Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 253 (2025) 3015–3024

Procedia Computer Science

www.elsevier.com/locate/procedia

6th International Conference on Industry 4.0 and Smart Manufacturing

Enhancing Maintenance Operations in Industry 5.0: A Conceptual User Interface Design for Task Assignment

Ludovica Oliveri[a], Ferdinando Chiacchio[a], Nazareno Lo Iacono[a], Micaela Vitti[b], Francesco Facchini[b]

[a] *Dipartimento di Ingegneria Elettrica, Elettronica ed Informatica, University of Catania, Via Santa Sofia 64, 95123, Catania, Italy*
[b]*Department of Mechanics, Mathematics and Management, Polytechnic University Of Bari, Via Orabona 4, 70126, Bari, Italy*

Abstract

The Fifth Industrial Revolution, or Industry 5.0, fosters an innovative, resilient, competitive, and society-centered industry. This era emphasizes enhanced human-machine interactions, enabling individuals to manifest their creativity through personalized products and services. As smart factories evolve, the demand for flexibility and adaptability necessitates increased cognitive efforts, particularly in maintenance tasks critical to the flexibility of production systems. Despite the potential of emerging technologies like Augmented Reality and Artificial Intelligence to aid operators, the complexity of tasks combined with the novelty of such technologies can overwhelm workers, thereby impacting workplace well-being. To tackle these challenges, the DESDEMONA project, funded by the European Union through PRIN as part of NextGenerationEU, is developing a Decision Support System (DSS). This system aims to provide real-time suggestions for assigning the most suitable operators for maintenance tasks characterized by high cognitive demands. The DSS considers three primary factors: the operator's profile (including skills and age), their emotional state, and the availability of smart devices. This manuscript details the project's initial results, presenting a simplified mathematical model capable of ranking the optimal list of operators. To demonstrate the effectiveness of the DSS, it is compared, through a simulation approach, with a simulated maintenance supervisor. This comparison highlights the system's ability to identify, from the k-permutations of N operators, the number of optimal tuples that best fit the operational needs.

© 2025 The Authors. Published by Elsevier B.V.
This is an open access article under the CC BY-NC-ND license (https://creativecommons.org/licenses/by-nc-nd/4.0)
Peer-review under responsibility of the scientific committee of the 6th International Conference on Industry 4.0 and Smart Manufacturing

Keywords: Decision Support System; Industry 5.0; Maintenance; Cognitive demand; Emotional state.

**Corresponding author. Tel.: +39-095-7382404.*
E-mail address: ludovica.oliveri@phd.unict.it

1877-0509 © 2025 The Authors. Published by Elsevier B.V.
This is an open access article under the CC BY-NC-ND license (https://creativecommons.org/licenses/by-nc-nd/4.0)
Peer-review under responsibility of the scientific committee of the 6th International Conference on Industry 4.0 and Smart Manufacturing
10.1016/j.procs.2025.02.026

1. Introduction

The advent of Industry 5.0 marks a paradigm shift towards a more human-centred approach in industrial operations, emphasizing the importance of well-being, creativity, and personalized experiences in the workplace [1]. Unlike its predecessor, Industry 4.0, which primarily focused on integrating cyber-physical systems and the Internet of Things (IoT) to enhance productivity and efficiency [2], Industry 5.0 aims to harmonize advanced technologies with human skills and well-being. This evolution is particularly significant in sectors where workers' cognitive and physical demands are high, such as maintenance operations. Maintenance tasks in industrial settings are often complex and carry substantial risks to health and safety [3]. Ensuring that operators are well-trained and in an optimal psychophysical state is crucial for minimizing these risks. An experienced operator who is fatigued is more likely to make errors than a less experienced but well-rested and cognitively sharp operator. Therefore, enhancing the well-being of maintenance operators is paramount to improving safety and efficiency in industrial environments.

The significance of this work lies in addressing one of the critical challenges faced in modern smart factories: the cognitive load associated with complex maintenance tasks. As smart factories become increasingly automated and interconnected, the role of human operators remains vital, particularly in maintaining and troubleshooting sophisticated machinery. However, these tasks often demand high cognitive engagement, leading to mental fatigue and potential errors, which can compromise safety and productivity. By developing a Decision Support System (DSS) that optimizes task assignment based on operators' cognitive load, this research contributes to the broader goal of enhancing human-machine interactions in Industry 5.0. Effective human-machine collaboration is essential in mitigating the cognitive demands placed on operators, ensuring that maintenance tasks are performed efficiently while safeguarding the well-being of workers. The DESDEMONA project addresses these challenges by proposing a system that not only considers the technical skills required for tasks but also the cognitive and emotional state of operators, thereby fostering a more resilient and adaptive industrial environment.

