Integration of AI Use Cases in Training to Support Industry 4.0

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***Abstract*—As the demand for Artificial Intelligence (AI) continues to grow across industries, there is a need for effective training programs that support the successful deployment of AI in various organizational contexts. This study aims to bring attention to the importance of training programs in preparing industry professionals for AI implementation and highlights key considerations for designing effective training initiatives. It identifies the needs of the industry, hands-on learning experiences, and continuous skill development to ensure the optimal utilization of AI technologies in the context of Industry 4.0. In line with the objective of this work and with the support of an EU project and an associated Digital Innovation Hub (DIH), three comprehensive training programs in Maintenance, Production, and Quality are being developed. Industries can benefit from these training programs, which foster a workforce that is equipped with the necessary knowledge, skills, and awareness to enhance the implementation of Industry 4.0-related technologies and concepts, including AI and supportive technologies. The paper is terminated with concluding remarks and briefly looks into possible future work.**

***Keywords*—training program, Artificial Intelligence (AI), Industry 4.0, Digital Innovation Hub (DIH), machine learning**

I. Introduction

Artificial Intelligence (AI) has emerged as a transformative technology that holds immense promise across various industries. From revolutionizing healthcare to enhancing transportation systems and powering intelligent virtual assistants. AI refers to the way the computers and machines are programmed to perform tasks typically requiring human intelligence. AI systems are designed to reason, learn, and make decisions based on data gathered from heterogeneous sources [1, 2]. AI systems can analyze vast amounts of data, extract valuable insights, and support data-driven decision-making. AI technologies enable human capabilities (e.g., understanding, reasoning, planning, communication, and perception) to be undertaken by software increasingly effectively, efficiently, and at low cost [3, 4].

The adoption of AI offers numerous benefits. For example, AI technologies can enhance productivity by automating repetitive tasks, freeing up human resources to focus on more complex and creative endeavors. AI technologies encompass a wide range of techniques and tools that enable machines to simulate human intelligence and perform tasks typically requiring human cognitive abilities. The well-known sub-fields of of AI include Machine Learning (ML) (which is the focus of attention in this work), natural language processing, computer vision, robotics and automation, and expert systems. These are just a few examples of AI technologies that are driving innovation and transforming various industries [5].

AI has found applications in numerous fields. Manufacturing and education, among others, are two key areas where AI is making a significant impact. AI has the potential to further transform the manufacturing industry by optimizing processes, improving efficiency, and enabling smart decision-making. The main key applications of AI in manufacturing include predictive maintenance, quality control and defect detection, intelligent robotics and automation, supply chain optimization, energy management and sustainability, process optimization, autonomous vehicles and logistics, inventory management, and smart decision-making [6, 7], whereas these applications support the transformation towards Industry 4.0 [8, 9]. On the other hand, AI plays a significant role in training and education, by revolutionizing traditional learning approaches, providing personalized, adaptive, and interactive learning experiences, enhancing teaching, and improving educational outcomes. The key applications of AI in the field of education include adaptive learning, intelligent tutoring systems, automated grading and

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feedback, natural language processing, intelligent content creation, smart content recommendation, data analytics, virtual assistants and chatbots, and personalized learning paths.

In other words, two main types of AI applications can be allocated: the first one when the AI is directly used to enhance the educational process and the other when the AI is a constituent part of the learning program. In the first case, AI helps to unlock new opportunities to improve teaching methods, enhance student engagement, and create more personalized and effective learning environments [10, 11], leading to improved learning outcomes and better preparedness for real-world challenges [12, 13]. Thus, the integration of AI into training programs has the potential to reform the way people learn and acquire new skills. Nonetheless, it is essential to also consider ethical aspects, such as data privacy, algorithmic biases, and the responsible use of AI, to ensure equitable and inclusive educational experiences for all learners [14]. In the second case, the students learn how to apply the AI for specific use-cases, in the current work, for instance, to address different manufacturing-related issues.

Training AI is essential for unlocking the potential of Industry 4.0. By training AI models on relevant data, companies can drive efficiency, productivity, and competitiveness in the context of Industry 4.0 [15]. Prior studies reported that AI integrated into training programs (for the workforce) can be applied across different industries and sectors such as healthcare, finance, retail, transportation, energy, agriculture, and manufacturing [16]. Furthermore, by utilizing AI technologies, companies can achieve increased productivity, improved efficiency, better decision-making, and enhanced customer experiences in the context of Industry 4.0. AI-driven automation, data analytics, and intelligent systems enable companies to adapt to the rapidly evolving technological landscape, drive innovations, and transform their operations in the era of Industry 4.0 to gain a competitive edge in their respective industries [8, 9, 17].

