

Digital Twin-Based Mathematical and Deep Learning Framework for Sustainable Employee Behavior Management in Industrial IoT Environments

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Abstract

Energy consumption, safety, productivity, and resource utilization are affected by operational behavior in the Industrial Internet of Things (IIoT) and sustainable cooperation between humans and machines requires human-machine coordination. This study introduces a novel Digital Twin Based Mathematical and Deep Learning Framework (DT-MDLF) that combines five parameters – equipment utilization, energy consumption, safety compliance, task completion efficiency, and idle operation ratio. The mathematical sustainability predictions are achieved by merging a composite mathematical sustainability index with a lightweight deep-learning model to predict the operational behaviour states and to guide sustainability-oriented interventions. The performance of the framework is compared to a threshold-based and standalone deep-learning strategies through a numerical evaluation performed on 100 employee-workstation Digital Twins during 30 days. The proposed DT-MDLF resulted in 22.6% reduction in energy consumption, 27.4% reduction in using idle operations, 96.3% compliance with safety rules, 93.1% task completion efficiency and reduction of sustainability cost from 0.68 to 0.42. The results illustrate the viability of the framework for human-machine coordination in such an IIoT environment, for resource efficiency, safe operation, and sustainability.

Keywords: Digital Twin, Industrial Internet of Things, Deep Learning, Sustainable Employee Behavior, Human-Machine Coordination, Mathematical Modeling

1. Introduction

Industrial Internet of Things (IIoT) has revolutionized the concept of smart manufacturing by allowing a continuous flow of interactions between humans, machines, sensors, communication systems and digital management platforms. In these interconnections, the interaction between employees and worksites plays a crucial part in shaping industrial sustainability, impacting areas like energy consumption, equipment usage, safety protocols, task completion, and general resource efficiency. Energy saving in equipment operation, minimizing unnecessary downtimes, properly using workstations and safety measures are thus crucial in the sustainability of industrial operations. In

digital twin technology, computational representations of these dynamic physical and operational states offer a valuable tool to create a model for continuous evaluation of human–machine interactions. But industrial monitoring systems are mostly conceived as separate systems, each focusing on one of the following monitoring goals: machine performance, energy usage, worker productivity, safety, and operational efficiency. This lack of a cohesive monitoring framework hampers the potential to establish linkages between the different behavioural, operational and sustainability metrics and to convert expected future scenarios into effective management actions. Furthermore, the behaviour of employees when operating has not been sufficiently integrated with the Digital Twin model, sustainability indicators are often assessed individually without a common mathematical format and approaches based on prediction are not always accompanied by a decision-making mechanism. Digital Twins, mathematical sustainability modelling and light-weight deep learning for employee–workstation management in IIoT systems are therefore not sufficiently explored.

To overcome these limitations, this study presents a framework that involves a Digital Twin-based mathematical and deep learning framework (DT-MDLF) to capture the dynamic status of employees and workstations and to determine the next operational state. The key contributions are a five-parameter Digital Twin representation considering utilization of equipment, energy consumption, safety compliance, task completion efficiency and idle operation ratio, a unified mathematical sustainability model, a light deep-learning architecture for the prediction of the behavioral-state and a decision framework assessed by five sustainability-oriented performance metrics in various IIoT operating conditions.

2. Related Work

The Digital Twin (DT) technology is an emerging part of Industrial Internet of Things (IIoT) and represents a dynamic simulation of a physical object or process [1]. In smart manufacturing, DT systems facilitate condition monitoring, production supervision, resource management, energy management, operational optimization etc. via cyber-physical synchronization [2]. The majority of industrial DT applications have focused on machine/equipment health, production systems and process level performance [3]. Few studies, however, have been aimed at integrated representations of human–machine operational states, especially the interaction between human and workstations with industrial resources [6].

Collaboration between humans and machines is a key feature that continues to be gaining importance in human-centred manufacturing, as per Industry 4.0 and Industry 5.0. Employee – workstation interactions may impact safety compliance, equipment utilization, how energy is used, efficiency of task completion, and excess idle operation [7]. Hence, the behavior of the employees in this context is seen as measurable operational interactions with the industrial resources and work stations and not as a direct individual monitoring [8]. Traditional methods, however, mainly study human factors, safety, productivity and resource utilization in isolation [13].

In general, mathematical sustainability models offer quantification approaches to appreciate the performance of industries by composite sustainability indices, multi-criteria formulations, energy-efficiency indicators, equipment-utilization measures, weighted decision models, cost of operation functions, and constrained optimization [9]. Initial mathematical evaluations, however, can miss out on being able to capture dynamic operational-state changes [10]. Neural networks and multilayer perceptron configurations have been used to predict industrial processes, classify operational states, detect anomalies, assess workstations, and provide predictive information for decision making, among others [4]. Operating variables can be correlated by deep learning but predicting states is not enough to translate to action that can make a difference for sustainability [14]. The IIoT concept together with the proposed DT-MDLF and its integration of a Digital Twin representation, employee–workstation behavioral modeling, mathematical sustainability assessment, lightweight deep-learning prediction, and decision support, motivates the researchers to develop presented DT-MDLF [11], [12], [15].