The DESDEMONA project, funded by the European Union through PRIN as part of NextGenerationEU, addresses this need by developing a Decision Support System (DSS) designed to optimize task assignment in maintenance operations. This DSS aims to provide an easy-to-use tool for maintenance supervisors, facilitating their decision-making process by considering the tasks' complexity and the operators' skills, workload, and psychophysical state. By integrating these factors, the DSS ensures that maintenance tasks are assigned to the most suitable operators, thereby enhancing both productivity and operator well-being.

This manuscript details the initial results of the DESDEMONA project, presenting a simplified mathematical model capable of ranking the optimal list of operators for maintenance tasks. To demonstrate the effectiveness of the DSS, it is compared with a simulated maintenance supervisor using a simulation approach. This comparison highlights the system's ability to identify, from the k-permutations of N operators, the number of optimal tuples that best fit the operational needs.

The structure of the paper is as follows: section 2 provides a brief history of DSS and their applications, with particular attention to human resource management and maintenance operations; Section 3 presents the preliminary elements of the mathematical model; Section 4 introduces the interface and the main functionalities of the platform. Thus, the results of a simulation campaign are presented to demonstrate the effectiveness of the DSS compared to a simulated maintenance supervisor. Finally, section 5 discusses the results and outlines the next research steps.

2. Research context

Decision Support Systems (DSS) have evolved significantly since their inception in the 1960s [4]. Initially developed to assist in managerial decision-making [5], DSS are computer-based systems that help users make informed decisions by compiling useful information from raw data, documents, personal knowledge, and business models [6]. The primary goal of DSS is to enhance the decision-making process by providing relevant data and tools to analyze and visualize this data effectively.

DSS has been widely implemented across various fields. In Table 1, below are collected some applications of DSS and the algorithms utilized. In the realm of Human Resource Management (HRM), DSS are used to optimize the allocation of human resources. These systems consider various inputs to assign tasks effectively. For example, the paper [7] discusses using data mart analysis to incorporate employee skills, availability, and past performance into the decision-making process. Additionally, the paper [8] highlights the integration of psychological factors such as job satisfaction into HR DSS. Maintenance management is also a critical area in which DSS can play a pivotal role. Efficient task assignments in maintenance can significantly reduce downtime and increase the lifespan of equipment. However, literature on DSS specifically designed for maintenance management, particularly those incorporating real-time data and operators' cognitive load, is sparse. Several studies have explored DSS in various maintenance contexts:

- Predictive Maintenance: Utilizing machine learning algorithms to predict equipment failures and schedule maintenance proactively [9].
- Resource Allocation: Using optimization algorithms to allocate maintenance resources efficiently [10].
- Scheduling: Implementing heuristic algorithms to schedule maintenance tasks effectively [11].

Table 1. Some applications of DSS and the algorithms used.

Field of application	Algorithm used	References
Finance	Neural Networks	[12], [13], [14]
Agriculture	Fuzzy C-Means, Fuzzy logic, Partial Least Squares Regression (PLSR)	[15], [16], [17]
Supply Chain Management	Linear Programming, ALOHA Algorithm, Heuristic Techniques	[18], [19], [20]
Environmental Management	Genetic Algorithms	[21]
Maintenance	Fuzzy Analytic Hierarchy Process	[10]
	ML Algorithm	[11]
Industry 4.0	Analytical Framework	[22]
Human Resource Management	Data Mart Analysis	[7]
	Genetic Algorithm, MUSA	[8]

Despite these advancements, there is a noticeable gap in the research regarding DSS that assigns maintenance tasks in real time based on the cognitive load of operators.

Our research addresses this gap by proposing a DSS that dynamically assigns maintenance tasks considering the real-time cognitive load of operators. This approach ensures not only the efficient distribution of tasks but also the well-being of the maintenance staff, which is crucial in high-stress industrial environments. This novel approach aims to enhance both operational efficiency and human factors in Industry 5.0 settings.

3. Model Requirements

The developed Decision Support System (DSS) will aim to assist maintenance managers in effectively assigning maintenance tasks to available operators to minimize each operator's cognitive workload (CWL). The following key requirements have been identified:

1. **Task-Skill Matching Matrix**: The system must link maintenance tasks to the required skills, allowing assessment of operator suitability.
2. **Operator-Skill Assessment**: Operators are scored on their relevant skills to determine their capability for specific tasks.
3. **Cognitive Workload Classification**: Each task is classified by its cognitive workload level (CWL) to ensure proper distribution of tasks based on mental effort.
4. **Preliminary Task Allocation**: The system should generate an initial task allocation based on operator-task matching.
5. **Final Task Allocation Considering CWL**: Task assignments are adjusted to balance CWL across operators, considering past workloads.
6. **User-Friendly Interface**: The platform must provide an intuitive interface for easy task assignment and operator management.

Unlike conventional methods, this system will jointly consider the characteristics of both the operators and the maintenance tasks. This approach aligns with the Industry 5.0 paradigm, which prioritizes human well-being in redesigning production systems [23].

