Multicriteria task classification in human-robot collaborative assembly through fuzzy inference

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Multicriteria task classification in human-robot collaborative assembly through fuzzy inference

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Abstract

The advent of new technologies and their implementation in manufacturing is accelerating the progress of Industry 4.0 (I4.0). Among the enabling technologies of I4.0, collaborative robots (cobots) push factory reconfiguration and prompt for worker empowerment by exploiting the respective assets of both humans and robots. Indeed, human has superior dexterity, flexibility, problem-solving ability. Robot excels in strength, endurance, accuracy and is expendable for risky activities. Therefore, task assignment problem in a production line with coexisting humans and robots cannot limit to the workload balancing among workers but should make the most of everyone respective abilities. The outcomes should not be only an increased productivity, but also improved production quality, human safety and well-being. Task assignment strategy should rely on a comprehensive assessment of the tasks from the viewpoint of suitability to humans or robots. As there are several conflicting evaluation criteria, often qualitative, the study defines the set of criteria, their metrics and proposes a method for task classification relying on Fuzzy Inference System to map each task onto a set of collaboration classes. The outcome of the study is the formal description of a set of evaluation criteria with their metrics. Another outcome is a Fuzzy Classification procedure that support production managers to properly consider all the criteria in the assignment of the tasks. The proposed methodology was tested on a case study derived from a manual manufacturing process to demonstrate its application during the process planning.

Keywords Human–Robot collaboration · Task allocation · Industry 4.0 · Fuzzy Inference System

Introduction

The advent of Industry 4.0 (I4.0) marked a disruption with established production management strategies. I4.0 decentralized production control systems and made factories autonomous and smart (Almada-Lobo, 2015). The novelty does not consist in new production methods or tools but in the synergic integration of several technologies belonging to different fields. This has led to the definition of a new paradigm and the identification of key enabling technologies for I4.0. Bibliographic analysis conducted by Bigliardi et al. (2020) shows that the technologies most frequently considered in literature are Smart products, Big Data and Robots. In particular, Robots, with the support of Artificial Intelligence (AI), are fundamental to enable the factory of the future. They make possible a different kind of automation characterized by flexible collaborative cells where humans and robots work side-by-side. These new collaborative work cells are located halfway between manual and fully automated ones (Michalos et al., 2010). Human-Robot Collaboration (HRC) allows at the same time flexibility, efficiency and quality (Chen et al., 2014; Faccio et al., 2019). Nonetheless, HRC is an opportunity to exploit the added value of humans in the value chain in order to guarantee quality and robustness of the production system (Nardo et al., 2020). To make the most of human factors, employees' well-being, satisfaction, safety, and other needs cannot be ignored either