3. Proposed Digital Twin-Based Mathematical and Deep Learning Framework

3.1 Overall Framework Architecture

DT-MDLF combines Operational monitoring, mathematical sustainability assessment, prediction and decision support in IIoT. It starts with five parameters of the employee-workstation: equipment

utilization (EU), energy consumption (EC), safety compliance (SC), task completion efficiency (TC) and the idle operation ratio (IR) as demonstrated in Figure 1. The parameters are preprocessed and normalized, then used to construct the employee-workstation Digital Twin state, $DT_i(t)$, representing pair i at decision interval t . The output of the model is fed into the lightweight deep learning prediction module built with the given 5–32–16–8–1 MLP architecture. The model is able to calculate the operational behavior state and classifies it as sustainable, moderately sustainable or unsustainable. The predicted behaviour state is further passed to the layer for sustainability-related decision. The framework recommends an optimal operational action based on the state of the Digital Twin and mathematical assessment of sustainability, and anticipates the state of the system at any given time from the set of possible actions. Selected action can simply no change in the ongoing operating condition or can give a recommendation for the use of resources, or it can suggest a resource management adjustment in the operating schedule or a supervisory review. Lastly, the new operational state is added to the Digital Twin state update. The feedback connection shown in Figure 1 provides an opportunity to use the updated state as the basis for the next decision interval, which produces a circle closed (closed-loop) computational model for continuous sustainability-oriented employee–workstation management.

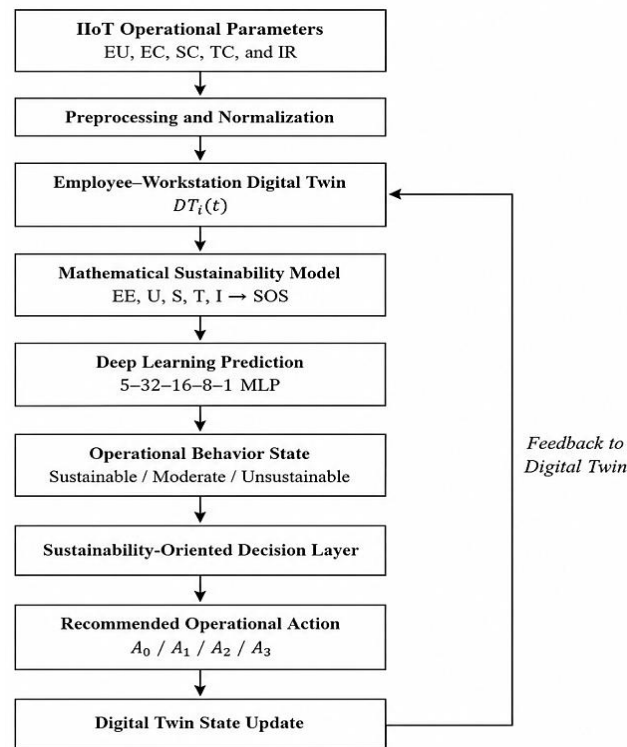


Figure 1. Architecture of the Proposed DT-MDLF.

3.2 Input Parameters and Digital Twin State Representation

The proposed DT-MDLF will represent each employee-workstation combination based on 5 operational parameters, selected so that they represent resource utilization, energy behavior, safety, productivity and unnecessary equipment operation. The 5 major inputs can be summarised as follows: equipment utilisation (EU), energy consumption (EC), safety compliance (SC), task completion efficiency (TC), and idle operation ratio (IR) as shown in table 1 below. The given operating ranges give numerical limits for the creation of and evaluation of Digital Twin states for the given operating conditions of IIoT.

Table 1. Primary Input Parameters and Operating Ranges

Parameter	Symbol	Operating Range
Equipment utilization	EU	40–95%
Energy consumption	EC	1.5–8.0 kWh/shift
Safety compliance	SC	60–100%

Task completion efficiency	TC	50–100%
Idle operation ratio	IR	0–35%

For employee–workstation pair i , the Digital Twin state at decision interval t is represented by the five-dimensional state vector given in **Equation (1)**:

$$DT_i(t) = [EU_i(t), EC_i(t), SC_i(t), TC_i(t), IR_i(t)], \quad (1)$$

In **Equation (1)**, $EU_i(t)$ denotes equipment utilization, $EC_i(t)$ represents energy consumption, $SC_i(t)$ indicates safety compliance, $TC_i(t)$ represents task completion efficiency, and $IR_i(t)$ denotes the idle operation ratio. Consequently, $DT_i(t)$ provides a compact numerical representation of the current employee–workstation operational condition. The five inputs are in widely varying ranges and units and min–max normalization was performed by using Equation (2) to get comparable numerical scales.

$$x_{i,k}(t) = \frac{x_{i,k}(t) - x_k^{min}}{x_k^{max} - x_k^{min}}, \quad k = 1, \dots, 5, \quad (2)$$

where $x_{i,k}(t)$ represents the k -th operational parameter, while x_k^{min} and x_k^{max} denote its lower and upper operating limits defined in **Table 1**. For equation (2) it is sufficient to transform each parameter to lie within the range $[0,1]$ so as to keep similar numerical ranges with the same relative operational variations. The normalized Digital Twin state is then given by Equation (3):

$$\widetilde{DT}_i(t) = [EU_i^N(t), EC_i^N(t), SC_i^N(t), TC_i^N(t), IR_i^N(t)], \quad (3)$$

All five normalized parameters are kept in the Digital Twin representation and then provided to the mathematical sustainability assessment and deep-learning prediction phases (as shown in Equation (3)). The Digital Twin is upscaled on a regular basis at a specified 30-minute interval, and the changes in the equipment utilization, energy usage, safety, task completion, or idleness are mirrored in the next states. If the operations vary from one interval to the next, this creates a sequence which changes over time,

$$\widetilde{DT}_i(t) \rightarrow \widetilde{DT}_i(t+1),$$

In contrast to considering an employee/workstation arrangement as fixed. The updated 5-dimensional state is fed to the 5–32–16–8–1 MLP and the classified state and selected action are fed back through Figure 1 for the next sustainability assessment.