To assign maintenance activities to the available operators, the decision-maker can use the DSS in two distinct modes: the default mode and the customized mode. In the default mode, the decision-maker will use information related to maintenance tasks and operators' skills preloaded into the software, sourced from surveys previously conducted by the authors. In the customized mode, the decision-maker will make personalized assessments of different variables. In presenting the model requirements, the system will be described assuming the default use mode, although the scenario to be evaluated can be customized by varying the system's parameters.

The decision-maker's use of the DSS will mainly involve 3 phases (intended as the steps required to carry out a complete assignment process).

The objective of the first phase, i.e., the preliminary task-operator assessment, is to define the degree of suitability of each of the available operators to perform a specific maintenance task. Notably, within this work's scope, tasks are assumed to be elementary operations (e.g. inspection of a hydraulic circuit, checking a fluid level in a tank, filter replacement, etc.) that constitute a complex maintenance activity. The information shown at this stage will be arranged in three matrices, shown in Figure 1.

As can be seen, the first matrix of the DSS (Fig. 1a) is based on the combination of a set of maintenance tasks T_z (z = 1, 2,…, n) and of key operator skills affecting correct task execution f_j (j = 1, 2..., m). They will be identified based on evidence from the literature and according to the opinion of industry experts, so they will be preloaded in the DSS and cannot be changed by the decision maker. The matrix will also show the assessment of the impact of operator skills on correct task execution $Ev(f_j,T_z)$. This value will be obtained as a weighted average of the individual scores provided by industrial experts responding to a survey conducted by the authors and will then be preloaded into the DSS.

	f_1	f_2	f_3	f_m	$CWL(T_z)$
T_1	$Ev(f_1,T_1)$	$Ev(f_2,T_1)$	$Ev(f_3,T_1)$	$Ev(f_m,T_1)$	$CWL(T_1)$
T_2	$Ev(f_1,T_2)$	$Ev(f_2,T_2)$	$Ev(f_3,T_2)$	$Ev(f_m,T_2)$	$CWL(T_2)$
T_n	$Ev(f_1,T_n)$	$Ev(f_2,T_n)$	$Ev(f_3,T_n)$	$Ev(f_m,T_m)$	$CWL(T_n)$

(a)

	f_1	f_2	f_3	f_m
Op_1	Op_1f_1	Op_1f_2	Op_1f_3	Op_1f_m
Op_2	Op_2f_1	Op_2f_2	Op_2f_3	Op_2f_m
Op_s	Op_sf_1	Op_sf_2	Op_sf_3	Op_sf_m

(b)

T_z	f_1	f_2	f_3	$Ev(Op_k,T_z)$
Op_1	$Op_1Sc_{1,z}$	$Op_1Sc_{2,z}$	$Op_1Sc_{3,z}$	$Ev(Op_1,T_z)$
Op_2	$Op_2Sc_{1,z}$	$Op_2Sc_{2,z}$	$Op_2Sc_{3,z}$	$Ev(Op_2,T_z)$
Op_s	$Op_sSc_{1,z}$	$Op_sSc_{2,z}$	$Op_sSc_{3,z}$	$Ev(Op_s,T_z)$

(c)

Fig. 1. Information required in the DSS for the first phase (a) task-skills matrix; (b) operator-skills matrix; (c) evaluation of the degree of suitability of each operator in performing the z-th task.

However, under the assumption of a customized use mode, it is possible for the decision-maker to determine, in his own opinion, the importance that each skill has on the correct accomplishment of each task. In correspondence with each of the identified tasks, an evaluation will also be reported on its objective CWL class ($CWL(T_z)$), i.e., very low CWL, low CWL, medium CWL, high CWL, and very high CWL. It will be defined based on the assessment of the objective complexity of maintenance tasks, obtained, for example, by calculating its information content following the Task Complexity Index (TACOM) [24]. In this case, since this result comes from the application of an analytical model, it will not be possible for the decision maker to change the value of the $CWL(T_z)$. The second and third matrices illustrated during the first phase serve instead to define the characteristics of the available operators (Fig. 1b) and the degree of suitability of each in the execution of the z-th task (Fig. 1c). Specifically, in the second matrix, the decision-maker will need to define the characteristics of each of the available operators Op_k ($k = 1, 2, ..., s$) by scoring them according to the degree to which the individual operator possesses the j-th skill (Op_kf_1, Op_kf_2, ... Op_kf_j) (e.g., 0 indicates a poorly operator's skill). Notably, in this case, the decision-maker must enter the variables, as they must reflect the specific industrial situation analyzed. Finally, in the third matrix, the DSS will allow the decision maker to know the degree of suitability of each operator in performing the z-th task. In particular, the DSS will carry out a combinatorial $Op_kSc_{j,z}$ evaluation, which will simultaneously take into account the degree of possession of the j-th skill by the k-th operator and the relative importance of the j-th skill on the successful performance of the z-th task. Finally, the DSS will combine the operator's ratings for the individual skills and define the overall suitability degree $Ev(Op_k,T_z)$.

