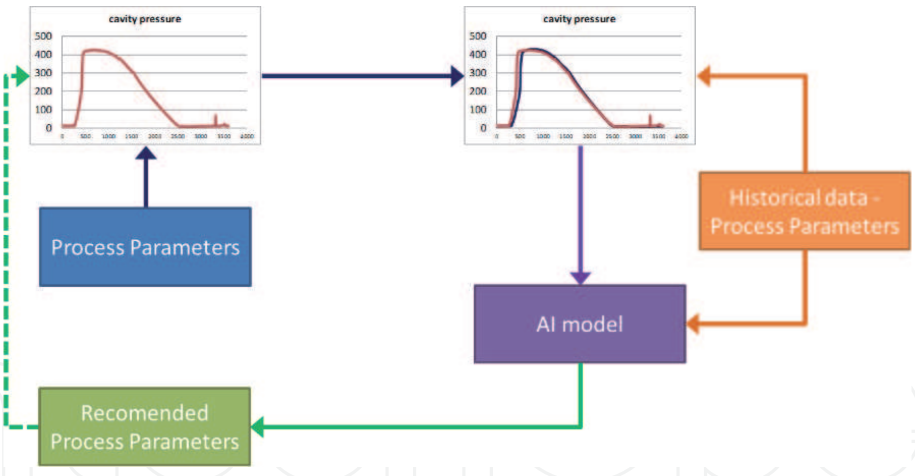

Figure 12.
Iterative comparison to optimized production setup comparing known optimal process parameters versus new acquired ones.

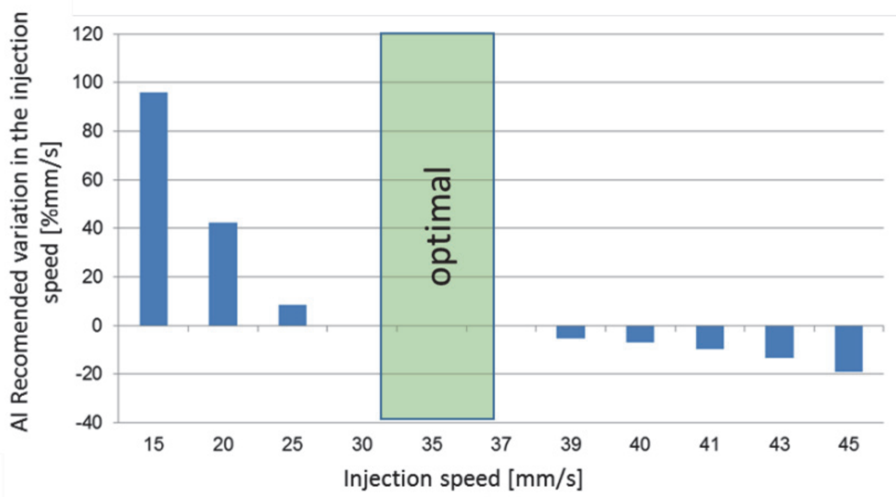

Figure 13.
Process optimization recommendation. The PREVIEW project result.

4. Artificial intelligence for quality

It is a well-known problem that high added-value industrial and manufacturing processes combining several operations (welding, milling, etc.) and thus heterogeneous data sources do not always reach their maximum performance potential due to the lack of powerful and tailored solutions for data analysis toward the zero defects manufacturing paradigm. Today's artificial intelligence and machine learning based solutions are mature enough to boost production processes by means of exploiting the process data generated thanks to the in-line sensors, workers' feedback, reports, quality control, etc. Thus, developing a tailored predictive quality solution based on artificial intelligence and machine learning has become a crucial key element for impacting OEE to prevent the manufacturing of non-quality parts and its exportation to the final client. Several research works have been carried out for different manufacturing processes, including plastic injection molding, foundry, milling, welding, etc. (e.g., see [20–24]) showing the potential benefits of applying AI and ML to exploit process data.

Continuous quality estimation at each step of the manufacturing process by means of machine learning and artificial intelligence, applied on the in-line acquired data, enables predictive warnings and alarms even before the target quality is affected and thus quality indicator of OEE is degraded. Two different approaches can be implemented when developing AI predictive quality tools: supervised versus unsupervised solutions. Supervised solutions can provide a better accuracy when predicting undesired quality deviations, but a properly tagged dataset is required. Unsupervised methods have the benefit of not requiring the tagged dataset and are typically used for anomaly detection, meaning strong quality deviations. Moreover, supervised system results can be tracked down and analyzed to provide process insights which can lead to knowledge discovery [25] solutions that help to address the root cause of the undesired quality deviation and thus improve quality and, therefore, OEE.