3.3 Mathematical Sustainability Model

The mathematical sustainability model normalizes the five employee–workstation inputs and then overlays them together and produces Sustainable Operational Score (SOS). The energy-efficiency indicator is modeled as in Equation (4):

$$EE_i(t) = 1 - \frac{EC_i(t) - EC_{min}}{EC_{max} - EC_{min}}, \quad (4)$$

A lower value of energy consumption in equation (4) is more favourable with respect to the energy-efficiency value. The terms EC_{min} and EC_{max} represent the minimum and maximum energy-consumption limits defined for the considered operating range. The utilization of the equipment is expressed by the indicator as given in Equation (5):

$$U_i(t) = \frac{EU_i(t)}{100}, \quad (5)$$

The equipment utilization is normalized in (5) using the range $[0,1]$ and a higher value represents that it is more utilized. Equations (6) represent the safety indicator:

$$S_i(t) = \frac{S_i(t)}{100}, \quad (6)$$

A safety-compliance percentage higher than 100% results in a high normalized safety score as per Equation (6). Likewise, the task-efficiency indicator is obtained from Equation (7):

$$T_i(t) = \frac{T_i(t)}{100}, \quad (7)$$

The efficiency of task completion is normalized in equation (7) and a value of closer to 1 suggests greater efficiency. The idle-efficiency indicator is expressed as in Equation (8):

$$I_i(t) = 1 - \frac{IR_i(t)}{100}, \quad (8)$$

The idle-operation ratio is a parameter appearing in Equation (8) and a lower ratio leads to a higher idle-efficiency score, thus guaranteeing the same interpretation for all five sustainability indicators: the larger the value, the more favorable the operating condition. The five normalized indicators are combined into the Sustainable Operational Score (SOS) as in Equation (9):

$$SOS_i(t) = w_1 EE_i(t) + w_2 U_i(t) + w_3 S_i(t) + w_4 T_i(t) + w_5 I_i(t), \quad (9)$$

The sustainability oriented employee–workstation state is presented in a unified mathematical manner in equation (9). The weighting coefficients w_1 to w_5 control the relative contribution of energy efficiency, equipment utilization, safety, task efficiency, and idle efficiency, respectively. The coefficients satisfy the constraint indicated in Equation (10):

$$\sum_{j=1}^5 w_j = 1, \quad w_j \geq 0, \quad (10)$$

The weighting vector is given in Equation (11) for the initial evaluation:

$$[w_1, w_2, w_3, w_4, w_5] = [0.25, 0.15, 0.25, 0.20, 0.15], \quad (11)$$

The energy efficiency and safety standards are more important factors in Equation (11) than the task efficiency, equipment utilization and idle efficiency. These are not universal weights but initial weights, as they may not apply to every situation and are explored in Section 5.5. Therefore, the mathematical model turns the five heterogeneous DT-MDLFs into one consistent sustainability score that can be fed to the following mathematical deep-learning prediction and decision stages.

3.4 Deep Learning-Based Behavior Prediction

The deep-learning part of the suggested DT-MDLF will predict the operational sustainability state of each of the DTs of the employees–workstation by following the five normalized parameters as defined in section 3.2. To keep computation complexity low and yet having a sufficient nonlinear modelling capability, a lightweight multilayer perceptron (MLP) is used. The network architecture takes the form of Equation (12)

$$5 \rightarrow 32 \rightarrow 16 \rightarrow 8 \rightarrow 1, \quad (12)$$

There are five input neurons, three hidden layers with 32, 16, and 8 neurons and one output neuron; the whole structure is shown in Fig. 2. The input vector that is given to the MLP at decision interval (t) is normalized as shown in Equation (13):

$$X_t = [EU_t^N, EC_t^N, SC_t^N, TC_t^N, IR_t^N], \quad (13)$$

The features in Equation (13) match with the 5D-dimensional Digital Twin representation, and the features are normalized according to Equation (2) before feeding into the network. Forward propagation: Each hidden layer applies learned weights, biases and the RU (rectified linear unit) activation function to its input. The hidden representation of layer (l) is equal to:

$$h^{(l)} = \text{RELU}(W^{(l)}h^{(l-1)} + b^{(l)}), \quad (14)$$

where $W^{(l)}$ and $b^{(l)}$ represent the trainable weight matrix and bias vector of layer l , respectively. The initial hidden-layer input is $h^{(0)} = X_t$. The final prediction is obtained using the sigmoid output function given in Equation (15):

$$\hat{y}_t = f_{\theta}(X_t) = \sigma(W^{(4)}h^{(3)} + b^{(4)}), \quad 0 \leq \hat{y}_t \leq 1, \quad (15)$$

where θ represents the complete set of trainable network parameters. Equation (15) yields a continuously predicted sustainability-state score for which there is no binary label. The value is then classified into three operating modes based on.

$$State_t = \begin{cases} \text{Unsustainable}, & 0 \leq \hat{y}_t < 0.40 \\ \text{Moderately Sustainable}, & 0.40 < \hat{y}_t < 0.70, \\ \text{Sustainable} & 0.70 \leq \hat{y}_t \leq 1 \end{cases} \quad (16)$$

Therefore, the output of the continuous network is transformed into the three operational categories needed by the DT-MDLF decision layer, as specified by Equation (16). The Adam optimizer is used with a learning rate of 0.001, a batch size of 32 and a number of training epochs of 100 for training the MLP. The architecture, accordingly, is kept at 5–32–16–8–1, and the numerical evaluation is performed throughout the duration. To track the convergence and generalization, training and validation sets are employed, and the performance of the prediction is evaluated through accuracy, precision, recall, F1-score and AUC. In Section 3.5, this predicted operational-state value is input to the sustainability-oriented making decision mechanism, as shown in Figure 2, which connects the five normalized inputs with the hidden layers and finally to the predicted operational-state value.

