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Machine Learning Model for Improving the Overall Equipment Effectiveness in Industrial Manufacturing Sites

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Abstract—Manufacturers have always pursued greater speed, scale, qualitative products and services, and simplicity across operations to optimize production while enhancing efficiency and reducing costs. With technologies like artificial intelligence (AI), industrial internet of things (IIoT), machine learning (ML), and analytics, companies can create hyper-connected ecosystem leveraging data to constantly optimize critical efficiency related key performance indicators (KPI) such as overall equipment effectiveness (OEE) score. The metrics can help accurately identify, predict, and prevent unplanned equipment failures and downtimes, including quality issues. This paper discussed the best possible ML model to predict the OEE score in order to improve the quality of production and the end production goals in order to fulfil customer orders based on availability, performance, and quality within manufacturing sites. Our results shows that ML with the advancement of quantum machine learning models could potentially gain the productivity, performance, and quality factors that are the key ingredients to gain maximum OEE score that could be the most effective manufacturing production solutions worldwide.

Keywords—Artificial intelligence, Industry 4.0, Machine learning, Smart factory, Supervised learning, Unsupervised learning

1. Introduction

Due to the high demand for productions and customer-centric businesses, manufacturers are highly focused on digitalization, the adoption of intelligent equipment, and highly focused process integration and management (e.g., ERP & SAP) software to support and fulfil the customer's demands. They are capable of processing the order, and sales and operational planning as per schedule (e.g., sales orders, make-to-order (MTO), and make-to-stock (MTS)), which are significantly challenging, and fulfilling these customer demands is highly critical (Cabanillas, 2013). Most industrial production sites heavily utilize industrial automation, digitalization, and changes to industrial IOTs, sensors, machines, and equipment, which need a better OEE score and production optimization. Even in Industry 4.0, the most suitable digitally integrated technological innovation revolves around machines, equipment, and industrial sensors (Riesbeck). These elements collect, process, and optimize enterprise data per the manufacturing business process flows to gain production and OEE performance scores (Kao, 2017). Manufacturers

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are adopting the best practices and applications of novel technologies such as machine learning (ML) and the industrial application of quantum computing (QC) and artificial intelligence (AI) to gain absolute results while considering production efficiencies (Puvanasvaran, 2010). OEE is the most standard and optimized global manufacturing practice (GMP) to support global compliance and enhance competitiveness in manufacturing industries. Based on global manufacturing best practices, the overall equipment effectiveness (OEE) is measured in percentage in a competitive manufacturing environment. Moreover, time invested in manufacturing a product that is truly productive and result-oriented in a specific production unit is the surest source of truth in the measurement of the OEE score (Kim, 2018). Based on the OEE score, manufacturers can easily understand the production scorecard, losses, and profit on a specific industrial production, the rate of production parameter, and the TCO and ROI of smart factories. The current OEE score for a particular manufacturing practice is 85% or above, which is "exceptional".

Based on literature, the following are the best benefits for OEE score in industrial manufacturing and smart factory production sites: (a) Ability to understand the equipment capacity that has been used at production sites; (b) Better visibility of the manufacturing and production processes in smart industrial sites; (c) Ability to understand the production factory's capabilities, turnover, and quality score; (d) Global compliance and international standards as per the new products and new markets; (e) Global competitiveness and international market shares; (f) Industrial automation and smart factories in Industry 4.0; (g) High profitable and low-cost of ownership in longer run and (h) Improve the highest level of production score and less defects or scraps.

In terms of manufacturing execution system and overall equipment effectiveness, we have stated that the most current trends of manufacturing effectiveness and the scorecard of OEE apply to industrial manufacturing practices and are the trends in industry 4.0/5.0. Manufacturers have a little higher in competitive, dynamic markets where production efficiencies must be higher than expected. Customer expectations are much higher than previous trends, and the industrial production score, quality score, and overall equipment effectiveness (OEE) are ideally under the normal range of 85%, which is the most competitive score for manufacturers in high-end productions (Acosta, 2020). In industrial manufacturing, the key performance indicators (KPIs) are based on the quality of productions, the availability of production scores, improving changeover setup times for machines or equipment, reducing production scrap, or changing the capacity to produce the best quality of products or services free of defects. Adopting the best technological innovations could quickly achieve production qualities and overall equipment effectiveness. These include new trends in the use of smart factories and smart industries; quantum computing's industrial revolutions, and AI and ML models to support the industrial innovations of Industry 4.0 (Rabie, 2000; Ulutas, 2011). Occurrence is impossible to achieve through traditional approaches or legacy systems that cannot manage the OEE score in production factories. Essential to the overall equipment effectiveness in manufacturing factories are the key indicators of production score, which conveys how well the equipment and machines are used to attain overall equipment efficacy in a manufacturing site (El Hassani, 2021; Abajo, 2004; Shi, 2007). There are a few key considerations and dependencies on the score of OEE, as stated below:

(a) ***The availability factors***. It is the percentage of time that a piece of equipment can easily operate without the need for routine or planned maintenance.
(b) ***The quality factors***. It is the proportion of qualitative factors that may have an impact on the goods, services, or manufactured parts.
(c) ***The performance factors***. It is the percentage of a machine's maximum operation speed that is used by the machine or other equipment in a manufacturing site.

The core of the automation pyramid is depicted in Fig. 20.1, explaining the components of manufacturing execution systems and the flow of information across enterprises. The enterprise manufacturing execution systems are backed by back-office solid systems (ERP-SAP HANA S/4), which could save time, money, and manual efforts across the enterprise levels (Rostami, 2015). Enterprise manufacturing execution systems are backed by back-office solid systems (ERP-SAP HANA S/4), which could save time, money, and manual efforts across the enterprise levels. In industrial manufacturing, facilities require robust back-office systems (ERP-S/4HANA), which could save manual tasks and actions and integrate the complex business process within the manufacturing business process. Most of the complex production, operation, supply chain, warehouse, and shop floor activities could be controlled and managed by the HANA Manufacturing Execution System (MES) and deliver the most tangible benefits of the machine and operations in industrial activities.

The manufacturing execution systems and solutions could help the manufacturing business process, tasks, production orders, shop floor activities, and production status. It also involves updating the new or old material per customer order demands, order fulfillment per customer demand (MTO or MTS), updating the batch information, and managing the preventive and predictive maintenance as per the business needs in manufacturing and supply chain management (Singh, 2013; Wollschlaeger, 2017). The best practices of any manufacturing execution system also perform the required manufacturing activities. They can

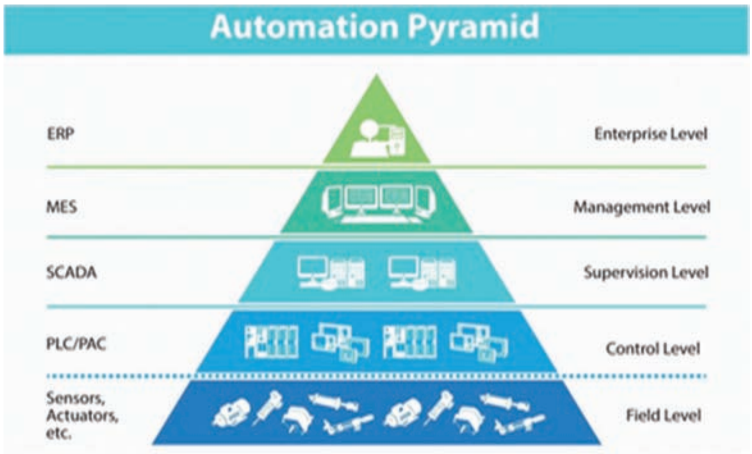

Fig. 20.1 MES automation pyramid and smart factory

manage work orders, production orders scheduling, warehouse management, tracking and trading, and work center and shop-floor activities management to support order fulfillment processing (sales orders, make-to-order, and make-to-stock) within the financial, supply chain, operational, and production planning lines of business (Nguyen, 2020; Nurpihan, 2019, Afefy, 2013). All these activities depend on the OEE score, production performance, and quality index in shop floor units (Corrales, 2020). Below are the core components of MES-manufacturing execution and optimization (Rathi, 2022). Production site key performance indicators:

(a) Production order management (MTS, MTO, and customer order) and supplier contracts.
(b) Work orders or manufacturing orders.
(c) Production scheduling and shop floor activities at production sites.
(d) Downtime tracking and overall equipment and device efficiencies.
(e) Integration with the WMS system and tracking and trading.