Focusing on supervised solutions, a proper dataset labeling is a key element. It is highly recommended to perform a Design of Experiments (DOE) where quality deviations are forced in order to obtain a more balanced dataset compared to the typical production dataset where non-quality parts are rare. In the case of qualitative quality labels (e.g., good, bad, type of defect, etc.), a classifier will be preferred, while for quantitative quality indicators (e.g., weigh, tensile strength, etc.), a regressor will be implemented.

Let us consider as illustrating example a plastic injection molding quality prediction problem. The four-cavity mold used for the experimental trials can be seen in **Figure 14**. Only one cavity was sensorized to obtain the pressure and temperature evolution of the melt during the production cycle. The machine pressure and screw position were also acquired for each one of the 199 injected parts of the trial. The injection cycle was 7.2 seconds and was sampled at 500 Hz. Thus, the dataset is the time series evolution of the key parameters of the process.

The DOE was designed in order to obtain seven different part qualities: good, short shot, shrinkage, flash, jetting, over-compaction, and flow lines. The different qualities were obtained by means of varying the injection machine configuration. A total of 199 parts were produced (**Figure 15**).

Depending on the data granularity (continuous, cycle, or batch), different preprocessing techniques can be implemented to boost the performance of the later machine learning classifier. For instance, entropy analysis and complexity reduction algorithms such as principal component analysis (PCA) [27] can provide a substantial advantage as seen in **Figure 16**, where the PCA projection of the screw position sensor is plotted.

In order to compare the performance of different machine learning classifiers, a benchmark based on cross-validation techniques was implemented, using a stratified shuffle split [28] strategy to preserve the percentage of samples of each class

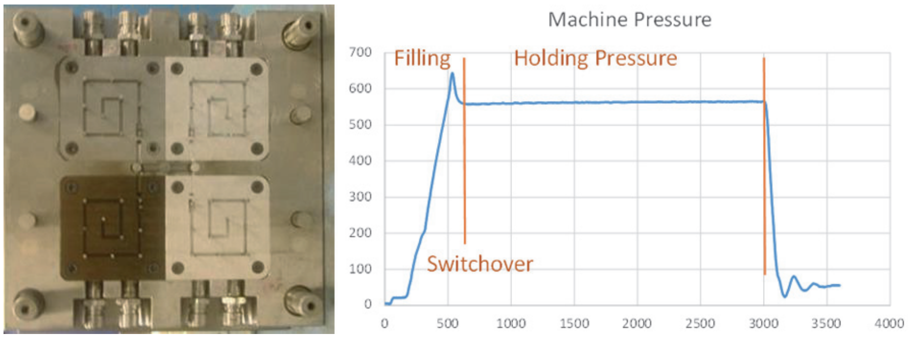

Figure 14.
Mold cavity picture and example of acquired machine pressure. Experimental data provided by EURECAT [26].