Despite the well-documented advantages of AI in industry and education (mentioned above in part), there is still a need for more investigation, demonstration, and wider dissemination of success stories of specific AI application use cases in the context of Industry 4.0. Another issue is the insufficient feedback loop between the industry and academia. Therefore, on the one hand, educational programs should be better shaped to meet the requirements of the industry. On the other hand, the industry should take advantage of the latest knowledge generated in academia. Given that, a key research question that emerges in this study is:

Research question: How AI educational initiatives can foster the adoption of Industry 4.0 principles in manufacturing?

The following hypothesis is set for this work in order to answer the research question:

Hypothesis: The AI educational initiatives can foster the adoption of Industry 4.0 principles in manufacturing if they are appropriately integrated into the industrial context, showing the added value of its use in existing manufacturing processes of the target SMEs.

Considering the above mentioned, this work aims to introduce three training programs in three domains: Maintenance, Production, and Quality (MPQ) to support Industry 4.0 transformation in companies (of all types and sizes). The training programs are supported by the ENHANCE project (http://eplus-enhance.eu/) and some local Digital Innovation Hubs (DIHs) in Morocco and Tunisia. The training programs are designed to promote and upskill the current and future workforce of companies who should take full advantage of the latest AI advancements. In this direction, DIHs play a crucial role in enhancing the training system by providing access to cutting-edge technologies, fostering collaboration and networking, offering specialized training and capacity building, promoting innovation and experimentation, facilitating industry engagement, supporting entrepreneurship, and enabling continuous learning and upskilling. DIHs empower training institutions to stay at the forefront of digital innovation and equip learners with the skills needed to thrive in the digital economy. On that account, this work attempts to establish a bridge between academics/DIHs and industries by transferring knowledge and technology from educational settings to companies and also embracing a set of industry 4.0 relevant technologies [18–20]. A similar procedure was experimented with in our prior study [21] which was supported by the ED-EN HUB project (https://edenhub.eu/). Fig. 1 clarifies the contribution of the current work.

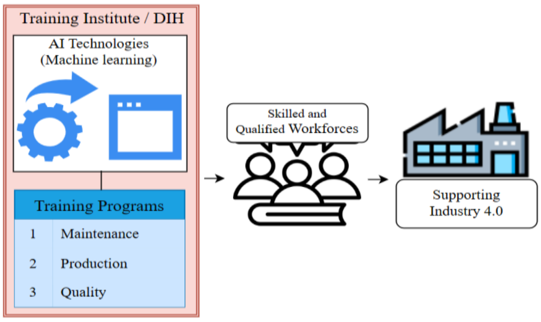

Fig. 1. Integrating AI technologies into training programs for upskilling workforces and supporting Industry 4.0.

The underlying idea of the presented research is to address the issue of AI and more specifically ML knowledge, that is acquired in academia, and applicability in the industrial context. Hence, the new generation of engineers particularly from developing countries can get an insight into the current industrial needs and acquire the needed set of skills to be able to address modern industrial challenges. Moreover, the first steps towards the development of a framework for smooth integration of the courses into the educational process that should consider both industrial context and students' expectations are presented. This feedback loop is an important constituent of EU supported ENHANCE project. During the iterative process a set of Industry 4.0 related courses, in particular courses targeting the application of Industrial AI, are developed and presented to the target audience in the testing mode. It is important to note that the courses target specific manufacturing aspects such as quality control or inventory management, revealing real-world scenarios and contain both the theoretical and practical parts. After each iteration, the feedback from students, educators, and professionals is collected and then the courses are adjusted correspondingly. Some of the presented courses are now in good shape and underwent multiple iterations.

In terms of innovative contribution, the presented research provides an insight into a forthcoming Industry 4.0 educational program. This program encompasses courses that delve into facets pertinent to digital manufacturing. The program is modular, and some modules are built on top of the other modules. The modular structure offers a set of benefits for grasping the complexity of ML and AI processes that includes a set of preparatory stages such as data acquisition that cannot be left out of consideration. Furthermore, the modularity allows us to have a specific look at ML itself or at the corresponding auxiliary processes. Therefore, the students can get an overview of the whole process from data harvesting to the model results assessment, or they can select a specific module of interest, e.g., addressing the application of ML in the supply chain.

The remainder of this work is structured as follows. Section II summarises the related work in this field. Section III evaluates the related industrial needs. Section IV describes the provided training programs. Section V provides the concluding remarks and some suggestions for possible extensions of our work.