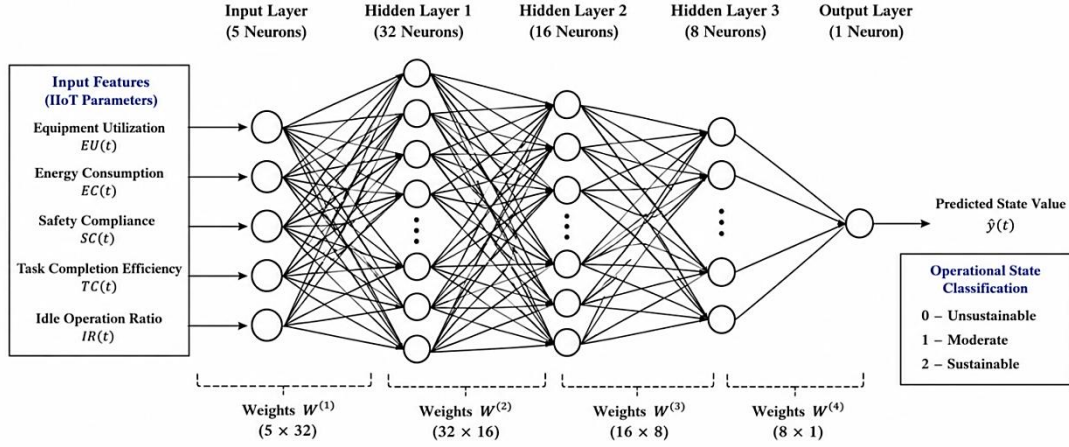


Figure 2. Deep Learning Prediction Structure of the Proposed DT-MDLF.

3.5 Sustainability-Oriented Decision Model

The sustainability oriented decision model transforms the forecasted operating condition into an action based on the existing SOS, the existing resource condition and the required operation. The resulting closed loop from prediction and action selection to execution and updating of the Digital Twin is shown in Figure 3, which includes a finite number of discrete actions that can be selected, as defined in Equation (17):

$$\mathcal{A} = \{A_0, A_1, A_2, A_3\}, \quad (17)$$

In Equation (17), A_0 maintains current operation, A_1 recommends resource-use improvement, A_2 adjusts the operational or task schedule, and A_3 initiates supervisory review when substantial sustainability, safety, or operational deviations occur. An operational sustainability cost function is defined in Equation (18) to quantitatively assess the actions of the candidates:

$$J(A, t) = \alpha C_E(A, t) + \beta C_I(A, t) + \gamma C_S(A, t) + \delta C_T(A, t) + \lambda C_A(A, t), \quad (18)$$

where C_E represents the energy-related cost, C_I denotes the idle-operation cost, C_S represents the safety-deviation cost, C_T denotes the task-inefficiency cost, and C_A represents the cost associated with implementing a particular intervention. The coefficients α , β , γ , δ , and λ determine the relative importance of these components and satisfy the normalization constraint

$$\alpha + \beta + \gamma + \delta + \lambda = 1, \quad \alpha, \beta, \gamma, \lambda \geq 0, \quad (19)$$

All of the parameters in Equation (19) are positive and their sum equals 1 to ensure that there are no uncontrolled scale-up or scale-down of the composite operational cost. In each decision interval the DT-MDLF considers the possible actions and chooses the one with the lowest corresponding sustainability cost, as per Equation (20):

$$A_i^*(t) = \arg \min_{A \in \mathcal{A}} J_i(A, t), \quad (20)$$

With the chosen action, Equation (20) guarantees the best energy efficiency, idle operation, safety compliance, task efficiency, and need for interventions for the condition the aircraft is operating in. The decision is not made based on one parameter or a fixed threshold, but rather is based on the mathematical sustainability assessment as well as the operational state predicted by the MLP. As shown in **Figure 3**, execution of $A_i^*(t)$ influences the operational parameters observed during the subsequent interval. This new state can be drawn as

$$DT_i(t+1) = [EU_i(t+1), EC_i(t+1), SC_i(t+1), TC_i(t+1), IR_i(t+1)], \quad (21)$$

These new parameters, in Equation (21) are preprocessed and normalized before the old Digital Twin state is replaced. This creates the feedback path shown in Figure 3, where $DT_i(t+1)$ becomes the input state for the next **30-minute decision interval**. It, therefore, acts in an iterative manner instead of delivering one single static suggestion and is adaptable to changes in the behavior of the employee–workstation operating conditions over multiple intervals during the sustainability assessment, prediction of behavior and decision process.