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when designing work cells or in task allocation (Simões et al., 2022; Tausch et al., 2022). These aspects become crucial for the advent of a fruitful collaboration between human and robot. Indeed, HRC can be declined in several ways, according to ISO/TS 15066: co-existence of humans and robots with spatial or temporal separation, and collaboration in a shared workplace. The main problem is the conflict between operational efficiency and safety requirements (Bauer et al., 2016). There are other obstacles hindering the full application of HRC in factory: safety issues, psychological distress or cognitive overload of human worker, need for a reorganization of the operational procedures. Present study addresses the last issue, reorganization of operations, with the belief of also improving the human factors. The work reorganization in HRC implies the allocation of tasks to humans and robots to leverage their reciprocal assets. In turn, task allocation should be based on a preliminary classification of the tasks that indicates which operator is preferable and whether the task is to be performed individually or in collaboration (Gjeldum et al., 2022). Once the tasks have been classified, their allocation can be performed according to company goals: cycle time reduction, workload reduction, cost reduction, workspace layout optimization. Several task assignment strategies have been proposed in literature, extending standard methods based on optimization of cycle time. As an example, Bänziger et al. (2020) propose a genetic algorithm to optimize the task allocation in HRC. Tasks that can be performed alternatively by human or robot and their execution time are calculated using with MTM (methods-time measurement), after they are brought back to a standardized description. The underlying hypothesis is that human and robot are interchangeable and that the task is executed by one operator per time. Cesta et al. (2018) organize the work to distribute the workload evenly among operators and to correct for temporal uncertainties due to human freedom and unpredictable robot breakdowns. Gjeldum et al. (2022) recognize that the allocation problem is multicriteria and propose a decision support system to find the best compromise solution. In last years, some authors started to take into account the difference between human and robot in executing a task. Ranz et al. (2017) proposes capability indicators to assist the task allocation. These indicators are derived by the combination of 25 criteria related to the goals of process time, additional costs and process quality. Bruno and Antonelli (2018) propose the allocation of tasks in order to leverage the respective skills of human or robot, on the basis of 4 performance indicators: dexterity, strength, accuracy, mobility. El Makrini et al. (2019) sets a framework for task allocation of human-robot assembly applications based on capabilities and ergonomics considerations. All the cited studies face the allocation problem assuming that the tasks are pre-classified and dealing with the tasks where both robot and human can alternate in the execution. Indeed, task classification in HRC is not trivial as there is a multiplicity of aspects involved by employing workers as different as human and robot. In the cited papers, task classification is overcome by assuming that an expert production manager has defined in advance which operations are only manual and which can be executed indifferently by humans or robots. Indeed, advances in robotics and the adoption of cobots made task classification no longer a trivial problem. For this reason, Zhang et al. (2021) developed a method to minimize the cost of misclassification in a collaborative workspace. The aspect to consider in the classification of tasks executed by human experts is that their evaluation is subjective and based on their past experience with conventional non-collaborative robots. To overcome this problem, Evangelou et al. (2021) introduce a human-centered framework and a decision-making system based on AI, adapting to unforeseen changes in the workflow. Even in this case, task classification still depends on experts' evaluation, but it can be questioned again during the work. Another limit of existing classifications is their binary nature: a task is suitable to human or to robot or indifferently to both. The evolution of robotics leads to a situation in which robots will be able to carry out all the tasks assigned to humans but with a different degree of skill, sometimes greater and sometimes less. Therefore it would be useful to have a classification method for the tasks complemented with assessing of the suitability level for both human and robot. This way task allocation can be easily revised during the operations on the workplace. With the aim of providing a more objective classification, present paper proposes a list of formal criteria. As the classification is a multi-criteria assessment it is useful to have a measure of confidence in the decision. This outcome can be obtained by adopting a Fuzzy Inference System (FIS) as a decision support system for task classification. Human–Robot collaboration, task classification section introduces the methodology describing the outcome, the proposed indicators and the rules introduced in the Fuzzy Inference System. In Practical application section the developed procedure is applied to a case study. Results and discussions section discusses the results and Conclusion section concludes with recommendations for future works.