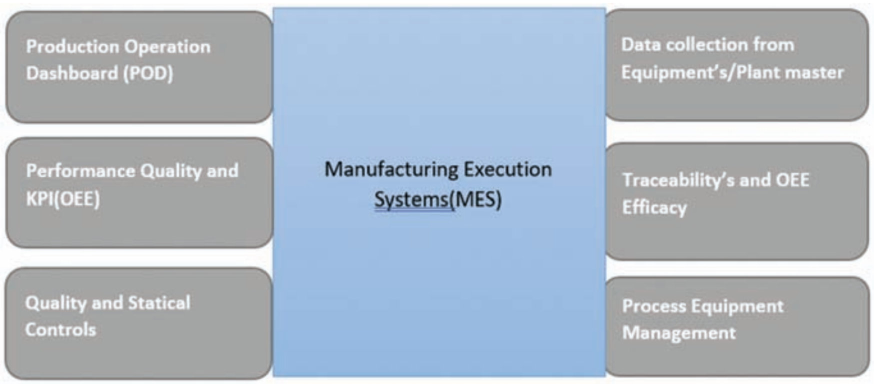

Fig. 20.2 Manufacturing execution systems and core components

Recent advancement in production is reaching its full potential and transforming the way goods are manufactured using AI. It includes predictive maintenance, quality control, supply chain and process optimization, and personalized manufacturing. Overall, the utilization of intelligent algorithms in manufacturing is astronomically increasing product quality and cost efficiency in general and provides an exciting future for timely and uninterrupted deliveries. In this paper, we have discussed the best possible machine learning model to predict the overall equipment effectiveness score, and an optimized solution to cover industrial manufacturing sites. The goal of the OEE score is to reduce downtime, unpredictable losses due to equipment breakdown, setup, minor stoppage, reduced speed, or even scrap production, and improve the quality of production and the end production goals while continuing to fulfil customer orders in the manufacturing objectives (Sales Order, Make to Order, and Make to Stock)

2. Related Literature

2.1 Overall Equipment Effectiveness (OEE) and Manufacturing Execution Systems

Researchers in manufacturing industries said that if we can get our efficiency measured in quality parameters, observe our performance, and understand our availability factors, we are improving our overall equipment effectiveness (OEE) score. It is the continuous measurement that needs to be followed throughout the lifecycle - a measurement to manage the effectiveness of the equipment level in the manufacturing industry. In manufacturing and production sites, the overall equipment effectiveness management (OEE score) could allow measuring the most key parameters and KPIs in the production sites. These include the analytical components of machines, equipment, plants/production facilities, and the site performance in either way (e.g., real-time and historical values).

Most of the time, the OEE score is also dependent on the equipment parts, device attributes, sensors, and IIOTs, which are used to manage the manufacturing business and optimize production planning activities. Some of the manufacturing key metrics are measured based on the capacity of the machine, devices, and industrial equipment, which may come from the various data sources within the production sites (Purr, 2015), the availability and performance of equipment, and the quality of goods produced by that equipment. In OEE systems, the following building blocks and critical KPIs could be measured per the equipment's performance and planned maintenance at production sites. Below are the critical functional building blocks in the OEE:

(a) Master data and its attributes in core ERP SAP applications.
(b) Shop floor integration frameworks and ERP dashboard for SFC.
(c) Dashboards used for the OEE configuration and access management.
(d) For the automated data collections within the SAP OEE systems.
(e) Capabilities on collecting reporting and analytical measurements.

2.2 SAP Manufacturing Execution Systems and SAP OEE for Large Industrial Manufacturing Sites

In manufacturing sites, the overall equipment effectiveness (OEE) of any equipment or machine is a widely utilized metric for measuring manufacturing performance and the efficiencies and effectiveness of the associated devices across the production units (Hugget, 2018). Actual equipment effectiveness OEE functionality could be easily captured and monitored within the back-office application (SAP S4 MES) based on the equipment/product master data and connected equipment across the production units. In SAP OEE, functions are collecting and utilizing familiar data sources (manufacturing and operational data) from various sources to obtain metrics that could measure the availability and performance of machines connected to factory production sites. It will also determine the quality of goods produced, production rates, and production efficiencies determined by that equipment. OEE is also for measuring plant or machine performance in real-time and historical time from various data points. While most OEE KPIs are calculated in real-time as displayed on the production order dashboard (PoD), OEE and its constituent KPIs are calculated using order-operation data converted into terms of time. Availability is a measure of the uptime of the resources: A) Performance is the metrics of whether the asset/resource is producing as per the rated capacity or nominal sped. It does not include downtime losses and B) Quality is the measure of good products produced versus the total quantity generated.