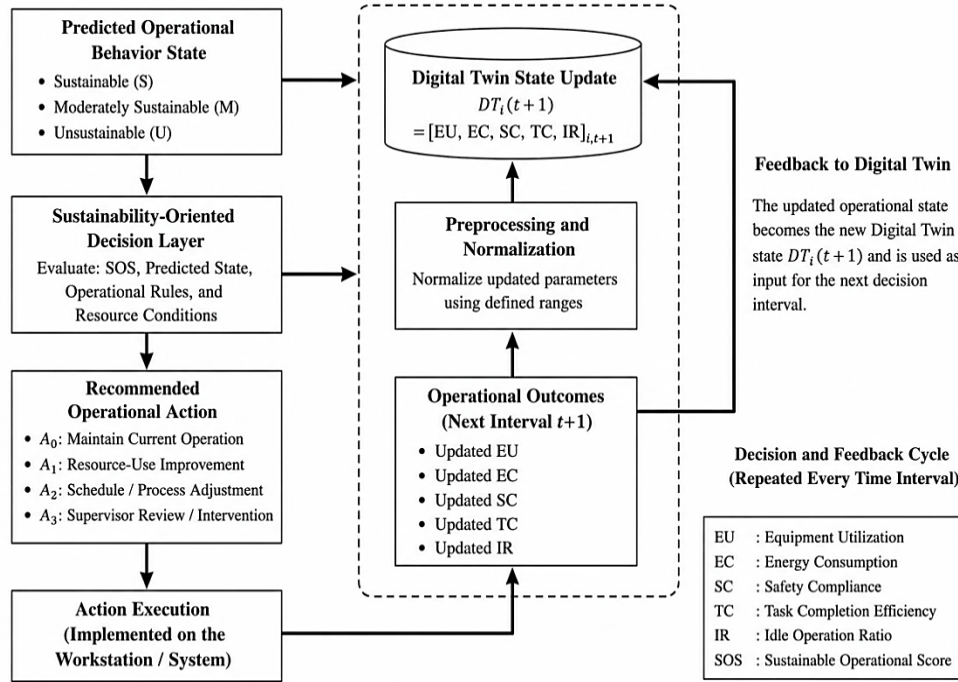


Figure 3. Digital Twin Decision and Feedback Mechanism

4. Numerical Evaluation Methodology

The proposed DT-MDLF was tested using a controlled computational framework to investigate their performance on the decision-making aspects while operating under various conditions of the IIoT and predicting its sustainability. The implementation was done in Python, TensorFlow/Keras for the 5–32–16–8–1 MLP, NumPy and Pandas for numerical processing, SciPy for computational analysis and Matplotlib for visualization of results. A total of 100 employee–workstations Digital Twins were evaluated for a 30-day period, with 3 shifts of 30 minutes in the day, and a 30-minute interval for updating the Digital Twin. To minimize reliance on any one operating sequence, the evaluation conditions were evaluated for over 30 repetitive computational runs each.

Operating States were created within the ranges defined in Table 1 for the equipment utilization (EU), energy consumption (EC), safety compliance (SC), task completion efficiency (TC) and idle operation ratio (IR). At every update interval, the resulting five-dimensional state was normalized using Equation (2), incorporated into $DT_i(t)$, and processed by the mathematical sustainability and deep-learning components. The operating scenarios were Normal, Moderate and High variation. Normal is relatively stable; Moderate adds in larger fluctuations; and High makes for more severe simultaneous changes in the five Digital Twin inputs. The numerical perturbation levels are specified in table 2.

Table 2. Numerical Evaluation Scenarios and Parameter Variations

Parameter	Normal	Moderate	High
Equipment utilization (EU)	±5%	±10%	±15%
Energy consumption (EC)	±5%	±12%	±20%
Safety compliance (SC)	±3%	±6%	±10%
Task completion efficiency (TC)	±5%	±10%	±15%
Idle operation ratio (IR)	±5%	±12%	±20%

As can be seen in Table 2, High variation yields the greatest perturbations, notably in energy consumption and idle operation. None of the values are out of the Table 1 operating ranges. Four approaches were evaluated in the same conditions and with the same MLP: B1: threshold-based without fixed limits; B2: with only the Digital Twin prediction without feedback from the Digital Twin and without the whole mathematical sustainability-cost decision mechanism; B3: Digital Twin prediction without full mathematical sustainability-cost decision mechanism; and B4: the proposed

approach, which integrates Digital Twin state, SOS, prediction, sustainability-cost evaluation, selection of sustainability decisions, and feedback in the MLP. The Energy Consumption Reduction (ECR) is the amount of energy reduction compared to baseline, and can be calculated from Equation (22):

$$ECR = \frac{EC_{base} - EC_{proposed}}{EC_{base}} \times 100, \quad (22)$$

Energy Consumption Reduction (ECR) is calculated as the energy saved compared to baseline (see Equation (22) below). The definition for Idle Operation Reduction (IOR) is given in Equation (23).

$$IOR = \frac{IR_{base} - IR_{proposed}}{IR_{base}} \times 100, \quad (23)$$

Higher values of IOR are thus signs of a better reduction of unnecessary workstation idle operation. The Safety Compliance Rate (SCR) is an assessment of the percentage of operational instances that meet the requirements for safety and is given by Equation (24):

$$SCR = \frac{N_{safe}}{N_{total}} \times 100, \quad (24)$$

where N_{safe} denotes the number of safety-compliant operational instances and N_{total} represents the total evaluated instances. A higher SCR means that the machine is running in a safer manner, that meets the safety requirement. The Task Completion Efficiency (TCE) is used to assess productive task performance based on the equation of Equation (25):

$$SCRed = \frac{J_{base} - J_{proposed}}{J_{base}} \times 100, \quad (25)$$

In Equation (26), J_{base} represents the sustainability cost obtained using the baseline approach, while $J_{proposed}$ represents the corresponding cost obtained using DT-MDLF according to the cost formulation introduced in Equation (18). The higher the value of the SCRed, the better the reduction in the combined energy, idle-operation, safety-deviation, task-inefficiency, and intervention costs will be. Hence, the five above-mentioned system-level evaluation metrics have been applied consistently in the following results analysis, namely ECR, IOR, SCR, TCE and SCRed. The metrics used to evaluate the predictive action of the MLP are Accuracy, Precision, Recall, F1-Score and AUC, which are considered secondary metrics and not among the five major sustainability metrics.