Human–robot collaboration, task classification

Methodology used in task allocation

To facilitate the transition from manual assembly to HRC, Mateus et al. (2018) defines a hierarchical model of the work obtained by breaking down the assembly sequence. The work is broken down into activities, then into operations which are ultimately broken down into actions. Tasks conventionally identify the assembly of 2 or more parts, in a complete and independent way. Operations are generic assembly actions and can be used as building blocks in every task. To program the robot, operations must be further decomposed in specific robot actions, like open/close the gripper, move to a point in the workspace, etc. Hierarchical Task Analysis is a method firstly developed in the context of ergonomic studies (Stanton, 2006). Given the hierarchical model, optimal allocation strategy and job execution time of the job can be estimated by using the predetermined time method systems (PTMS) (Mateus et al. 2018). The assignment of tasks in a collaborative production can be either static, i.e., determined before the work begins or dynamic, whenever task allocation is determined during the execution of the work and can be modified from one job to another. These approaches are both subjected to drawbacks: in the static case,outages cannot be remedied and lead to production delays; in the dynamic case, task allocation could be non-optimal and there are higher safety risks. In the context of I4.0, technology supports humans, and cobots serve to perform repetitive, risky activities, or to improve production quality of work. I4.0 affects also, task assignment that shouldn't be oriented to time optimization alone, but also at reducing ergonomic, cognitive and psychological stresses on human operator "machines at the service of humans". All these factors are objects of the present study. It is essential to assess the degree of compatibility of a human/robot operator for a given task because presently either humans or robots can execute most of the tasks but with different level of efficiency. Considering the level of suitability for a task has two immediate consequences: it is possible to manage collaborations between multiple robots and individuals in a more efficient way. In a perspective of dynamic assignment of tasks, it makes the collaboration more flexible and efficient allowing to overcome In perspective, the collaborative team will have the sufficient flexibility to cope with most of the outages that occur during production. In this paper, a specific approach for task classification in a HRC is described. The main contribution of the proposed approach is to complement task scheduling goals (coming from managers) with the regard for human factors: health and well-being, ergonomic and technical limitations operators' skills. Task allocation becomes resilient and capable of dynamically reallocating tasks according to contingency. The method is structured as follows: a job is broken down into tasks and subtasks. For each of them, an information sheet is filled in to provide the basis for subsequent evaluations. When task allocation is forced by safety or technical constraints, veto rules are applied. When allocation is unconstrained, FIS (Mamdani & Assilian, 1975) a decision method based on Fuzzy Logic, evaluates the remaining tasks and assigns them to the most suitable operator , providing an estimate of salience. The algorithm is structured in several steps to evaluate different kinds of tasks, from those requiring specific and exclusive competences of robot (precision or repeatability) or of human-operator (flexibility and dexterity), to those for which both operators can be equally suitable. The information sheet consists of several fields, Where possible every criterium is, corresponding to a measurable physical quantity for sake of objectivity. Some criteria have quantitative values, but their accurate determination is complex or impractical (e.g., the reflectivity index of surfaces) and unnecessary for the sake of task classification. Therefore, they are considered as qualitative criteria. A standard set of task evaluation criteria for HRC has not yet been defined. In Liau and Ryu (2020) the proposed criteria are: economic performance, ergonomic, resource mobilization. Malik and Bilberg (2019) propose a method to differentiate the tasks with higher complexity of handling, mounting, human safety and part feeding from low complexity tasks. They define a set of assembling attributes affecting HRC, that can be grouped as: part complexity, process complexity, human safety. Savino et al. (2020) shows how the ergonomic exposure of workers affect the workforce allocation making use of a quantitative index named Overall Ergonomic Score. Michalos et al. (2018) in a method for planning human robot shared tasks give one of the most exhaustive lists of criteria: robot reach, strength, payload, ergonomic (using NIOSH equation), operation cost, investment cost, floor space, time saturation, fatigue, handling time. All of these criteria are quantitative and have been evaluated in a automotive case study. Unfortunately, in manual production most data are missing. These criteria can be evaluated only approximately. Combining and rearranging all the criteria presented here the following is proposed in Table 1

The choice of these input was made in order to provide useful indications for the evaluation for the following dimensions:

1. Ergonomics and safety,
2. Technical feasibility,
3. Cognitive load and time,
4. Cost and quality.

The use of FIS together with the major use of quantitative inputs is also intended to develop an unbiased objective procedure to determine the task assessment and its allocation. Notwithstanding, FIS cannot guarantee the rigorous respect of health and safety (H&S) standards. Therefore Veto rules have been introduced to enforce current legislation regarding H&S of the worker. Veto rules generate two possible outcomes: an exclusive assignment of the task to the only possible operator or, for those tasks where the skills of both operators are required, a collaborative assignment (HRC). The veto rules, to be evaluated in this order, are as follows:

1. *if* ergonomic risk is present, *then* task is assigned to robot operator (R)

Table 1 List of criteria used for task assessment

Input	Quantitative	Qualitative
Ergonomics (Niosh index)	X	
Safety risk	X	
Required dexterity		X
Technical feasibility(Room lighting)	X	
Technical feasibility(Surface Reflection)		X
Component supply variability		X
Cognitive load (CLAM index)	X	
Time H (human execution time)	X	
Time R (robot execution time)	X	
Quality: errors in the sequence of tasks (TSRE)	X	
Quality level		X

2. *if* task execution is dangerous, *then* task to robot operator (R)
3. *if* task execution is too difficult for robots, *then* task to human operator (H)
4. *if* parts recognition is too difficult for robots, *then* task to human operator (H)

The meaning of the values used in the evaluation of the veto rules, dangerous, difficult, etc., are explained in the Proposed indicators for assessing task allocation section. Whenever veto rules aren't activated, the decision is demanded to FIS that will generate output in the shape of a fuzzy set. It allows to deal with imprecise inputs and still obtain a meaningful response of the system. The indicators used in the evaluation and their FIS implementation are described in depth in the following paragraphs. The implementation of the proposed algorithm was done using Matlab software. Figure 1 provides a graphical interpretation of the workflow.