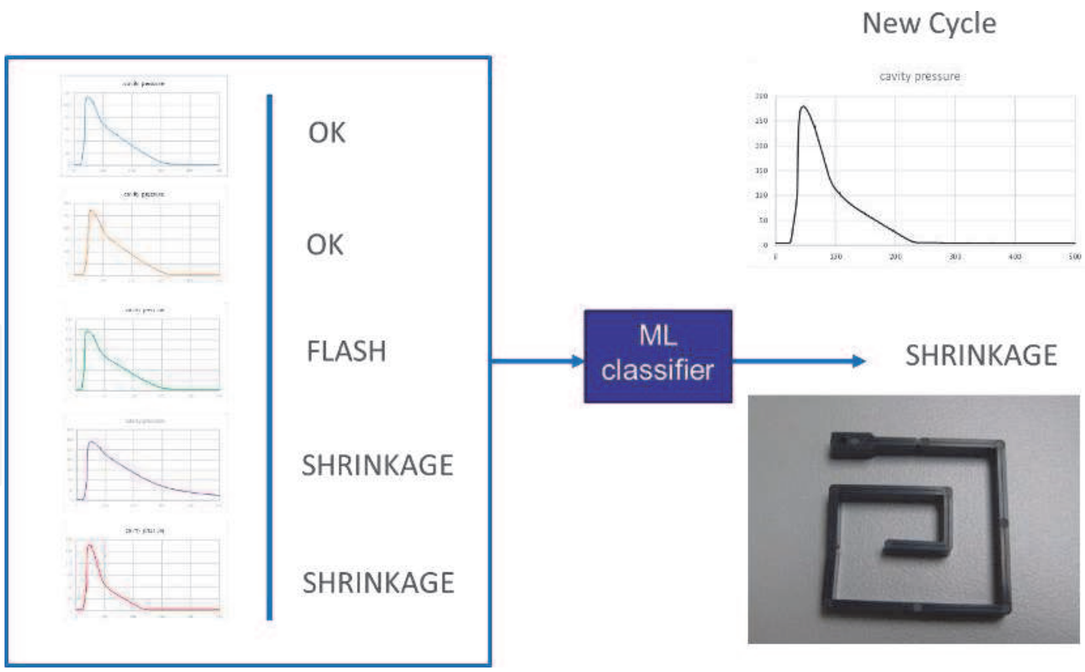

Figure 15.
Supervised approach for quality prediction.

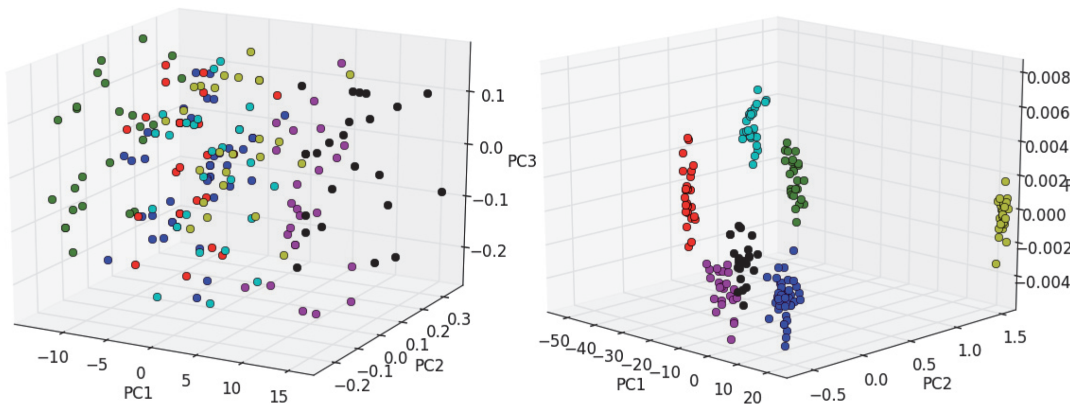

Figure 16.
3D PCA data projection using the raw data or a preprocessed data where the 10 time stamps with higher entropy are selected. Each color represents a different part quality or defect.

(quality). This test can be run for each sensor or by applying data fusion and combining all sensors in a single dataset (**Figures 17** and **18**).

As can be seen in **Figure 19**, support vector machines [29] with a linear kernel show a low performance, while ensemble algorithms like random forest trees and gradient boosting [30] present higher accuracy rates, especially when 50 estimators or more are used.

When combining all sensor information by means of applying data fusion, the quality prediction accuracy increases near to 100%, as can be seen in **Figure 18**. This result and system allow for an in-cycle quality preventive alarm that can lead to an important reduction of scrap rate and exported non-quality, which automatically translate to a higher quality rate and a reduction of costs due to wasted raw material and energy consumption while improving OEE.

Other manufacturing processes can have different sampling rates or even create batch datasets where for each part a set of relevant values are recorded. Typically, large batch datasets present a high degree of data heterogeneity, compiling sensor values, reports, environmental data, etc. Moreover, part traceability may not be