2.3 Applicability of Extended OEE 4.0 within the Smart Manufacturing Sites (Industries 4.0/5.0)

Manufacturing sites in innovative industries and Industry 4.0/5.0 require more accurate and precise calculative OEE scores, which can only be calculated by applying the best practices of extended overall equipment effectiveness (EOEE) and the assistance of digital applications (ML, AI, Quantum AI, ML). Industries 4.0 and the industrial application revolution in 5.0 well manage the extended overall equipment efficiencies. In total production planning and total predictive maintenance (TPM), the OEE4.0 plays a vital role concerning the overall equipment lifecycle and measures to identify, monitor, and optimize the availability, performance, and quality key performance indicators of the manufacturing process in manufacturing sites. Some ERP applications, like SAP S/4 Hana OEE, can predict measurable KPIs, obtain the best production services, manufacture additional value-added services within the machine and equipment, and manage the equipment master data with the equipment registered in the whole life maintenance plans.

Any profitability or losses can be calculated as per the existing master data, equipment classes, and their various critical attributes effectively and quickly as needed by industrial manufacturing sites. The OEE prediction score is an innovation from smart manufacturing best practices. It is derived from the "Japan Institute of Plant Maintenance," which is an integral part of good manufacturing practices and is the best philosophy of total productive maintenance in manufacturing sites. More than 98 million connected equipment, devices, and IIOTs were used and connected to industrial manufacturing facilities in the digital smart factory and shop floor center to perform the best production outcomes. The number of devices and equipment is still growing. According to a 2019 survey, manufacturers and researchers expect this number to exceed 160 million connections by 2025. A vast amount of operational data and manufacturing intelligence information could be used to gain more successful practices, which is the best way to calculate OEE scores.

2.4 Benefits of Extended OEE 4.0 in Manufacturing Businesses

The extended OEE 4.0 creates more effectiveness in production units and shop floor activities in manufacturing facilities and offers tremendous benefits to production sites which could quickly fulfil customer orders (MTO/MTS). A few of the benefits are listed below:

(a) On the go monitored and perform checks on overall system availability in sites.
(b) Capable to provide detailed reports on quality, availability, and performance of the equipment.
(c) Data acquisition and assignment automation and utilizations.
(d) Capable to read the actual machine utilization times.
(e) Update as per the TPM.
(f) Service and support management of the predictive and preventive and corrective maintenance and service.
(g) Review of effectiveness of measures taken along with preventive maintenance planning.
(h) Maintenance of the key major losses due to production losses and OEE (KPI).
(i) Related to production data such as downtimes, quantities, reason codes, and preventive maintenance per units.
(j) Out of box integration within the back-office (SAP ERP), MII, and analytical tools from SAP S/4 HANA in-memory computing.

3. Decision Making System to Improve the OEE Score at Manufacturing Production Sites

In this paper, we would like to highlight the best AI and ML models that could improve overall equipment efficiency and utilization of the smart industrial revolution. We determine the score of the OEE in a manufacturing production unit and compare it with another similar unit where smart manufacturing is not in the scope of implementation. A focus on and check the implications of various machine learning models with real-time production data variables, which could hamper the OEE score in real-time scenarios. There are few viewpoints on machine learning models and how the OEE score can be impactful in response to industrial manufacturing processing units. Here are a few novel research key characteristics:

(a) How the machine learning and AI models can impact the OEE score and manufacturing process in real-time.
(b) Effective management of OEE factors in real analytical tools (availabilities, quality, and performance)

Fig. 20.3 OEE and components

The concepts of overall equipment effectiveness (OEE) were developed in the 1980s at the Japan Institute for Plant Maintenance (JIPM). They are still the best philosophy in the manufacturing space to control manufacturing production issues (Fig. 20.3).