Mamdani fuzzy inference system applied to task allocation

Fuzzy logic is useful when the boundary between two conditions is not clearly defined and ambiguous (Zadeh, 1988): they could both be true or false at the same time, but with different degrees of significance. Fuzzy logic was implemented

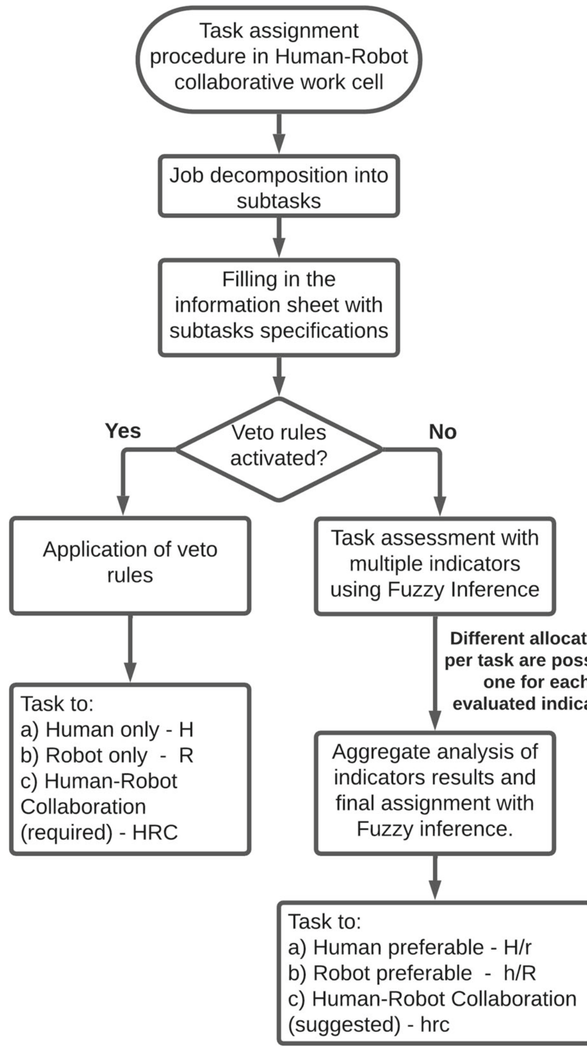


Fig. 1 Flowcahart of the task assignment procedure

for this reason and because of imprecise inputs. Even if data are not precisely defined, they can still be exploited to identify the nature of the situation: fuzzy logic evaluates the scenario with an approximate statement associated to a degree of truth, similar to human reasoning. In addition, fuzzy logic has several advantages: it is easy to implement and balances the precision and relevance of data. FIS is an inference system applying Fuzzy Logic. It replaces the usual numerical scales of the respective inputs and outputs with a set of membership functions (MFs): the fuzzy set. Each MF is denoted by a linguistic variable, and a corresponding degree of strength. Rules in FIS are applied using the "if-then" construct, eventually combined with logical AND/OR operators. An example of a rule may be as follows:

$$if\, X_1 \text{is} W_{11} \textbf{AND} X_2 \text{is} W_{21} \text{then} Y \text{is} Z$$

where X_i and Y are the inputs and output of FIS, W_{i1} and Z are input and output linguistic variables/fuzzy sets, respectively. The degree of fulfillment, is defined as the degree to which the input part of a Fuzzy rule is satisfied. Mamdani FIS was preferred to Sugeno because it is intuitive and has a more interpretable rule base, while Sugeno perform better in problems with high computational loads (Hamam & Georganas, 2008).