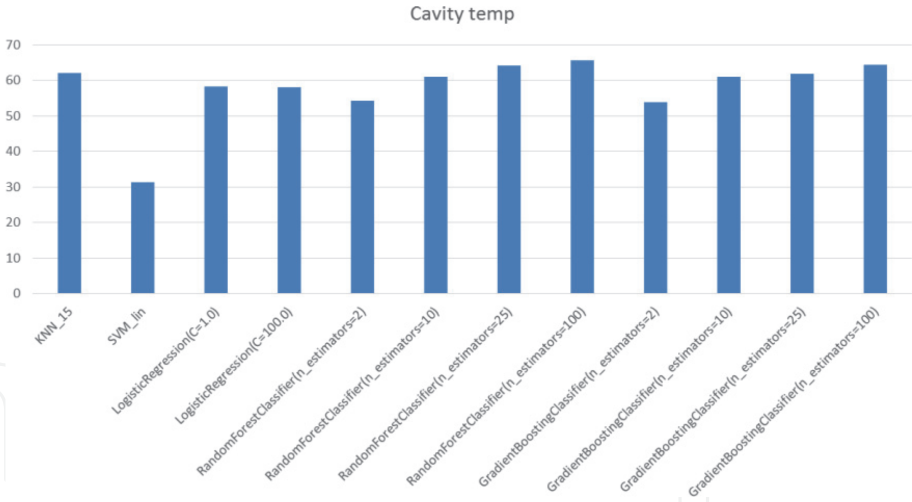

Figure 17.
Quality prediction mean accuracy for a 20-round cross-validation test using 70% for training and 30% of samples for test, using only the cavity temperature sensor data.

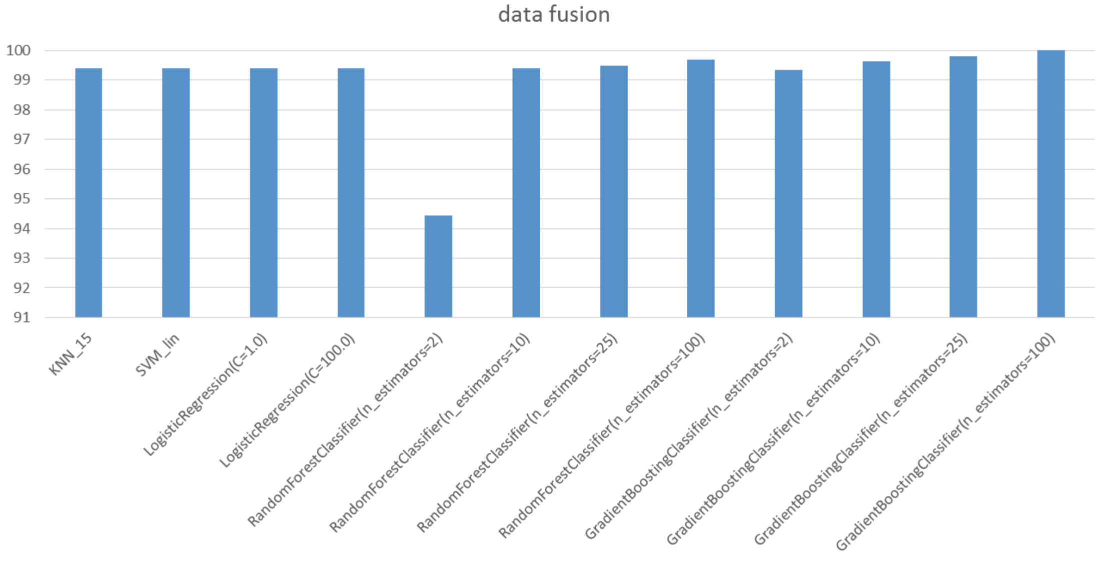

Figure 18.
Quality prediction mean accuracy for a 20-round cross-validation test using 70% for training and 30% of samples for test, combining the available cavity and machine sensor data.

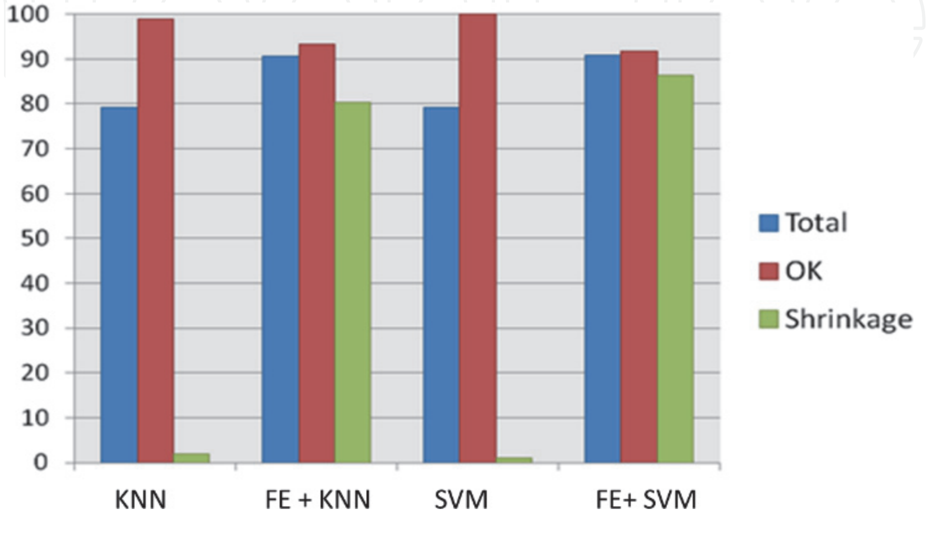

Figure 19.
Batch quality prediction with and without feature engineering (FE) for a heterogeneous and class-unbalanced dataset. Iron foundry case.