5. Results and Discussion

5.1 Deep Learning Prediction Performance

The accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC) were used to assess the predictive effect of the deep learning part. The following measures have been quantified to reflect the capability of the 5 – 32 – 16 – 8 – 1 MLP to distinguish between sustainable, moderately sustainable and unsustainable states of operation for the employee and workstation. The prediction performance obtained is shown in Figure 4.

Figure 4 shows that the classification accuracy of the DT-MDLF was 93.2% indicating a high percentage of states evaluated were classified correctly. The macro-precision obtained was 92.5% meaning that number of false-positives was relatively low within the operational-state categories. A macro-recall of 91.8% shows that the model had a good rate of correctly identifying examples of the different sustainability states. The macro-F1 score was 92.1%, which represents a good balance between precision and recall.

The best predictive was the macro-AUC (95.4%-0.954). This result confirms the good discriminative skill of this prediction model for the considered operational states. The range of values from 91.8% to 93.2% for accuracy, precision, recall, and F1-score reinforces this idea, as the metrics do not differ significantly, suggesting a well-rounded predictive performance rather than a metric-driven approach. To verify convergence, training/validation results were observed over the 100 epochs that were defined to develop the model and ensure that a significant difference between training and validation behavior did not occur. The training parameters were the fixed Adam learning rate of 0.001 and batch size 32 for the light weight MLP. The prediction metrics indicate a network capacity that was considered to be adequate to model the relationships between equipment utilization, energy consumption, safety compliance, efficiency of task completion and the idle operation ratio without a significantly deeper network architecture.

The overall results presented in Figure 4 show a consistent prediction of the operational state of the system given the deep learning component for the next DT-MDLF processing. Importantly, these

prediction measures assess only the classification performance of the MLP and cannot in themselves be called improvements to industrial sustainability.

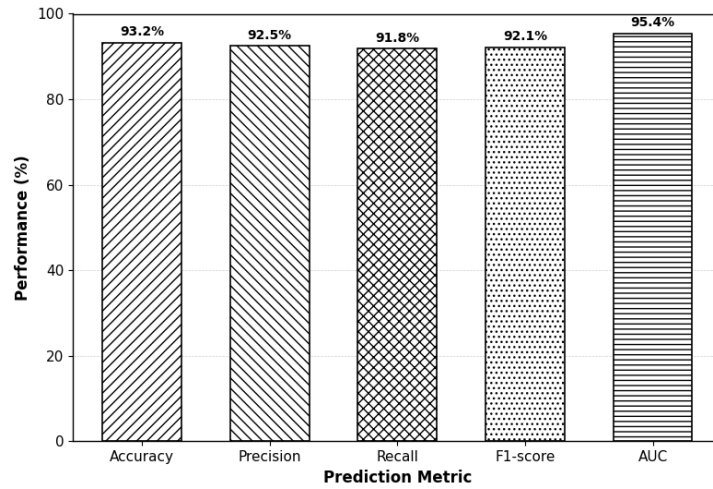


Figure 4. Prediction Performance of the DT-MDLF

5.2 Sustainability Performance Comparison

The effectiveness of the proposed DT-MDLF was compared to the conventional DT approach, DL-only approach, and DT + DL approach at the system level by applying five major evaluation measures described in Section 4.4. The comparison results are shown in Table 3. The results show that the integration of Digital Twin representation, predictive modeling, mathematical sustainability assessment and decision feedback into the management framework results in progressive improvement.

Table 3. Comparative Performance of the Evaluated Methods

Method	ECR (%)	IOR (%)	SCR (%)	TCE (%)	Sustainability Cost
Threshold-based	8.4	11.2	88.6	82.8	0.680
DL only	13.7	17.6	91.5	87.1	0.580
DT + DL	17.1	21.8	93.8	90.4	0.510
Proposed DT-MDLF	22.6	27.4	96.3	93.1	0.420

The proposed DT-MDLF was found to be having an ECR of 22.6% as shown in Table 3, which is lower than 8.4%, 13.7%, and 17.1% for threshold-based, DL-only and DT + DL, respectively. This is equivalent to 14.2 percentage points more energy-consumption reduction, compared to the threshold approach. The proposed framework offers an extra 5.5 percentage points energy reduction compared to DT + DL, which shows the impact of the mathematical sustainability and decision parts. The same tendency is seen when the motors are idling. DT-MDLF's IOR dropped below the threshold-based approach by 16.2 percentage points, and was 5.6 percentage points higher than DT + DL. This finding suggests that closed-loop decision mechanism of the new architecture is able to save unwanted use of workstations more effectively than prediction alone. The operational quality (88.6-96.3, 7.7 percentage-point) and safety compliance (82.8-93.1, 10.3 percentage-point) have been improved compared to the threshold-based management level. The relevance of these outcomes is that they suggest that saving energy use and non-productive operation has not resulted in a decrease in task performance or safety. The proposed framework also generated the least amount of sustainable cost (0.420), as compared to threshold-based management (0.680). The sustainability cost reduction is obtained using Equation (26) as

$$SCRed = \frac{0.680 - 0.420}{0.680} \times 100 = 38.24\%, \quad (26)$$

Therefore, DT-MDLF resulted in a near 38.2% reduction in the composite sustainability cost compared with the threshold based approach. As a whole, the results in Table 3 show that the combination of Digital Twin state representation, mathematical sustainability assessment, deep-learning prediction, and closed-loop decision support yields a fairly balanced improvement for all four criteria (energy efficiency, idle operation reduction, safety compliance, and task efficiency) when compared to the evaluated baseline configurations.