Proposed indicators for assessing task allocation

Adopting the terminology proposed by Bruno and Antonelli (2018), the following indicators were used to classify activities in the context of HRC. Each indicator outcome designates the most suitable operator for the specific activity: human-only execution (H), robot-only execution (R), human-preferred execution (H/r),robot-preferred execution (h/R), and human–robot collaboration (HRC). Robots are known to be inexhaustible machines; they can perform tasks with greater accuracy and repeatability than humans, even when transporting heavy loads. Humans, on the other hand, have unmatched dexterity, adaptability and flexibility. These differences must be considered when planning tasks in a collaborative cell, but just because a job is "suitable" for one player does not mean it is not suitable at all for the other. To classify the activities, the indicators need to be defined using their own rating scale. The indicators "Ergonomics & Safety" and "Technical Feasibility" are used in the veto rules as they hinder task execution to humans (due to safety and ergonomics issues) or to robots (due to technological limitations) Other indicators are "Time & Cognitive Load" to quantify the human cognitive load and the working time, "Quality" to express the expected process the indicators are considered in the assessment and classification of the task from the viewpoint of HRC. Table 2, presents the overview of all the criteria employed and where they are described in the paper.

Ergonomics and safety index

Assembly workers are prone to musculoskeletal disorders and at risk of injuries due to the nature of the activities performed. Ergonomics and safety risks have a negative impact on worker health and life quality as well on company economic results and reputation (Wongwien & Nanthavanij, 2017). For this reason, ergonomics and safety in industry are strictly regulated. The technical standard ISO 11228-1 is the reference benchmark and includes the revised NIOSH lifting equation (RNLE) for assessing the suitability of a task for human performance (Waters et al., 1993). The main outcome of the revised NIOSH lifting equation is the recommended weight limit (RWL). The RWL is specified as the maximum weight that a healthy worker can lift without an increased risk of developing lifting-related musculoskeletal disorders. It depends in particular on RWL, whose equation is the following (1):

$$RWL = LC * HM * VM * DM * AM * FM * CM. \quad (1)$$

where,

- LC is the load constant
- HM is the Horizontal Multiplier
- VM is the Vertical Multiplier
- DM is the Distance Multiplier
- AM is the Asymmetric Multiplier
- FM is the Frequency Multiplier
- CM is the Coupling multiplier

More details are provided in Waters et al. (1993). The RWL is used to assess the physical stress associated with a particular manual lifting task calculating the lifting index (LI) as in Eq. (2):

$$LI = \frac{L}{RWL}. \quad (2)$$

L stands for the load to lift in the specific task. If the ratio in Eq. (2) is much lower than 1 there are no risks related to the task, if it is slightly lower than 1 the risk of lower back pain is a possibility, if the value is above 1 the risk is a certainty, the reconfiguration of the task or of the workstation is necessary. The ISO 11228-1 standard does not prescribe any risk bands. They are instead indicated in local regulations, those adopted by UNI EN 1005-2 which are the same used in present study:

1. If $LI < 0.85$: the situation is acceptable, and no specific action is required.
2. If $0.86 < LI \geq 0.99$: the situation is close to the limits; a percentage of the population may be at risk and therefore caution is needed, no immediate intervention is required.
3. If $LI > 1$: the situation represents a risk and therefore requires primary prevention intervention. The higher the index, the higher the risk. There is a need for immediate preventive intervention for situations with an index greater than 3.

In the worst case ($LI > 3$) a veto condition is imposed, and the work must be performed by the robot. In addition to ergonomics, a risk assessment of the task has been carried out. The legislation that governs human safety in the workplace varies by country (for instance, European States use different local rules based on EU-OSHA guidelines, while the United States follow the OSHA standards), and several methods to perform risk assessment are available ranging from expert to participatory methodologies and from simple

Table 2 Overview of employed criteria

Classification criteria	Description
NIOSH index	Ergonomic evaluation (see Ergonomics and Safety index section)
Safety Risk	Safety evaluation (see Ergonomics and Safety index section)
Required dexterity	Dexterity requirement for the task (see Technical feasibility index section)
Room lighting	Feasibility index (see Technical feasibility index section)
Surface reflection	Feasibility index (see Technical feasibility index section)
Components supply variability	Feasibility index (see Technical feasibility index section)
CLAM	Cognitive evaluation index (see Cognitive load index section)
timeH	Task completion time by human (see Cognitive load index section)
timeR	Task completion time by robot (see Cognitive load index section)
TSRE	Risk of task sequence error (see Cost and Quality index section)
Required quality	Quality index (see Cost and Quality index section)