II. Related Works

A. *Introducing AI in Industrial Challenges and Roadmap*

AI has the potential to revolutionize industries, for example, it can improve efficiency and productivity, enhance decision-making, and open up new opportunities for innovation. Furthermore, AI is important for industries as it can bring automation, efficiency, data-driven decision-making, enhanced customer experiences, and innovation [22]. While AI holds immense promise for shaping industries worldwide, it also presents several challenges that need to be addressed for its effective and responsible implementation. Some of the key industrial challenges of AI include [23–25]:

- Data Quality and Availability: AI algorithms require large volumes of high-quality data to train and make accurate predictions. Obtaining clean and relevant data can be challenging, especially in industries where data is fragmented, unstructured, or subject to privacy and security concerns.
- Ethical and Legal Considerations: AI raises ethical and legal dilemmas, such as privacy concerns, algorithmic bias, transparency, and accountability. Ensuring that AI systems respect ethical standards and comply with legal regulations is crucial to maintain trust and mitigating potential risks.
- Lack of Skilled Workforce: There is a shortage of professionals with expertise in AI, including data scientists, machine learning engineers, and AI researchers. The demand for skilled talent often surpasses the available supply, posing a challenge for industries to build and retain AI-capable teams.
- Interpreting Black Box Models: Some AI algorithms, such as deep neural networks, operate as black-box models, making it difficult to interpret their decision-making processes. This lack of transparency can be a concern, particularly in safety-critical applications, where explainability and accountability are crucial.
- Integration with Existing Systems: Incorporating AI technologies into existing infrastructure and workflows can be complex. Legacy systems, compatibility issues, and resistance to change can pose challenges to the seamless integration and adoption of AI in industrial settings.
- Cost and Return on Investment: Implementing AI technologies can involve significant upfront costs, including infrastructure, hardware, software, and skilled personnel. Organizations need to carefully evaluate the potential return on investment and long-term benefits to justify the initial investment.
- Security and Trust: AI systems can be vulnerable to adversarial attacks, data breaches, or unauthorized access. Ensuring the security and reliability of AI applications, as well as building trust among users, customers, and stakeholders, is essential for widespread adoption.
- Bias and Fairness: AI algorithms can inadvertently inherit biases from the data they are trained on, leading to discriminatory outcomes. Addressing bias and promoting fairness in AI systems is crucial to prevent discriminatory practices and ensure equitable outcomes across different groups.
- Regulatory Environment: The rapid advancement of AI has prompted the need for appropriate regulations to govern its use. Developing robust regulatory frameworks that strike a balance between promoting innovation and safeguarding societal well-being is a significant challenge for policymakers.
- Continuous Learning and Adaptability: AI systems require continuous learning and adaptation to stay relevant in dynamic environments. Ensuring that AI models can adapt to changing data, evolving user needs, and emerging challenges is a complex task that demands ongoing research and development.

Addressing these challenges requires collaborative efforts from industry, academia, policymakers, and society at large. It involves investing in research and development, fostering interdisciplinary collaboration, establishing ethical guidelines, promoting diversity and inclusion, and ensuring ongoing education and training in AI-related disciplines. By proactively addressing these challenges, industries can harness the full potential of AI while minimizing risks and maximizing benefits [26].

B. AI Use Cases in Manufacturing

The modern state of manufacturing can be characterized by a high level of digitalization and networking. In fact, the modern manufacturing process consists of highly inter-connected pieces that are supported by numerous sensors and actuators leading to a significant increase in data being generated [27]. Moreover, other manufacturing-related processes, such as inventory management are also highly digitalized. All this data generated and harvested can have a significant influence on the manufacturing process if properly utilized and analyzed by means of AI and ML. As a result of AI and manufacturing convergence, the concept of Industrial Artificial Intelligence emerged [28]. The main idea behind the concept is that AI technologies are combined with the domain knowledge of manufacturing processes to enable some important abilities, such as self-perception, self-prediction, self-optimization, and self-adaptation.

AI and ML are applied to numerous aspects of the manufacturing process. In the context of Industry 4.0, one of the main triggers is resource usage efficiency [27]. The efficiency of resource usage is directly affected by, for instance, the number of scrapped parts produced. In order to assure the highest possible quality of the manufactured products to keep up with Industry 4.0 trends, the Zero Defects Manufacturing concept has emerged. ZDM can be defined as a set of techniques aimed at the reduction of scrap costs, detecting defects at early stages, preventing defects propagation, and ensuring high-quality production output [29]. A recent example of ZDM implementation in the industrial domain is the EU-funded Zero Defects Manufacturing Project (ZDMP). ZDMP delivers an ecosystem that provides a set of zComponents and zApps to deal with various manufacturing-quality related issues including AI- and ML-enhanced reasoning [30].

However, besides the analytics itself, other auxiliary processes such as data acquisition and data harmonization are of particular importance. Since, before AI and ML come into play, the data are collected (e.g., from sensors) and processed or “harmonized” to bring data into a form suitable for further processing. When the data are acquired and prepared, they are fed to the ML algorithm to derive useful data patterns relying on the fact that data are the reflection of physical equipment/process characteristics [31]. The ML algorithms can be split into two big groups namely, supervised and unsupervised. Their main difference is that in supervised learning the data are labelled, i.e., the correct response/desired solution is provided by the “teacher”—domain expert. In contrast, unsupervised learning presumes that there are no labels defined by domain experts. Due to the specificity of manufacturing processes, i.e., the convergence of AI, ML, and domain knowledge the focus is mostly made on supervised learning algorithms [32].