5.3 Energy and Idle-Operation Analysis

The energy and operational performance of the four evaluated approaches is presented in Figure 5 where Figure 5(a) represents the Energy Consumption Reduction (ECR) and Figure 5(b) represents the Idle Operation Reduction (IOR). Each step forward in the framework corresponds to a progressive improvement in the management, from traditional threshold-based approach to total DT-MDLF. As observed in Figure 5(a), the threshold-based approach lowered the ECR by 8.4%, the DL-only approach lowered the reduction by 13.7% and the DT + DL approach lowered the reduction by 17.1%. The proposed DT-MDLF had the highest ECR (22.6%) which improved by 14.2 points over threshold-based management and 5.5 points over DT + DL. This behavior shows that the connection between Sustainable Operational Score and the decision mechanism with the state information of the Digital Twin allows for more efficient identification of the operational conditions that are not energy efficient. This is similar to the improvement seen for unnecessary equipment running. The results show that IOR for the DL-only and DT + DL approaches were 17.6% and 21.8% respectively, higher than that of the threshold-based management approach of 11.2% as shown in Figure 5(b). The complete DT-MDLF achieved an IOR of 27.4%, which is 16.2 percentage points better than the DT based method and 5.6 percentage points better than DT + DL. The improvement is caused by the periodic analysis of equipment utilization, energy usage, task efficiency and idle-operation conditions via the Digital Twin feedback loop. If an undesirable operating state is detected, the decision layer can suggest either the adjustment of the level of resource usage or a schedule of operational state changes, applicable to subsequent intervals, but not continuing unnecessary equipment operation.

The trends in the Figure 5 show that prediction alone yielded the greatest improvement with both metrics as both metrics demonstrated improvements over fixed thresholds; integration of the Digital Twin provides state awareness; and closed-loop decisions with the mathematical sustainability assessments provide the greatest reduction.

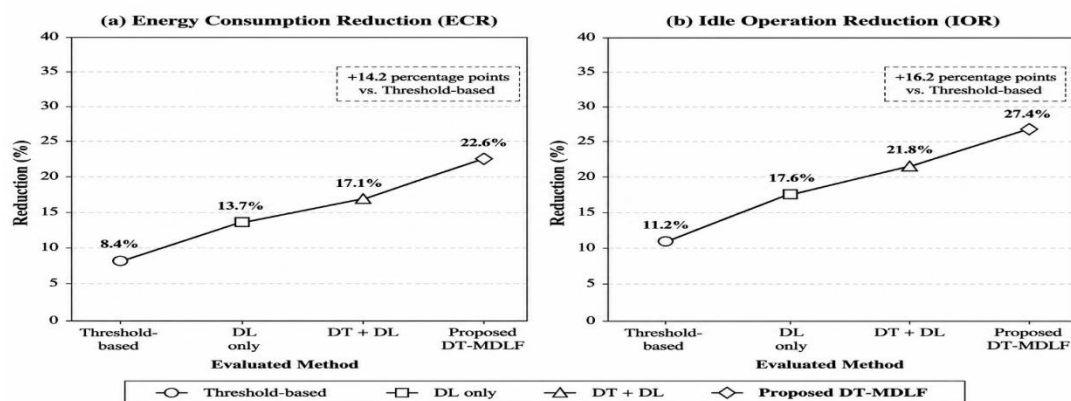


Figure 5. Energy and Operational Performance Comparison of the Evaluated Methods.

5.4 Safety and Task-Efficiency Analysis

The proposed DT-MDLF, in addition to reducing energy consumption and unnecessary machine idle, was also assessed for its ability to keep the task performance and its safety level as they are with an intervention which is sustainable. From the comparison results presented in Table 3, the proposed approach obtained the highest value of Safety Compliance Rate (SCR) of 96.3%, whereas the DL-only and the threshold-based approaches obtained the result of 91.5% and 88.6%, respectively, and the DT + DL approach obtained 93.8%. This is equal to a 7.7 percentage point improvement on the threshold-based management and 2.5 percentage point improvement on DT + DL. The findings show that the sustainability-oriented decision process does not focus on reducing resources separately from operations' safety.