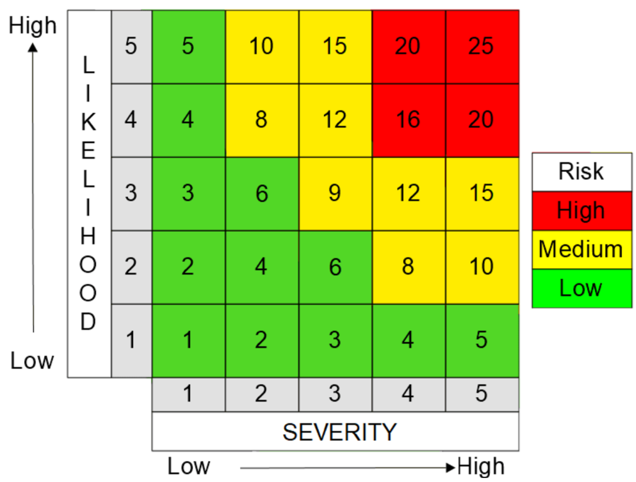


Fig. 2 The 3-level risk estimator matrix used

to complex methods (Guidance, 2022). Even though the regulations implemented may change, the assessment methods are comparable and most of them perform a qualitative risk evaluation rather than quantitative evaluation. Since the former approach is commonly applied in practice (OSHWiki, 2022), also in this paper was decided to adopt the same methodology: the likelihood of injury and the potential severity of the harm has been combined according to a risk matrix, such as the one proposed in British Standard 8800 (British, 2004) and showed in Fig. 2. In this case, three levels of risk are present, but they can vary depending on the application or the needs.

When the tasks are too dangerous to be performed by humans, they are assigned to the robot by default: this is another veto condition. Table 3 summarises the input and the output functions for FI, in Fig. 3 are depicted the membership functions in input and output.

Technical feasibility index

Cobots nowadays have several technical limitations if compared with conventional robots (Michaelis et al., 2020). Commercial cobots are slower than conventional robots and have a lower payload. Most of them cannot be equipped with tool changers. Workspace is limited by the limited extension of the arm. In this paper it was decided to not consider these limitations because it is reasonable to assume that, whenever cobots cannot be employed, there is no need for a task classification procedure. Furthermore, most of the limitations cited here will be released in the future thanks to the continuous developments in the automation industry. Therefore, it is assumed that the tasks subjected to classification be executable by the cobot and that the technical issue, when working with a human, consists in the variable positioning of workpieces. A number of innovative technologies have been proposed to allow cobots to work in a partially unstructured environment: vision systems, laser scanners, LIDARs, etc. The use of such tools increases the flexibility and efficiency of the robot, but requires specific environmental and working conditions to ensure a reliable functioning. Vision systems for cobots are spreading (Matheson et al., 2019) and they likely will become a standard equipment in future generation of cobots. This assumption also implies issues linked to known limits of vision systems. If the vision system is not enough reliable or if the task requires a level of dexterity unattainable by the robot it may be necessary to activate a veto condition that assigns the task to the human. Taking account previous assumptions, present study assesses the technical feasibility index only considering the vision system as auxiliary device to cobots. However, in advanced workcells when other devices and technologies are applied, technical limits for cobots can be partially or totally removed. The technical feasibility problem was broken down into two parts: one concerning dexterity and the other concerning the

Table 3 Fuzzy set for "Ergonomics & Safety" index

Input	Input fuzzy set	Output fuzzy set of Ergonomics and Safety index
NIOSH index	Low	H
	Medium	h/R
	High	R*
Safety Risk	Low	H
	Medium	h/R
	High	R*

*A veto rule forces the outcome of the algorithm in order to ensure the fulfilment of H&S standards