In the case of supervised learning, there are two addressed problems: regression and classification. For instance, Wuest and Weimer *et al*. [33] predicted a Remaining Useful Time (RUL) of a turbofan engine, while testing several algorithms including the Deep Learning (DL) approaches for solving a regression type of problem. On the other hand, the vivid examples of classification algorithms application in manufacturing are, for instance, the quality grade assessment on a scale of 1 to 10 or the classification of a product into two groups, defect or non-defect [34] based on some input parameters.

In this work, two aspects of data-enhanced manufacturing are highlighted: the data acquisition and the application of ML itself.

C. Future of AI in Industry and Manufacturing

In the future, factories will get smarter through the extensive usage of AI and ML for a wide range of manufacturing tasks. Arinez and Chang *et al.* [31] identified some recent challenges that should be addressed by future research works. The challenges are briefly presented in the following:

- **Systems-level.** Challenges are related to the fact that manufacturing systems are usually non-linear, of stochastic nature, and cover multi-stage and multi-domain processes. This imposes some limitations on the process of selecting appropriate AI tools and ML models, as well as requires knowledge of domain experts who understand the problem. Moreover, as the manufacturing process is multi-domain, domain knowledge of several domains is required. Another critical aspect is that there are still many stand-alone AI and ML tools that address a specific problem related to a specific process without taking into consideration related processes, which limits their performance to some extent.
- **Data Quality.** Due to the multi-stage and multi-domain nature of modern manufacturing systems, a lot of heterogeneous data are generated that need to be properly collected and processed. Considering the heterogeneity of data and different domain-specific viewpoints, there is also a need for proper data mapping and context consideration. This is specifically important for system-level solutions.
- **Transfer Learning and Data Synthesis.** Transfer learning is a promising research direction that has a goal of adapting the ML model from a well-established domain, i.e., the one that has enough data to represent different states, to a target domain with limited data available [31]. However, there are still some unexplored aspects, such as model transfer between different machines or the same machines of different suppliers, or model transfer among different working conditions. Another promising research direction, in the case of limited data availability, is the generation of synthetic datasets of sufficient quality to accurately capture the domain-specific problem.
- **Trust in AI.** With further advancement of AI and ML tools, there is increasing demand for explainability and interpretation of the model output. The issue of explainability is very important, as decision-makers might not possess sufficient knowledge of how the model performs requiring instant help from the data engineer. There are some

tools that already enable understanding of features' importance on the model output[1], but there is still a gap in terms of proper mapping of physical processes to a model outcome in the case of data-driven approaches.
- **Practical Implementation of AI.** In many cases research efforts related to the development of AI and ML tools for manufacturing conducted in the laboratory environment are not transferred or have limited use in the real-manufacturing environment. An important challenge is to further promote AI and ML usage in manufacturing and the proper transfer of technologies and knowledge among academia, industry, and technological providers.

III. Assessment of Industrial Needs

In the project's early phases, the evaluation of industry requirements and the examination of disparities between those requirements and the academic offerings have been successfully conducted. This led to the formulation of the corresponding methodology, encompassing the following steps [35]: (Step 1) conducting a survey among 32 Tunisian and Moroccan companies about Industry 4.0 requirements and technologies in-use, (Step 2) conducting a deep literature review to identify the related skills for the domain of Industry 4.0, leading to documentation a set of essential skills, (Step 3) analyzing the existing curricula of project partner institutions in three targeted topics namely, maintenance, production, and quality, (Step 4) carrying out a cross-analysis, relying on the previous steps to identify the gap between Industry 4.0 skills and existing curricula in Morocco and Tunisia. The literature review and the survey have culminated in the identification of pertinent technological concepts associated with Industry 4.0 such as Big Data, Autonomous Robots, Industrial Internet of Things, Cloud Computing, Additive Manufacturing, Augmented Reality, and ML and AI. Furthermore, a set of main capabilities were formulated which are presented briefly in the following:

- Capability to achieve Integrated Systems and Architectures—As the Industry 4.0-related technologies are not working stand-alone, there is a need for the skills to design, develop, and manage the Industry 4.0-related processes to achieve their joint operation within the integrated architectures.
- Capability to enable collaborative, cooperative, and self-emerging systems—A notable distinction in the concept of Industry 4.0 lies in the inclusion of intelligent objects that are not merely passive entities but actively engage and contribute to diverse processes (e.g., collective knowledge creation, contribution to the decision-making process). This creates the need for skills to enable innovative interaction patterns, e.g., among machines, among machines and humans, etc.
- Capability to enable advanced and smart connectivity and connectedness—To support the smart objects that are actively engaged in the Industry 4.0 environment, a set of skills is needed to implement, deploy, and maintain the networking infrastructure, enabling data acquisition, transmission of data and knowledge, and support of distributed systems.
- Capability to embrace core manufacturing process automation and sustainability—The competency requires a set of skills to design, model, and implement the manufacturing transformation strategies. This includes the ability to select, deploy, and seamlessly incorporate appropriate technologies and solutions into the existing Industry 4.0 ecosystem, thereby bolstering the implementation of transformational strategies.
- Capability to achieve data, information, and knowledge lifecycle management—In the Industry 4.0 environment, value creation is tightly coupled with knowledge creation. The knowledge creation process includes various stages from data acquisition and pre-processing to the knowledge generation itself.
- Capability to achieve prescriptive and adaptive decision support—The knowledge created within the context of Industry 4.0 is harnessed to bolster and elevate the process of decision-making. Therefore, there is a need to develop a set of skills to design different types of decision-making systems based on the systems' dynamics.