The second phase, i.e., the preliminary maintenance activity allocation, aims to provide the decision-maker with a preliminary list of maintenance activity allocations considering the suitability of available operators. The information displayed in this phase is illustrated in Figure 2. First, the decision-maker will need to select the tasks composing each maintenance activity (Fig. 2a). Based on the previously processed information, the DSS will then construct, for each maintenance activity A_p ($p = 1, 2, ..., r$), a matrix containing evaluations from each operator and a preliminary allocation list (Fig. 2b). This will be achieved through information processing using a multi-attribute utility analysis methodology, such as TOPSIS [25]. As can be observed, in the second phase, a preliminary allocation is made without considering the CWL associated with each activity. The objective of the third phase, i.e., the final allocation of maintenance activities, is to modify the preliminary allocation list to minimize the CWL to which each operator is subjected. The information illustrated in this final phase is depicted in Fig. 3.

(a)

✓	T_1
✓	T_2
✓	T_n

(b)

A_p	T_1	T_2	T_n	Preliminary allocation
Op_1	$Ev(Op_1,T_1)$	$Ev(Op_1,T_2)$	$Ev(Op_1,T_n)$	*
Op_2	$Ev(Op_2,T_1)$	$Ev(Op_2,T_2)$	$Ev(Op_2,T_n)$	*
Op_s	$Ev(Op_s,T_1)$	$Ev(Op_s,T_2)$	$Ev(Op_s,T_n)$	*

Fig. 2. Information required in the DSS for the second phase (a) selection of the tasks that constitute the A_p activity to be assigned; (b) matrix for the preliminary allocation of the A_p activity.

A_p	Preliminary allocation	TP_1	TP_2	TP_3	TP_c	Final allocation
Op_1	*	$CWL(Op_1,TP_1)$	$CWL(Op_1,TP_2)$	$CWL(Op_1,TP_3)$		*
Op_1	*	$CWL(Op_2,TP_1)$	$CWL(Op_2,TP_2)$	$CWL(Op_2,TP_3)$	$CWL(A_p,TP_c)$	*
Op_1	*	$CWL(Op_s,TP_1)$	$CWL(Op_s,TP_2)$	$CWL(Op_s,TP_3)$		*

Fig. 3. Matrix for the final allocation of the A_p activity.

As can be observed, in this final phase, previously obtained information is combined with input from the decision-maker. First, the definitive allocation list for each activity is provided considering the CWL to which each operator has been subjected in the three previous periods (TP_q, $q=1,2,3$) and the CWL of activity A_p being assigned for the current period (TP_c). It is worth noting that the $CWL(A_p)$ is derived as the maximum CWL among the tasks comprising the activity. Therefore, if A_p consists of three tasks with $CWL(T_z)$ of "medium," "low," and "very low," the $CWL(A_p)$ will be "medium." In this case, the decision-maker will provide data on the CWL to which each operator has been subjected in previous periods ($CWL(Op_kTP_q)$) or, alternatively, import data stored on the platform regarding previous assignments, and the DSS will provide the modified allocation list.

4. DESDEMONA Platform

Maintenance tasks in industrial operations are diverse and often highly specialized. They can be grouped into broader categories called activities, which are associated with specific maintenance fields. The maintenance of these complex systems requires a precise allocation of skilled operators to specific tasks.

Each maintenance task has a set of required features that define the competencies needed to perform it successfully. On the other hand, operators can possess the required features to accomplish the tasks and, for this reason, must be ranked accordingly. Figure 4 presents a draft of the platform interface. This minimal design makes it possible to carry out the steps discussed in Section 3. The idea is to simplify the use of the application, allowing the person responsible for the maintenance operations to have only all the functionalities required on one screen.

The proposed DSS within the DESDEMONA project is designed to meet the critical requirements outlined in Section 3. By leveraging a task-skill matching matrix, operator skill assessment, and cognitive workload (CWL) management, the DSS ensures that tasks are optimally assigned to operators. This approach minimizes the cognitive load on operators, thereby improving safety and efficiency in maintenance operations. The platform's user-friendly interface further enhances the decision-making process by providing a clear and intuitive way for supervisors to manage complex maintenance tasks. Together, these features ensure that the DSS effectively addresses the challenges of task complexity and operator well-being, aligning with the goals of Industry 5.0.

The maintenance supervisor can select among potential industrial sectors (Oil & Gas, Wind Power Plant, etc.); in this way, the tile "Activities" will show the maintenance tasks that characterize this field. For each activity of the field maintenance sector, it is possible to extend the menu tile and visualize each potential task that constitutes the activity (Figure 4a). In this way, the maintenance supervisor can select the tasks scheduled for that maintenance activity, that is the information required by the model in the matrix of Fig. 2a. Moreover, for each task of each activity – as discussed in Fig. 1a, $Ev(f_j, T_z)$ – it will be possible to modify the information regarding the features required that are initially retrieved from a database (Figure 4b).