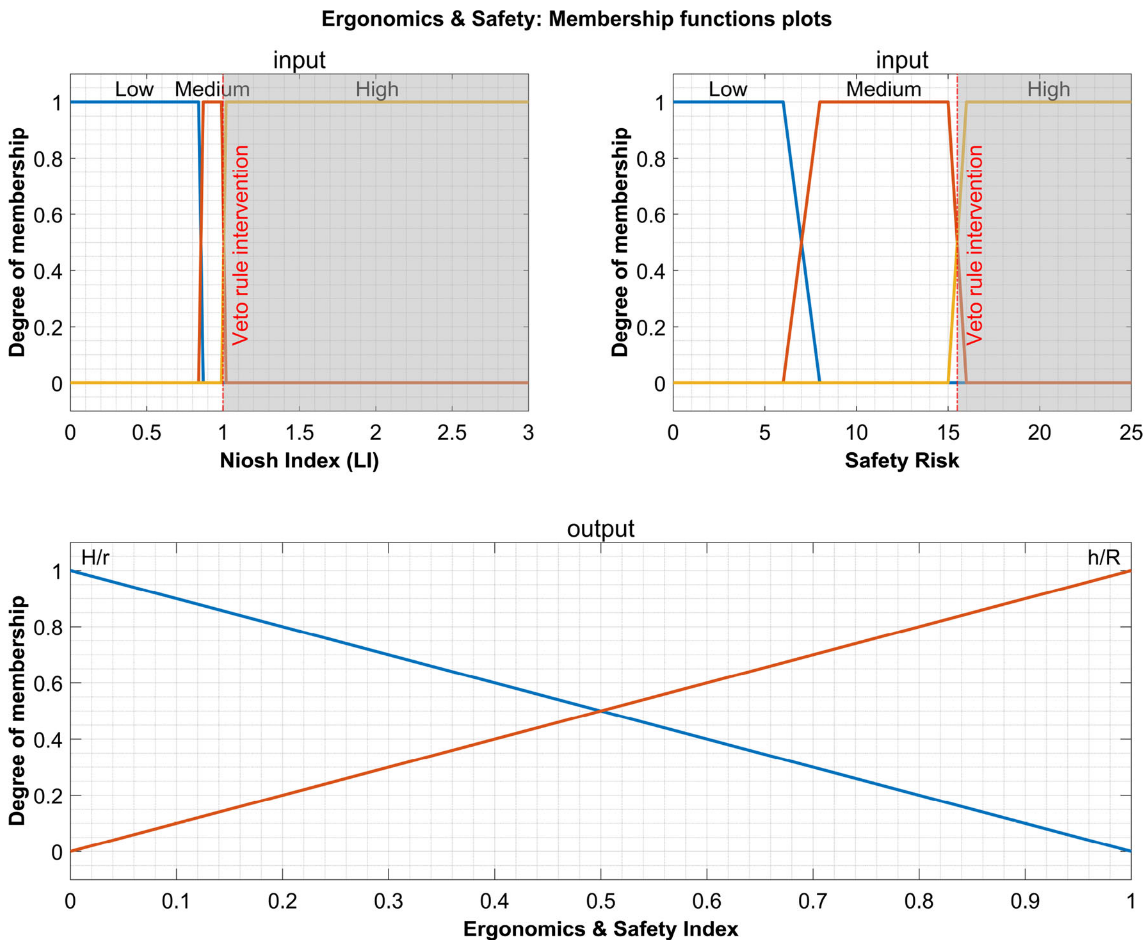


Fig. 3 Fuzzy set and membership functions: input and output representation for "Ergonomics and Safety index"

vision systems. Dexterity in the execution of a task can be estimated only qualitatively, while vision system allows for a semi-quantitative evaluation. Robot vision is biased by environmental factors such as room lighting or light reflection on surfaces. For this purpose a fuzzy inference is applied to determine the difficulty of part detection; the inputs used are the following: the level of illumination of the room (too low does not allow the objects to be distinguished, too high triggers phenomena of reflection and overexposure of the images), the manipulation of reflective objects (difficult to identify) and the way in which they are supplied in the work area (if piled up in crates or orderly disposed). Room lighting could be determined by means of sensors, that provide the actual value in lux, but the exact measure of lighting is unnecessary for the sake of present evaluation. The advantage of fuzzy inference is that it is not necessary to be accurate in defining parameters. For this reason, those which cannot be objectively determined can be evaluated qualitatively by individuals without affecting the results: the surface reflection of objects is determined using a scale from 0 (opaque) to 1 (reflective) as it is the variability for the supply of components (for which 0 stands for low variability and 1 for high variability). The identification operation can be easy, challenging or impossible. The detection is classified as “impossible” when all the inputs are against the artificial vision features. Table 4 and Fig. 4 summarize the input and the output for this assessment.