In the Industry 4.0/5.0 revolution, OEE plays a vital role while considering good manufacturing practices and an optimized performance rate for the units producing materials and services on any shop floor. Typically, a good OEE score depends on the core combination of the performance of machines and equipment, quality, and the availability of industrial resources and machinery or equipment objects. The overall equipment effectiveness score makes a factory or production unit much more profitable and economically manageable for sustainability in business. The OEE calculation is depicted in the Equations below:

$$\text{Availability } (Av) = \left[\frac{\text{Running Time}}{\text{Available Time}}\right]$$

$$\text{Throughhput } (Th) = \left[\frac{\text{Total Units} * \text{Ideal Cycle Time}}{\text{Running Time}}\right]$$

$$\text{Quality } (Qu) = \left[\frac{\text{Good Units}}{\text{Total Units}}\right]$$

$$\text{OEE} = \text{Availability} * \text{Performance} * \text{Quality Factor}$$

$$(\text{Availability}) = \left[\frac{\text{Actual Production Time}}{\text{Planned Production Time}}\right]$$

$$P(\text{Performance}) = \left[\frac{\text{Current Run Rate}}{\text{Ideal Run Rate}}\right]$$

$$Q(\text{Quality}) = \left[\frac{\text{Good Product}}{\text{Total Product}}\right]$$

where:

The Availability (A) for a particular part can be calculated as per the formula below:

$$\text{Availability } (A) = \left[\frac{\text{Available Time-Unplanned Downtime}}{\text{Available Time}}\right]$$

The planned downtime at a production or manufacturing facility may be caused by "excess capacity, planned breaks, planned maintenance, communication breaks, and team meetings," whereas "availability time = total available time-planned downtime." Unplanned downtime in production and manufacturing facilities is caused by a variety of factors, including breakdowns, setup and adjustment issues, delayed material delivery, and operator availability on-site. Unplanned downtime in production and manufacturing facilities is caused by a variety of factors, including breakdowns, setup and adjustment issues, delayed material delivery, and operator availability on-site. To calculate the quality rate in manufacturing sites, it can be derived by the formula:

$$\text{Quality Rate } (Q) = \left[\frac{(\text{Total Produced Parts-Defective Parts})}{\text{Total Produced Parts}}\right]$$

To calculate the Performance (P) or KPI of the production sites, use the following formula:

$$\text{Performance } (P) = \left[\frac{(\text{Total Production Parts})/(\text{Operating Time})}{\text{Idle Run Rate}}\right]$$

where:

$$\text{Operating Time} = \text{Available Time} - \text{Unplanned Downtime}$$

$$\text{Idle Run Rate} = \text{Number of Parts per Minute}$$

A good machine learning tool can be helpful to consider the optimal percentage of availability, percentage of quality or qualitative time, and percentage of the performance of the production sites, and we can expect the best percentage of overall equipment effectiveness of the production or manufacturing sites.

4. Implementation of Machine Learning to Gain Better OEE Score in Manufacturing Sites

To improve OEE in manufacturing sites, we must consider the key points below and gain greater visibility when it comes to implementing machine learning models for real-time prediction scores in manufacturing sites. Three types of machine learning algorithms are used to classify these techniques and provide the best prediction score for achieving OEE in manufacturing sites: supervised learning (Thakre, 2009), unsupervised learning (Ulutas, 2011) and reinforcement learning (Prasad, 2006). In the case of supervised learning, the issue is described by a vector X of input variables and a vector Finding a mapping function that connects X and Y, where $Y = f$, is the objective (X). The issue becomes an unsupervised learning situation if the only input variables are X and there are no target variables. Finally, reinforcement learning is a particular kind of machine learning in which an agent learns how to operate and make decisions in an environment by doing actions and receiving rewards. Since we are dealing with labeled data in the current study, we will explore a number of supervised machine learning algorithms (Biswaranjan, 2022).

4.1 Machine Learning Model for Availability (A)

A high availability score of 100% indicates that the process is always running planned production time over unplanned and planned stops or any breakdown maintenance of machines or equipment. We must consider the changeover time, which is the setup and adjustment time, and determine the opportunity for improvement. Through the help of virtual sensors (VS) and IIOT devices, ML can understand the real-production environment; simulate accurate sensor outputs, and any failure events on equipment or machines. Along with planned maintenance, ML can improve the availability score of the complex manufacturing site and help increase the overall OEE score. Our machine learning (ML) model can certainly help to manage the critical challenges while considering a good availability score, as described below:

(a) ***Process Complexity:*** Considered the most appropriate technologies and tools to support the process optimization of manufacturing sites and implement business process management (BPM) and BPML tools to manage them.

(b) ***Response Delayed:*** Considered the critical process management while handling the production of end products, materials, or the end products, which could be slow due to unavoidable delays in production or shopfloor constraints, or there could be issues due to failures or breakdowns in the maintenance of the sites.