The detailed results of the survey are out of the scope of this work, but are presented in [35]. However, the survey enabled us to identify the main Industry 4.0 technological concepts that are now in use by some local industries as well as the scope of their usage. Not only the data from the survey but also the challenges identified during the literature review enabled us to proceed with cross-analysis of the industrial needs and challenges as well as how they are reflected in the existing curricula of the ENHANCE partner institutions of higher education. The results show that many technological concepts and skills are not adequately presented in the existing curricula. Certain instances of technological concepts that were entirely absent from the existing curricula included Augmented Reality and Cloud Computing. Whereas some others such as AI and ML did not possess the necessary level of coverage and thus did not address relevant challenges. It should be added that the survey has been used to identify the existing gaps in the companies in regard to the focus areas such as:

- Maintenance—The majority of the companies indicated the importance of developing predictive and preventive maintenance and real-time monitoring solutions for the maintenance processes. Furthermore, it was indicated that mostly "elementary" technologies that only partially address the indicated needs are currently used.
- Production—In general, the companies indicated the need for solutions for the following production tasks: planning and scheduling, inventory

[1]https://shap.readthedocs.io/en/latest/

management, and production monitoring. Besides, promising technological concepts include IoT, Cloud computing, ML-enhanced predictive solutions, and 3D printing.
- Quality—In this area the importance of real-time monitoring solutions with predictive capabilities was indicated. Furthermore, the core challenges include in-process product quality control and post-production quality control.

It is important to state that at this stage of the project a set of courses is being developed. Some of them are in good shape to be integrated in the curricula. The iterative process of validating the courses among the students, teaching staff, and representatives of industry has not been accomplished although several iterations have passed. This implies that a certain amount of time is necessary for the complete integration of the courses into the curricula, at which point the final evaluation can be carried out.

IV. Proposed Training Programs

In this section, the courses and the use-cases are presented in regard to one of three categories: Maintenance, Production, or Quality. Every category described in this paper has exactly one course and one use-case, developed within the EU-funded project ENHANCE. Thus, the work demonstrated in this paper addresses only some topics covered by the ENHANCE agenda.

A. Maintenance

Course name: Downtime Forecast and Optimal Maintenance Planning.

The main purpose of maintenance is to ensure that all the machinery and equipment required for production are operating at maximal efficiency all the time, except the time required for the planned maintenance. On the other hand, maintenance planning aims at adjusting the maintenance actions schedule to increase the equipment's useful operation time, minimize unplanned maintenance, and maintain the balance between cost and efficiency. The maintenance planning employs a range of sophisticated diagnostics methods and approaches to determine the root causes of machine failure based on CPS/IoT-related instruments used to acquire and analyze process or machine health data. Analysis of these data makes it possible to forecast the downtimes with sufficient precision, which in its turn, enables the proactive approach instead of the reactive one when the downtime is predicted in advance and the maintenance actions are planned accordingly.

The goal of this course is to bring about an introduction to the large and important area of maintenance planning and provide insight into different maintenance approaches, downtime cost assessment, and machine learning techniques to support maintenance planning. The course allocates two main types of maintenance: preventive and corrective. Corrective maintenance is carried out after fault detection. Thus, components operate until failure. Then, repair or renovation actions are performed. On the other hand, Preventive maintenance is carried out to mitigate degradation and reduce the probability of failure and can be subdivided into the following sub-types: Scheduled maintenance, Condition-based maintenance, and Predictive maintenance. The target audience of the course should get an understanding of the important differences between these maintenance types and why preventive maintenance is the most promising considering ZDM and Industry 4.0 requirements [36].

Use-case name: Data Acquisition and Storage in Industry 4.0.

The main goal of the course is to provide an understanding and an example of the typical data acquisition process. In particular, the focus is made on the process data that is acquired from the sensors. Thus, this course is of particular importance as it provides fundamentals of IoT-related processes concerning data acquisition, basic pre-processing, and representation. In this case, it is important that students get familiar with the possibilities existing nowadays. Another important goal is to gain an understanding of different storage types. The two main paradigms of storage are discussed Structured Query Language (SQL) and NoSQL. In the provided example Mongo DB, which is a NoSQL document-oriented database, is considered. Data Acquisition and Storage are the forerunners and important parts of further data analysis. Finally, after data is acquired and stored, it is important to visualize data to have better insights into how they can be utilized. Fig. 2 visualizes the architecture of the solution for data acquisition, pre-processing, and representation used for practical exercise.