guaranteed, and thus quality rates may refer to the entire batch. In these scenarios, feature engineering [31] can provide a clear advantage for boosting the performance of the ML and AI algorithms. **Figure 19** shows the performance of KNN and SVM classifiers for a foundry dataset with more than 250 different parameters (chemical composition of the iron, climate, process data, sensor data, etc.) with and without feature engineering.

The dataset had two main difficulties: the extreme unbalance between classes (qualities) and the data heterogeneity. By applying feature engineering, the number of parameters can be reduced, focusing on the relevant ones. Bagging [32] and cost functions were used to face the class unbalance. Batch quality prediction based on process data can help in reducing the exported non-quality while providing knowledge discovery insights to find and correct the root causes of the undesired quality deviation.

5. Artificial intelligence for performance

Performance indicators consider any factor that causes the manufacturing process to run at lower speed than its maximum possible speed. For instance, slow cycle time affects performance indicators. For this reason, it is key to know the ideal cycle time, which is the fastest cycle time that can be achieved in optimal circumstances. Moreover, performance is also affected by idling time and minor stops.

Cycle time reduction is one of the main factors for improving productivity. A cycle time reduction contributes to reaching the optimal production throughputs, reduction of time to market, better scheduling, and a reduction of associated costs in terms of labor, energy, and raw material when combined with quality prediction and assessment. The reduction of cycle time has become a relevant topic both in research and in practical applications. Neural networks and machine learning algorithms can help to predict and optimize manufacturing cycle time in different sectors (e.g., see [33, 34]).

Preventive alarms generated by predictive quality systems based on AI and ML can prevent manufacturing at nonoptimal operation setups and thus prevent minor stops. Minor stops can also be reduced thanks to preventive maintenance systems. Case-based reasoning [35] systems can leverage past experiences to help manufacturing processes run faster. For instance, a CBR system can provide helpful recommendations for optimizing the cooling time based on the type of material and the thickness of the part that is being manufactured. The CBR system provides the most similar cases based on a defined similarity metric, and thus a previous cooling times of well-known and optimized processes can be taken as reference. Illustrating this case, the Des-MOLD project [36] developed an AI system based on CBR and argumentation [37] to help plastic injectors share their experiences and benefit from mold design and manufacturing process optimization [38].

6. Conclusions

Artificial intelligence and machine learning based solutions can provide a competitive advantage in today's manufacturing paradigm, redefined by the Industry 4.0 revolution and the massive data available thanks to CPS, virtual sensors, and IIoT devices. Leveraging this data has become a very relevant topic both in research and for practical applications due to its massive potential. Data-driven solutions are becoming more and more popular due to its potential both in terms of prediction and to its capacity to provide process insights for enhancing process owner's expertise.

This chapter has focused on how the leverage of the available process data by means of AI and ML solutions can impact into one of the most relevant manufacturing indicators: overall equipment efficiency. OEE has three main components: availability, quality, and performance. Each OEE component tackles a different challenge and thus may require a different approach. Through different experimental examples, each OEE component and how AI solutions can impact it have been described. It has been shown how predictive maintenance and virtual sensor solutions can help in reducing the undesired production breakdowns and thus increase equipment availability. Predictive quality solutions based on supervised algorithms, for either real-time cycle data or batch data, have been described, showing the importance of feature engineering for boosting prediction accuracy. And finally, equipment performance focusing on cycle time has been addressed by CBR for leveraging past experiences and providing process tuning types to run at the highest throughputs.

OEE will be further improved thanks to the new AI trends and technologies that are being researched right now, providing even more powerful and tailored solutions. Availability and performance indicators could be greatly improved when mature reinforced learning approaches are available at the production level, reducing setup times and optimizing cycle times thanks to the collaboration between human expertise and AI systems. Image processing through deep learning and convolutional neural networks can impact quality, especially for visual defects. Collaborative human-AI systems are envisaged as key for the next Industry 5.0.

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