In order to determine the correct operators' ranking, the platform presents within the same interface the list of the operators (retrieved from a database); in this way, the maintenance supervisor can select among the available ones (by using the tick/untick checkbox option). As shown in Figure 5a, the card associated with each operator shows the average score obtained as the mean of his/her features. Also, in this case, the maintenance supervisor can change the desired features (Figure 5b) before inquiring about the platform for the optimal operators' ranking. This corresponds to compiling the information of the matrix of Fig.1b, $Op_k f_j$ where Op_k can be constituted by several task T_z.

By clicking the button "Run Scenario", DESDEMONA will perform the algorithm to populate the information of the matrices of Fig.1c, Figure 2b and of the optimal operators' ranking of Figure 3.

(a) (b)

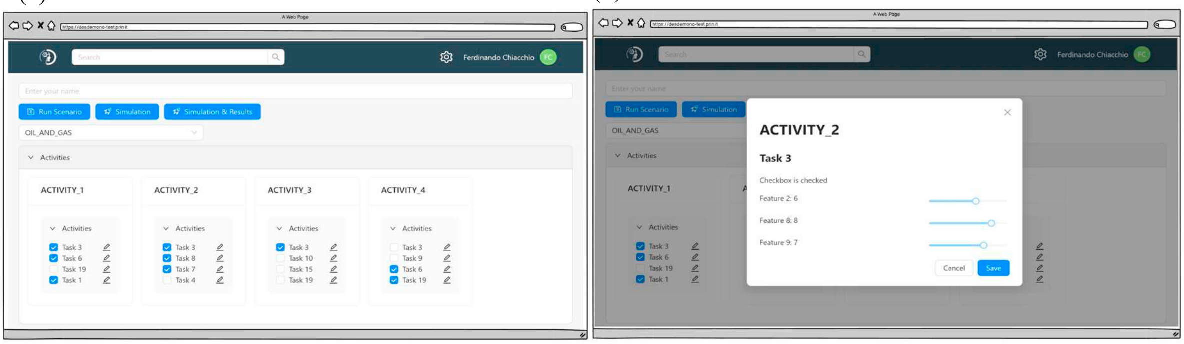

Fig. 4. Interface of DESDEMONA: (a) detail of the tasks and (b) feature values that the user can modify

4.1. Optimal Ranking Algorithm

This section presents the optimal ranking algorithm adopted in the project's current version, designed to select optimal operators for maintenance activities. As discussed in Section 3, the algorithm leverages a feature-based matching system, integrating task requirements with operator capabilities, to derive an optimal assignment. This approach ensures a deterministic yet efficient allocation of human resources in complex maintenance scenarios, optimizing performance and ensuring task completion with the highest quality and safety standards.

The DSS algorithm has been developed to address the selection of the optimal operators by systematically evaluating their skills against the ones related to each task and selecting the optimal set of operators for all maintenance scenarios that can be constituted by several activities and tasks.

(a) (b)

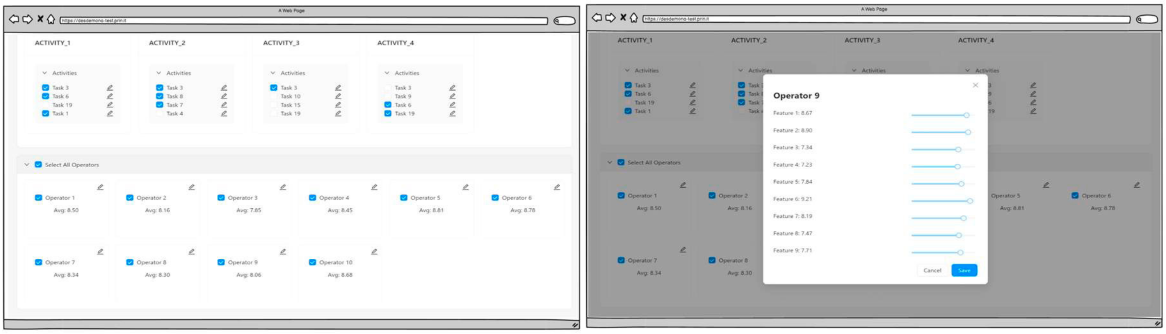

Fig. 5. Interface of DESDEMONA: (a) detail of the operator's menu and (b) feature values of the operators that the user can modify

Indeed, the DSS algorithm operates through a series of steps:

1. Feature Extraction: each task and each operator are modelled, encoding their features into a vector.
2. Feature Mapping and Calculation: extract the required features for each task and compare them with the operator features.
3. Scoring: calculate the differences between task requirements and operator competencies to generate a match score.
4. Aggregation: summarizing the scores across multiple tasks to rank the operators.
5. Selection and ranking: ordering the operators based on their aggregate scores to determine the best fit for the tasks.