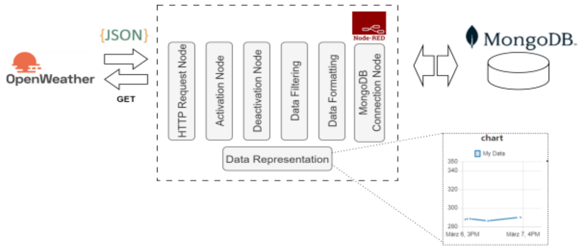

Fig. 2. Architecture of the solution for data acquisition, pre-processing, and representation used for practical exercise.

In the proposed scenario we use the third-party weather service (OpenWeather[2]) that provides the Application Programming Interface (API) for retrieving the sensor data about the temperature and humidity measured in different parts of the world. Thus, students get familiar with common ways of retrieving the data from remote sensors, as it is not always possible to perform processing close to the area where the sensors are deployed due to various reasons. To be able to retrieve, store, and later represent the data, the NodeRed[3] solution is used as middleware. The NodeRed enables the modular design, by providing so-called nodes, which are the blocks of code implementing certain functionalities in a user-friendly form. The students can assemble the complete solution by combining different nodes. However, some nodes need to be customized, this can be done by complementing the missing functionality by writing Javascript code. One of the nodes is used to send

[2]https://openweathermap.org/

[3]https://nodered.org/

the HTTP GET requests to the weather services and receive the response that comes as a JSON object. Then, the payload is extracted and pre-processed using another node that also adds the time-stamp when the payload was received (see code below in Algorithm 1).

Algorithm 1. Extraction and pre-processing of the OpenWeather payload

```
var temp = msg.payload.main.temp;
var humidity = msg.payload.main.humidity;
var city = msg.payload.name;
var curDate = new Date();

var data = {
"temp": temp,
"humidity": humidity,
"name": city,
"date": curDate
}

msg.payload = data;
return msg;
```

Moreover, when the NodeRed is running, it allows receiving and storing data in a close-to real-time manner. Having triggered the activation node, the process will be launched until the NodeRed is active. For the experimental purpose, another node that limits the number of received data is introduced. When the experiment is launched on the local machine, if the data is collected every second, the number of stored records will be quite large. In the real-world scenario, there might be a need for 24-hour recording, due to the instruments offered by NodeRed. However, the learners can get a basic understanding of tools and approaches for data harvesting. Another important instrument is the node that is responsible for the connection with the MongoDB and allows storing and receiving data for further representation. And finally, the NodeRed node for data pre-processing for further plotting is used that can send the data in a suitable format to the data representation node.

B. Production

Course name: Big Data and Predictive Inventory Analytics.

In general, the course is devoted to inventory management, addressing typical problems of inventory management and how machine learning techniques are employed to get those problems solved considering BigData factor. Initially, the course provides an insight into the typical problems that arise in the area of inventory management and the costs associated with them. Then after, it introduces some techniques that are widely applied within the area of inventory management. The course distinguishes between two core types of inventory management systems, the ones relying on continuous review and the ones relying on periodic review. Periodic review systems check the number of items stored at defined time stamps (every hour/day/week, etc.) and then the number of items to reach the safety level is ordered, while continuous review systems usually order the same number of items after the stock drops below the safety level, as the stock state is monitored continuously.

The course provides some insights into the employment of ML approaches to solving inventory management-related problems, such as demand forecasting problems. Furthermore, to give a broad understanding of data analytics with ML, the typical data analytics flow is introduced that includes such important steps as data acquisition, data pre-processing, feature engineering, and ML algorithms application.

Use-case name: Data-driven Inventory Management.

This use-case provides a practical example to support the theoretical background addressed in the course “Big Data and Predictive Inventory Analytics”. The use-case starts with the introduction of ML fundamentals, providing the basic definitions and taxonomy of ML techniques. Afterward, one of the inventory management problems (demand forecasting) is introduced and discussed. Demand forecasting deals with predictions of the future demand for goods based on historical demand records. Predicting demand is important in order to have enough products and goods to satisfy the demand at each point in time. For this purpose, a ML approach is applied to demand forecasting. As demand is a numerical value, it is a classical regression task requiring a supervised ML approach.