A similar improvement was observed for Task Completion Efficiency (TCE). The TCE results were DT-MDLF (93.1%), threshold based (82.8%), DL only (87.1%) and DT + DL (90.4%). So, the proposed framework led to an increase of 10.3 percentage points in comparison to the threshold management whereas 2.7 percentage points ahead of DT + DL. The findings suggest that there was not a significant reduction in productive use of the workstation with either intervention for energy reduction or idle operation reduction. These results are of special interest in conjunction with the ECR and IOR figures of 22.6% (c) DT-MDLF) and 27.4% (c) DT-MDLF), respectively. The goal of the framework is then not just to reduce the use of resources, but to keep a balance in the operations which is suitable, conceptually represented as:

$$\text{Energy Efficiency} \leftrightarrow \text{Safety} \leftrightarrow \text{Task Efficiency}, \quad (27)$$

When energy-saving actions have a negative impact on safety compliance and/or task execution, they are considered to be undesirable as expressed in Equation (27). This trade-off is considered in the sustainability cost function defined by the energy, safety-deviation, task-inefficiency, idle-operation and intervention components in Equation (18). This means that an action resulting in a reduction in energy consumption but with too much safety or productivity penalties is given a less than desirable overall SC. As a result, DT-MDLF provides greater levels of safety and task completion, and lower levels of energy use and idle operation, enabling joint, not single, optimization of sustainable performance of the employee-workstation system.

5.5 Sensitivity and Robustness Analysis

The sensitivity of sustainability weights, input variations, scenario severity, and DT-MDLF update interval on the stability of DT-MDLF was tested. The baseline sustainability weights in Equation (11) [0.25, 0.15, 0.25, 0.20, 0.15] were each perturbed by $\pm 10\%$ and $\pm 20\%$, and the other ones were subsequently scaled proportionally to maintain the constraint in Equation (10). The resulting Sustainable Operational Score (SOS) for the convenient weight perturbations of $\pm 10\%$, respectively $\pm 20\%$, was found to be varying by about $\pm 3.6\%$, respectively $\pm 6.9\%$. Nevertheless, the proposed DT-MDLF had the lowest sustainability cost of the four evaluated approaches, suggesting that the relative performance of the proposed DT-MDLF was not sensitive to a particular weighting configuration.

Increased perturbations in the five inputs and predicted state and SOS across the Normal, Moderate, and High scenarios in Table 2 led to increased variability in these measures. The percentage of repeated runs with framework choosing the same sustainability oriented action when in similar states (decision consistency) stayed above 88.6 percent for all three variations, Normal (95.2 percent), Moderate (92.4 percent) and High (88.6 percent). It is expected that the reduction under severe variation will be because the energy consumption, utilization, safety, task efficiency and idle operation are expected to vary also at the same time which increases the probability of transitions between the neighboring operational states.

The sensitivity of 15, 30, and 60 minutes update-intervals was compared. The participants reported that keeping the update time at 15 minutes was more responsive but also heavier on the processor and a 60 minute update time was less responsive but less heavy on the processor, making 30 minutes a good compromise. The ranking of the evaluated approaches was the same and relative changes in the overall SOS were less than about 5% when the update interval was varied around around the baseline configuration.

Input-level perturbation analysis also revealed that DT-MDLF remained stable for the varying the five operational parameters within the ranges specified for the three scenarios. The changes in the sustainability cost were found to be comparatively strong due to the fact that both measures of resource-efficiency and decision objective are directly affected by energy consumption and idle operation. Safety compliance also had a significant influence as those safety deviations that are unfavorable are assigned a relatively high weight in the mathematical sustainability model. The variations of the overall score were more moderate for equipment utilization and task efficiency.

The overall sensitivity analysis does suggest that the proposed DT-MDLF is reasonably stable when the weighting coefficients, operational parameters and the severity of the scenarios and the frequency of updates are varied by moderate amounts. While a larger uncertainty may cause more variation in SOS, and maybe even rearrange energy performance rankings in the operational actions, the framework maintains the overall ranking in energy performance, compliance with safety regulations, task efficiency, and reduction in idle operation. The findings confirm that the proposed decision

mechanism is stable under the computed conditions of IIoT, and not just for one specific set of decision parameters.

6. Conclusion

This research was an effort to develop DT-MDLF model for sustainable employee–workstation management in IIoT. All of them are implemented in the Digital Twin, which adopts EU, EC, SC, TC, IR, a mathematical model is formed from the normalized indicators of the Digital Twins into the SOS, the mathematical model is lightweight and has 5–32–16–8–1 structure, which predicts the state of operation of the Digital Twin, and a closed loop decision mechanism selects and returns appropriate actions.

In numerical evaluation, DT-MDLF achieved 22.6% ECR, 27.4% IOR, 96.3% SCR, and 93.1% TCE, while sustainability cost decreased from 0.680 to 0.420, a 38.2% reduction. The MLP achieved 93.2 per cent accuracy and 0.954 macro-AUC, while sensitivity analysis also maintained the same ordering of the models despite changes to the weights, inputs, the severity of the scenarios and the frequency of updates. These results show that it is possible to achieve improvements in resource-efficiency without sacrificing safety or the productivity performance of tasks, within the operating conditions for the IIoT. However, there are a few limitations in this study. The evaluation was limited to the controlled computational IIoT operating conditions and the Digital Twin representation limited to five measurable operational indicators. Current mathematical representation did not consider complex psychological, organizational, ergonomic and social factors that affect employee behavior. The connections between large worker groups, between several interdependent machines and between production-line dependencies were also not specifically represented. Moreover, industrial integration and validation of deployment in a longitudinal model were not investigated in the present study and the findings mentioned should be viewed as computational evidence and not as a confirmation of the performance in the deployed industrial facilities.

Future research and development work should address integration with physical IIoT, industrial validation over time, stream of real-time sensor information, weighting of assets for sustainability, multi-worker/multi-machine twins, operational modelling while preserving privacy and human-in-the-loop validation, and more complex uncertainty-aware optimization for practical and scalable sustainable industrial coordination.

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