Specifically, the Feature Extraction encodes the *n*-task and *m*-operators features (which are stored in a database) into two different groups of vectors that express the required proficiency levels of the different skills.

Formally, let f_j be the feature vector for the operator Op_k and T_z be the feature vector for the z^{th} task. Each element in these vectors represents a specific feature such as technical knowledge, manual dexterity, safety observance, etc.).

In the Feature Mapping and Calculation, each task is broken down into its constituent features, which are mapped to corresponding operator features. The algorithm calculates the difference between each task feature and the corresponding operator feature. This step involves computing:

- The Algebraic sum S_{jz} corresponds to the net difference between operator feature values and task feature values. This indicates the overall match level.
- The Positive Sum (P_{jz}): The sum of positive differences where operator features exceed task requirements. This reflects areas where operators are overqualified.
- The Negative Count (N_{jz}): The number of negative differences where operator features are below task requirements. This highlights deficiencies in the operator's competencies.

Given a task T_z with features $\{f_1, f_2, \ldots, f_m\}$ and an Operator Op_k with corresponding features $\{Op_1, O_2, \ldots, O_s\}$ the differences are calculated as shown in equation 1:

$$\Delta_{ij}(f_j) = Op_k(f_j) - T_z(f_j) \tag{1}$$

Where $\Delta_{ij}(f_k)$ represents the difference between the operator's feature value and the task's required feature value for feature f_k .

The third step of the algorithm assigns scores to operators based on the differences calculated in the previous step. The scores are used to evaluate the suitability of operators for specific tasks. Operators with fewer negative differences and higher positive sums are considered better suited for the tasks. For each operator O_i and Task T_j, it is possible to compute the following indexes:

- Algebraic Sum S_{jz} : $S_{jz} = \sum_{j=1}^{m} \Delta_{ij}(f_j)$ (2)

- Positive Sum P_{jz} : $P_{jz} = \sum_{\Delta_{ij}(f_j)>0} \Delta_{ij}(f_j)$ (3)
- Negative Count N_{jz}: $N_{jz} = \sum_{\Delta_{ij}(f_j)<0} 1$ (4)

The aggregation phase, the fourth step of the algorithm, aggregates the scores across multiple tasks to form a comprehensive evaluation of each operator. This step involves summing the algebraic sums, positive sums, and negative counts for each operator across all tasks they are evaluated against. For a set of tasks $\{T_1, T_2, \ldots, T_z\}$ and an operator Op_k, it is then possible to compute:

- Total Algebraic Sum S_i: $S_i = \sum_{j=1}^{m} S_{jz}$ (5)
- Total Positive Sum P_i: $P_i = \sum_{j=1}^{m} P_{jz}$ (6)
- Total Negative Count N_i: $N_i = \sum_{j=1}^{m} N_{jz}$ (7)

The last step, Selection and Ranking, uses aggregated scores to rank the operators. The ranking process prioritizes operators with the lowest negative counts (indicating fewer deficiencies) and higher algebraic sums (indicating better overall match). The final selection ensures that the best-suited operators are chosen for the tasks. In other words, operators are classified primarily by their negative total count N_i and secondarily by their total Algebraic Sum S_i.

4.2. Simulation Campaign

The primary objective of the proposed simulation campaign is to demonstrate the advantages of using DESDEMONA and benefit from a deterministic optimal ranking algorithm for given maintenance activities. In contrast, human supervisors rely on experience and heuristic approaches, which can be subjective and prone to errors, especially as the number of available operators increases. To illustrate this, it is possible to compare DESDEMONA with an analytical model based on probability theory.

Assuming n operators, there are $n!$ possible permutations of operator rankings. A human supervisor, selecting operators randomly or based on heuristic judgment, has a probability of choosing the optimal ranking by chance as follows: $P_{\text{correct ranking}} = 1/n!$. This model assumes a uniform distribution, implying that each permutation is equally likely. As the number of operators increases, the factorial growth of permutations leads to a rapid decrease in the probability of a correct selection by a human supervisor. For example, with two operators ($n = 2$), there are 2! = 2 possible rankings, leading to a 50% chance (1/2!) for the supervisor to hit the optimal ranking. With three operators (n =3), there are 3! = 6 possible rankings, leading to a 16.67% chance (1/6). Therefore, as n increases, the probability of hitting the optimal ranking decreases exponentially, demonstrating that human supervisors are less likely to make the decision as the number of available operators grows.

A series of simulations were conducted to validate the algorithm's effectiveness, varying the number of available operators from 2 to 10. Each simulation is characterized by 10,000 iterations, where an iteration models a generic maintenance scenario constituted by two main activities with three tasks each. Using the model of equations (1-7), the optimal algorithm can provide a deterministic ranking of operators, compared against a simulated human supervisor's choice. The human supervisor's selections will be modelled using a uniform distribution, reflecting the random nature of their decisions due to the increasing complexity. This experimental design aims to quantify the algorithm's advantage and highlight its practical implications in enhancing the efficiency and effectiveness of maintenance operations. Table 2 shows the simulation results for a maintenance supervisor to select the optimal operators. As shown, the simulation model with 10,000 iterations converges to the theoretical result if the number of operators is less than 7 (in the scenario with five operators, the max relative error is 10.00%). Moreover, as the number of operators grows, the probability of the maintenance supervisor hitting the optimal ranking decreases exponentially, indicating the challenges in decision-making in more complex settings.