Besides the domain knowledge, students need to understand from which stages the typical ML flow consists and in which sequence they are executed (see Fig. 3). The main goal of ML is to derive meaningful insights from the available data. The assumption of this course is that the data is ready-to-use. Thus, the stage of data acquisition is skipped. Consequently, the focus is made only on the application of ML for a particular problem. In the second stage, data is pre-processed and prepared to be fed to the ML algorithm. The pre-processing stage might include data filtering, filling in missing data, and feature engineering. After data is prepared, ML is applied and the results, in particular case demand predictions, are achieved. At the final stage, the results are visualized and performance metrics, such as Root Mean Square Error (RMSE) are calculated to assess results. The dataset used for this exercise is a synthetic dataset generated from the real-world data of a big European car manufacturer and the goal is to predict the demand for different types of car batteries that are installed during the car assembly stage.

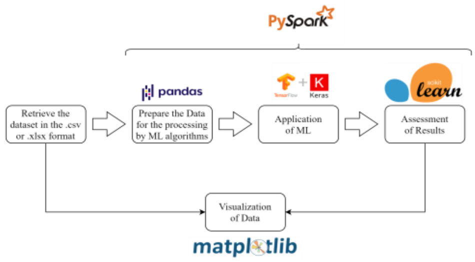

Fig. 3. Typical ML flow.

The proposed use-case consists of two parts. In the first part, a Big Data aligned approach relying on the PySpark[4]

[4]https://spark.apache.org/docs/latest/api/python/getting_started/index.html

library is used. In the second part a non-Big Data approach, combining various libraries for data pre-processing and machine learning, such as Pandas[5], TensorFlow[6], scikit-learn[7], is utilized. The dataset used for the exercise is not a real Big Data dataset, i.e., it does not possess all the Big Data characteristics [37]. However, it is important to provide learners with a broad view of tools and capabilities that are available and can be selected depending on the particular task. One of the disadvantages of PySpark is that it has a limited number of ready-to-use ML algorithms and no standard implementations of Deep Learning (DL), so it has to be used, for instance, in conjunction, with Keras.

During the practical exercise, students build and apply a DL model for demand prediction. The applied model is the Long Short Term Memory (LSTM) neural network that demonstrates significant efficiency, addressing the regression type of problems [38]. Moreover, learners try to implement different architectures with different numbers of hidden layers, units within hidden layers, batch sizes, and epochs to see how those parameters affect the end result. Finally, the predicted demand and the real demand are compared and represented on the plot (see Fig. 4).

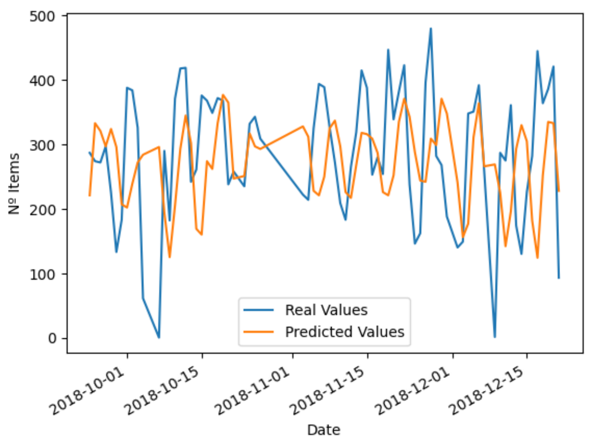

Fig. 4. Demand prediction plot for one type of the car betteries types.

C. Quality

Course name: Prescriptive and Adaptive Decision for Quality Control.

This course provides fundamentals in the area of Prescriptive and Adaptive Decision Making. Decision-making can be described as a series of steps taken by an entity to gather information, assess alternatives, and select the right and effective course of action for the purpose of achieving the desired result. The decision-making process relies on business analytics that can be of three types: descriptive, predictive, and prescriptive. The type of business analytics determines the goal of the decision-making process. In the case of descriptive analytics, the decision-making process targets the issues of what should be done to avoid the possible consequences. Predictive analytics aims at foreseeing upcoming events, for instance, the wearing out of an important machine part. Prescriptive analytics, on the other hand, takes another step forward, while defining what actions have to be undertaken to avoid certain situations and events from happening. To support the decision-making process, decision-making systems are employed. This course considers two types of decision-making systems namely, Multi-attribute and Multi-objective decision-making systems.

During the course, the target audience will be introduced to some typical decision-support systems architectures and get familiar with various taxonomies of decision-support systems, such as online and offline decision-making systems. Additionally, the course underlines the importance of decision-making in the area of quality in some examples. An obvious and vivid example is maintenance planning based on the machine health data, when the decision-making system can suggest if and when the maintenance actions should be in place.

Use-case name: Prescriptive and Adaptive Decision for Quality Control.

This use-case is intended to provide a demonstrator for the theoretical part presented in the course on “Prescriptive and Adaptive Decision for Quality Control”. The use-case considers the publicly available data set from the quality domain. It is important to provide the students with a use-case that can clearly show how the decision-making can be applied to manage the quality of the products being manufactured or the machines’ states that are used in the manufacturing process. In the quality area, decision-making can be used, for instance, to analyze the data and select which parameters need to be tuned to improve the quality and/or to define possible reasons for the quality decline. Product defects can be due to numerous reasons, for instance, due to the wearing-out of machine parts or the quality of the material used, erroneous production parameters, etc. In this regard, it should be noted that the design of the decision-making system for the specific production area often requires a quality engineer, who is familiar with typical problems and nuances of the production process and equipment. This course is not yet ready and the work on it is ongoing.