(c) ***Quality of signals to the devices:*** Most of the time, the sensor from the device or equipment could be delayed due to poor connectivity or signal issues as industrial sites are connected with multiple devices, sensors, and IoT and IIoT equipment with another apparatus, which could have low signal flows.

In our research paper, we examined various ML algorithms and compared the best-suited models for use in industrial manufacturing facilities. Listed are the best machine learning models and their scores: A) XGBoost; B) KNN (K-Nearest Neighbors) and C) Random Forests.

4.2 Machine Learning Model for Quality (Q)

The quality score in industrial manufacturing sites should ideally be 100%, as expected in each production. There would be no compromise regarding the quality factor. This will enhance the overall equipment effectiveness score (OEE). In intelligent factories (Ritika, 2020), machine learning and AI could bring the most relevant qualitative factors as high as expected. It also considers data from business processes, smart meters, in-line sensors, IIOTs, IOTs, feedback from shop floor workers, manufacturing reporting, and quality control parameters from production sites. There are numerous advantages to using ML and AI tools, which will undoubtedly improve the capacity of smart factories (Gabahne, 2014). A few machine learning models could increase production capabilities and reduce the quality issue while supporting early fault prediction in connected devices and equipment. Visual anomaly detection detects defects and replaces manual efforts and process optimization by reducing the cycle times by 30%.

4.3 Machine Learning Model for Performance (Q)

Performance indicators and factors in production sites are critical when considering a better OEE score (Singh, 2013). It is the most effective method of monitoring the manufacturing process by observing the performance of equipment and devices in the field. Operating and idle time are the most important factors when considering the performance of the machines and equipment in production factories. We can improve the cycle time reduction in factories with the help of machine learning tools. In that case, the equipment's performance could quickly improve, and OEE can undoubtedly be better.

4.4 SAP OEE Supports in Manufacturing Sites

The SAP S/4 Digital solutions automate the manufacturing process effectiveness procedure, which is crucial in industrial manufacturing sites. The most well-known industrial indicator of total productive maintenance is OEE, which aids in measuring the vital elements in achieving availability, performance, and quality concerning the manufacturing process for specific goods and services. Inventory optimization is maintaining the proper amount of inventory to satisfy demand, function as a safety net in case of unforeseen disruption and prevent an unnecessary surplus. Inventory optimization is an agile approach that, at its finest, can anticipate and plan for risk and opportunity in addition to responding promptly to it. According to the SAP HANA solution, OEE (overall equipment effectiveness) evaluates equipment availability, production performance, and product quality elements to determine manufacturing productivity. By isolating and determining the root cause, OEE measurement and reporting are essential for attributing equipment-based losses to their source (s). Real-time and historical plant performance measurement and analysis are made possible by this component, which is part of the SAP MII core solution package. Utilizing popular manufacturing data sources, SAP OEE generates metrics that let you assess the equipment's performance and availability and the caliber of the commodities it produces.

5. Application of IOT and 6G for the Improvement of Production and OEE

Table 20.1 show the overall equipment effectiveness (OEE) is the benchmarking and baseline method to measure OEE and understand the utilization of a manufacturing operation or piece of equipment used in production factories. OEE is the most accurate way to understand the performance, capacity, and qualitative attributes of production units and calculate manufacturing productivity.

Table 20.1 Benchmarked OEE scores with applications of ML, QML and Digital Twins [4] [17]

OEE Scores	Benchmarks	Recommendations
100%	Perfect Production	Recommended to make a best practice
85%	World Class Scores	Absolutely recommended for long term goals
60%	Fair Discrete Manufacturing Agency	Highly recommended and best for industrial innovations
40%	Poor Score	Need serious improvements for digital solutions and AI, ML and Quantum Information sciences

Through instrumentation and analytics, the Internet of Things (IoT) assists manufacturing industry agencies in improving their OEE evaluation by providing a detailed understanding of equipment performance. Several of the critical factors of IoT-based industrial automation improve the OEE score:

(a) Capable of understanding and analyzing historical data related to maintenance planning, scheduling, and resource allocations in real-time.
(b) Advance notification of the predictive maintenance, failure notices, and downtime-related events at equipment and machines.
(c) Ability to lower the cost of labor, raw materials, and supplier costs and increase equipment availability to greater extents.
(d) Monitored and managed the production quality, availability, and performance of equipment in shop floor activities.
(e) Manage and monitor the industrial equipment, which helps the production process, calibration, temperature, speed, and production time of the machines.
(f) Better management of supply chain processes and the planning and operational activities of industrial manufacturing.
(g) Increase the OEE score effectively and in real-time.