The "Optimal Tuples" row shows another interesting result achieved thanks to the simulation approach. It allows identifying, among the k-permutations of N, the number of optimal tuples of operators (with k = 2, 3,…, 10) that have been identified. This demonstrates the model's capability to discern between more or less effective operator groupings and emphasizes the practical utility of simulation in optimizing team structures. In other words, DESDEMONA retrieves the tuples of operators that perform better, regardless of the allocation of maintenance activities and tasks. This represents an important practical result that could significantly influence strategic planning and operational efficiency, providing a clear guide to assembling teams based on their potential for success in various tasks.

Table 2. Simulation results and comparison with theoretical model

Operators	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Simulation Result	50.00%	17.09%	3.96%	0.75%	0.130%	0.010%	0.020%	0.000%	0.000%
Theoretical Result	50.00%	16.66%	4.167%	0.83%	0.1389%	0.0198%	0.0025%	0.0003%	0.00003%
Relative error	0.00%	-2.54%	4.96%	10.00%	6.40%	49.60%	-706.40%	100.00%	100.00%
Optimal Tuples	66	282	731	1,244	1,458	1,172	583	160	19
Theoretical Tuples	90	720	5,040	30,240	151,200	604,800	1,814,400	3,628,880	3,628,880

5. Conclusions

The DESDEMONA project, funded by the European Union through PRIN as part of NextGenerationEU, addresses the critical need to optimize task assignments in maintenance operations within the framework of Industry 5.0. This Decision Support System (DSS) provides an easy-to-use tool for maintenance supervisors, facilitating their decision-making process by considering not only the complexity of tasks but also operators' skills, workload, and psychophysical state. By integrating these factors, the DSS ensures that maintenance tasks are assigned to the most suitable operators, thereby enhancing both productivity and operator well-being. This novel approach aims to improve both operational efficiency and human factors in Industry 5.0 settings, ultimately contributing to a more resilient, competitive, and society-centered industry.

The DESDEMONA project's initial results demonstrate the DSS's effectiveness through a simplified mathematical model capable of ranking the optimal list of operators for maintenance tasks. A simulation comparison with a simulated maintenance supervisor highlights the system's ability to identify the best fit for operational needs from the k-permutations of N operators. As the number of operators grows, the effectiveness of human decision-making can decrease, thus emphasizing the importance of DSS support. Future research steps will involve further refining the DSS to incorporate more real-time data, integrate cognitive workload features, and refine the mathematical algorithm to ensure its applicability to a broader range of industrial contexts. This ongoing development will ensure that the DSS remains a valuable tool for optimizing maintenance operations and promoting the well-being of industrial workers.

Acknowledgements

Funded by the European Union NextGenerationEU

This research work is part of the activities carried out in the context of the DESDEMONA project (DEcision Support system for the Diagnosis and Evaluation of the Maintenance OperatioNs Activities) of the Italian Ministry for Universities and Research MUR (Project PRIN – CUP D53D2301836 0001) funded by the European Union – NextGenerationEU, component M4C2, investment 1.1.

References

[1] Maija. Breque, Lars. De Nul, and A. Petrides, *Industry 5.0 - Towards a sustainable, human- centric and resilient European industry*. 2021.

[2] E. Oztemel and S. Gursev, “Literature review of Industry 4.0 and related technologies,” 2020. doi: 10.1007/s10845-018-1433-8.

[3] A. P. Wirani, O. Julyanto, and D. A. Kartini, “The Effect of Work Shift on Mental Workload of Maintenance Operator Using Nasa Task Load Index (TLX),” *Journal of Industrial Engineering & Management Research*, vol. 3, no. 3, 2022.

[4] D. J. Power, “A Brief History of Decision Support Systems,” *Decis Support Syst*, vol. 4, no. 1969, 2007.

[5] V. S. Jacob and H. Pirkul, “Organizational decision support systems,” *Int J Man Mach Stud*, vol. 36, no. 6, 1992, doi: 10.1016/0020-7373(92)90074-U.

[6] P. Waller, H. G. Sol, C. A. T. Takkenberg, and P. F. D. V. Robbe, “Expert Systems and Artificial Intelligence in Decision Support Systems.,” *The Statistician*, vol. 37, no. 3, 1988, doi: 10.2307/2348181.

[7] A. K. Hamoud, M. A. Ulkareem, H. N. Hussain, Z. A. Mohammed, and G. M. Salih, “Improve HR Decision-

Making Based on Data Mart and OLAP," in *Journal of Physics: Conference Series*, 2020. doi: 10.1088/1742-6596/1530/1/012058.