V. Conclusion

AI has become increasingly important in the industry due to its transformative potential and numerous benefits. For example, AI has the potential to enhance efficiency, improve decision-making, increase customer experiences, automate processes, optimize supply chains, detect risks, drive innovation, and contribute to sustainability. Embracing AI technologies allows businesses to stay competitive, adapt to changing market dynamics, and unlock new opportunities for growth and success. On the other hand, AI technologies offer significant support to training processes in various ways. By harnessing the power of AI technologies, the training processes and training programs can become more effective, efficient, engaging, inclusive, adaptive, and personalized. AI-driven tools and platforms offer valuable support to learners and

[5]https://pandas.pydata.org/
[6]https://www.tensorflow.org/
[7]https://scikit-learn.org/stable/

trainers, facilitating skill development, knowledge acquisition, and performance improvement.

This study draws attention to the importance of the integration of AI use cases and technologies into training programs. AI technologies bring numerous benefits to students and future workers, including personalized learning, adaptive assessments, intelligent tutoring, enhanced collaboration, language learning support, access to resources, personalized feedback, time efficiency, engagement, and data-driven insights. By leveraging AI, can have more tailored, engaging, and effective learning experiences, leading to improved educational outcomes. Furthermore, AI technologies can play a significant role in developing the skills and competences of students by, for example, providing targeted learning opportunities, tailored content recommendations, virtual simulations, data-driven insights, collaboration opportunities, and skill recognition – all of which contribute to upskilling students. AI technologies can help to transfer knowledge from training institutes and DIHs to industry, bridging the gap between theoretical learning and practical application. Therefore, the training institutes and DIHs can ensure that learners are equipped with relevant industry knowledge and skills, enabling a smooth transition into the workforce. The trained and upskilled students can play a significant role in supporting Industry 4.0 by bringing their enhanced knowledge and skills to the workplace. That is, the trained and upskilled students bring technological expertise, innovation capabilities, problem-solving skills, data analytics proficiency, adaptability, collaboration skills, and leadership potential to support Industry 4.0. Their contributions enable companies to embrace digital transformation, leverage emerging technologies, and thrive in the increasingly connected and automated industrial landscape.

In this study, we presented three training programs in Maintenance, Production, and Quality that were supported and developed by ENHANCE project and an associated DIH. These training programs aim at training and upskilling potential and interested students who can contribute to supporting Industry 4.0, particularly in local companies of Morocco and Tunisia.

One of the main goals of the ENHANCE initiative is to establish a feedback loop among academia, learners, and industrial partners. Therefore, all the courses undergo numerous iterative discussions with experts from academia and industry to collect the feedback and to make the necessary adjustments. Furthermore, the courses are also presented to the learners in a test mode for the same purpose of feedback collection. Each iteration allows fine tuning the content and the way the material is presented to make it clearer and more useful for the target audience. Course discussion meetings and presentations, including ones at Institutions in Morocco and Tunisia, are organized and held by ENHANCE on a regular basis. Another point is that the theoretical courses are accompanied by the corresponding industry-related practical use-cases giving the learners the opportunity to apply the theory in practice.

During the next steps the first two courses and use-cases from Maintenance and Production domains might undergo some small adjustments based on further discussions with partners from industry and academia even though these courses are in a high degree of readiness. Regarding the Quality course and use-case, the work is ongoing, the course itself has already defined structure and some of the chapters are in good shape. However, there were some delays related to the use-case, as one of the issues was to find a publicly available dataset that also fits the context of the course for practical exercise. One of the future work vectors is directed toward finalizing the Quality course and the use-case, as well as fine-tuning courses and use-cases in Maintenance and Production. Another point of the effort is to integrate the proposed courses and use-cases with other courses and use-cases developed within the ENHANCE project to create a comprehensive industry-focused educational program.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Conceptualization, A.N., M.Z., and J.S.; methodology, A.N., M.Z., and J.S.; validation, A.N., M.Z., and J.S.; formal analysis, A.N., M.Z., and J.S.; investigation, A.N., M.Z., and P.F.; resources, R.J.-G. and N.M.; data curation, A.N., M.Z., J.S., and P.F.; writing—original draft preparation, A.N., M.Z., and P.F.; writing—review and editing, A.N. and M.Z.; visualization, A.N., M.Z., and J.S.; supervision, J.S., R.J.-G., and N.M.; project administration, J.S., R.J.-G., and N.M.; funding acquisition, R.J.-G. and N.M. All authors have read and agreed to the published version of the manuscript.

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