6. Proposed Advanced Architecture in Digital Manufacturing Sites

Figure 20.4 depicts an advanced OEE architecture in smart factories that can be scaled up and deployed across manufacturing sites and are well-integrated with SAP Digital manufacturing cloud solutions. It also provides real-time integration with back-office functions (SAP S/4 HANA or legacy solutions). This will aid in managing innovative factory applications and shop floor activities, as well as providing a wide range of digital automation services in manufacturing facilities.

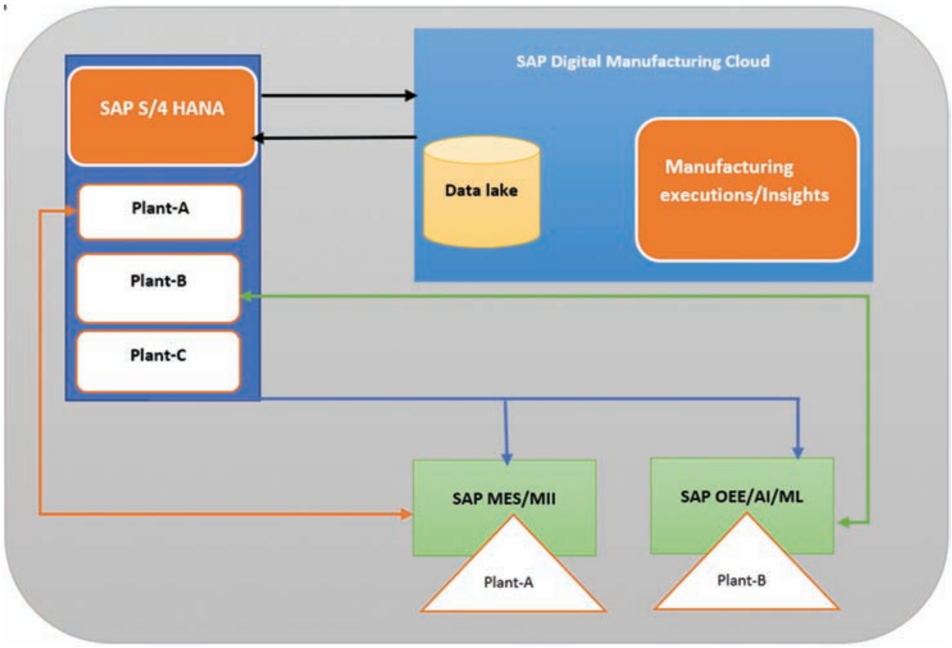

Fig. 20.4 SAP OEE advanced architecture diagram in industrial manufacturing sites

7. Conclusions

In the industrial revolution and smart manufacturing facilities, high-end enterprise resource planning systems like SAP S/4 Hana MES play a vital role and can manage the production efficiencies along with the high rate of OEE in industrial manufacturing sites. OEE score can be easily achieved with the help of the best machine learning tools and modeling them to gain the highest prediction score in real-time. The machine learning-based model could be the most effective, predictive, and more effective solution to support complex manufacturing problems and support the industry 4.0 revolutions and the decision-support processing in enterprise businesses in the production and supply chain industries. Our paper focuses more on the digital trends applicability to manufacturing and industrial solutions that could potentially save costs achieve the scope and understand the need for real-time effectiveness of OEE, qualitative factors, and production losses, as well as support to prevent breakdowns and preventive maintenance downtimes for the industrial equipment that is engaged in the production sites. We have also explained various ways to focus on and leverage the vital critical availabilities of manufacturing process sets and optimize the application of AI, ML, and quantum computing in production sites to gain the highest score of the OEE. It is demonstrated that using virtual sensor solutions and AI, ML-based IIOTs, and VS can reduce predictive maintenance, preventive maintenance, and machine downtime due to the goodness of a machine learning model (Djezeri, 2020; Kuo, 2011). ML can also help mitigate unfavorable production breakdowns by increasing equipment availability and effectiveness and predicting the best qualitative score most reliable for the production units.

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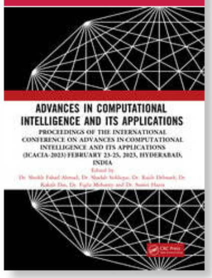

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