[8] I. Aouadni and A. Rebai, "Decision support system based on genetic algorithm and multi-criteria satisfaction analysis (MUSA) method for measuring job satisfaction," *Ann Oper Res*, vol. 256, no. 1, 2017, doi: 10.1007/s10479-016-2154-z.

[9] P. Fantini, M. Pinzone, and M. Taisch, "Placing the operator at the centre of Industry 4.0 design: Modelling and assessing human activities within cyber-physical systems," *Comput Ind Eng*, vol. 139, 2020, doi: 10.1016/j.cie.2018.01.025.

[10] J. Patalas-Maliszewska and S. Kłos, "An approach to supporting the selection of maintenance experts in the context of industry 4.0," *Applied Sciences (Switzerland)*, vol. 9, no. 9, 2019, doi: 10.3390/app9091848.

[11] A. Cimino, M. Elbasheer, F. Longo, L. Nicoletti, and A. Padovano, "Empowering Field Operators in Manufacturing: a Prospective Towards Industry 5.0," in *Procedia Computer Science*, 2022. doi: 10.1016/j.procs.2022.12.395.

[12] N. B. Korade and M. Zuber, "Stock Price Forecasting using Convolutional Neural Networks and Optimization Techniques," *International Journal of Advanced Computer Science and Applications*, vol. 13, no. 11, 2022, doi: 10.14569/IJACSA.2022.0131142.

[13] F. Kamalov, "Forecasting significant stock price changes using neural networks," *Neural Comput Appl*, vol. 32, no. 23, 2020, doi: 10.1007/s00521-020-04942-3.

[14] M. Shahvaroughi Farahani and S. H. Razavi Hajiagha, "Forecasting stock price using integrated artificial neural network and metaheuristic algorithms compared to time series models," *Soft comput*, vol. 25, no. 13, 2021, doi: 10.1007/s00500-021-05775-5.

[15] Z. Zhai, J. F. Martínez, V. Beltran, and N. L. Martínez, "Decision support systems for agriculture 4.0: Survey and challenges," 2020. doi: 10.1016/j.compag.2020.105256.

[16] A. Mishra, P. Praveen, A. Subudhi, S. Majila, and S. Negi, "Advancing agriculture with Industry 5.0-enabled crop-type prediction," in *Infrastructure Possibilities and Human-Centered Approaches With Industry 5.0*, 2024. doi: 10.4018/979-8-3693-0782-3.ch002.

[17] M. Adamu , A. Mayowa , and I. Jonah, "Decision Support System and Fuzzy Logic Controller for Capillary Irrigation System," *American Journal of Computing and Engineering*, vol. 6, no. 1, 2023, doi: 10.47672/ajce.1422.

[18] W. A. Teniwut and C. L. Hasyim, "Decision support system in supply chain: A systematic literature review," 2020. doi: 10.5267/j.uscm.2019.7.009.

[19] A. Pedram, S. Sorooshian, F. Mulubrhan, and A. Abbaspour, "Incorporating Vehicle-Routing Problems into a Closed-Loop Supply Chain Network Using a Mixed-Integer Linear-Programming Model," *Sustainability (Switzerland)*, vol. 15, no. 4, 2023, doi: 10.3390/su15042967.

[20] B. Unhelkar, S. Joshi, M. Sharma, S. Prakash, A. K. Mani, and M. Prasad, "Enhancing supply chain performance using RFID technology and decision support systems in the industry 4.0–A systematic literature review," *International Journal of Information Management Data Insights*, vol. 2, no. 2, 2022, doi: 10.1016/j.jjimei.2022.100084.

[21] J. Pereira, J. Mendes, J. S. S. Júnior, C. Viegas, and J. R. Paulo, "A Review of Genetic Algorithm Approaches for Wildfire Spread Prediction Calibration," 2022. doi: 10.3390/math10030300.

[22] D. Cavallo, S. Digiesi, F. Facchini, and G. Mummolo, "An analytical framework for assessing cognitive capacity and processing speed of operators in industry 4.0," in *Procedia Computer Science*, 2021. doi: 10.1016/j.procs.2021.01.169.

[23] European Commission, "Industry 5.0." [Online]. Available: https://research-and-innovation.ec.europa.eu/research-area/industrial-research-and-innovation/industry-50_en

[24] J. Park, W. Jung, and J. Ha, "Development of the step complexity measure for emergency operating procedures using entropy concepts," *Reliab Eng Syst Saf*, vol. 71, no. 2, pp. 115–130, Feb. 2001, doi: 10.1016/S0951-8320(00)00087-9.

[25] S. Chakraborty, "TOPSIS and Modified TOPSIS: A comparative analysis," *Decision Analytics Journal*, vol. 2, p. 100021, Mar. 2022, doi: 10.1016/j.dajour.2021.100021.