The output provided by the object detection assessment becomes an input for the corresponding veto condition and, if it is not fired, for the technical feasibility evaluation. Technical feasibility index is assessed considering previous results and the dexterity required to accomplish the task. Even in this case the dexterity is evaluated qualitatively using a scale from 0 -low- to 1 -high-. The inputs and output of the technical feasibility index can be found in Table 5, in Fig. 5 are depicted the membership functions for this index.

Cognitive load index

Humans encounter difficulties when they are not completely free to perform a task but must follow strict guidelines or must pay attention for long time. According to recent studies on this topic (Bäckstrand, 2009), excessive human cognitive load can affect productivity and/or quality of work. For this reason, the tasks to be performed in a collaborative cell should be appropriately distributed to avoid burdening human operators. A valid computational method to determine cognitive load was developed by Thorvald et al. (2019), called CLAM (Cognitive Load Assessment in Manufacturing), which is implemented here. The method allows the assessment of both the task and the work environment based on eleven factors: task-related factors (saturation, flora of variants, level of difficulty, production awareness, difficulty in using tools) and workplace-related factors (number of available tools, mapping of the workstation, identification of parts, quality of instructions, cost of information, poke-a-yoke and constraints). The result of the procedure determines the degree of complexity of the task. Time pressure leads to a conflict between the imposed completion time for a task and the time actually needed to perform it. More specifically, it leads to increased anxiety, causing more attention resources to be allocated to the task and thus increasing the cognitive load. More specifically, time pressure has been shown to be one of the most common stressors in the work environment (Galy et al., 2012). Based on these considerations, for the assessment of cognitive load, it is reasonable to consider the margin of time taken by each operator to complete the task with respect to the average completion time. If the human execution time is significantly longer than the robot’s, to avoid consequent states of emotional stress, the task should be assigned to the robot. The robot’s advantage margin (Δtime) was calculated according to Eq. (3b), and a preferential task assignment to the robot (h/R) is expected whenever its value exceeds the 10% threshold. The fuzzy sets used to implement the procedure in the algorithm are described in Table 6, in Fig. 6 the input membership functions are shown.

$$T_{mean} = \frac{T_{Robot} + T_{Human}}{2}. \tag{3a}$$

$$\Delta time = \frac{T_{mean} - T_{Robot}}{T_{mean}} * 100. \tag{3b}$$

Cost and quality index

In industrial environments, continuous improvement of process and product quality is pursued. The “Cost and Quality” indicator was introduced to allow the task to be assigned to the most suitable operator to meet certain quality and cost objectives. For the sake of task classification, the cost of execution does not consider the overall process cost but the loss due to mistakes (quality cost), e.g., the need for reworking a part. The desired quality level is expressed as “high”, “medium” or “poor” and is based on the numerical value assigned to the activity during the definition of the objectives. The unrivalled dexterity of humans makes them the most suitable candidate to perform activities requiring a high level of quality. The enormous flexibility of humans’ approach in performing tasks distinguishes them from robots.Conversely humans are less repetitive and their performance is subjected to variability because of fatigue. While overall quality level is evaluated qualitatively, it is possible to estimate the expected frequency of mistakes. As an example of quantitative quality index it is reported here the risk of error in the sequence of tasks (TSRE), that is calculated as the composite probability of dependent events (Eq. 4):

$$TSRE = 1 - P(A) \cdot P(B \mid A). \tag{4}$$

where $P(A)$ is the probability of performing task A, $P(B \mid A)$ is the probability of performing task B when task A has already been performed. The fuzzy sets for each corresponding input and output are described in Table 7. Figure 7 shows the membership functions of the index.

Output of fuzzy inference system

The advantage of the proposed procedure is that it is able to allocate tasks to the workers involved in HRC in a similar way to what would happen in a human-to-human collaboration. The presence of normative constraints, different workers’ skills and specific production needs, as well as the existence of “simple” tasks (which do not require special skills for their execution) and complex tasks (where the necessary skills cannot be found in a single operator), imply the adoption of multiple assignment types. The assignment types adopted in this analysis differ between:

Table 4 Fuzzy set for "Object detection using vision system"

Input	Input fuzzy set	Output fuzzy set for Object detection using vision systems
Room lighting	Poor	Challenging
	Good	Easy
Surface reflection	Matt	Easy
	Reflective	Challenging
Components supply	Low	Easy
variability	High	Challenging

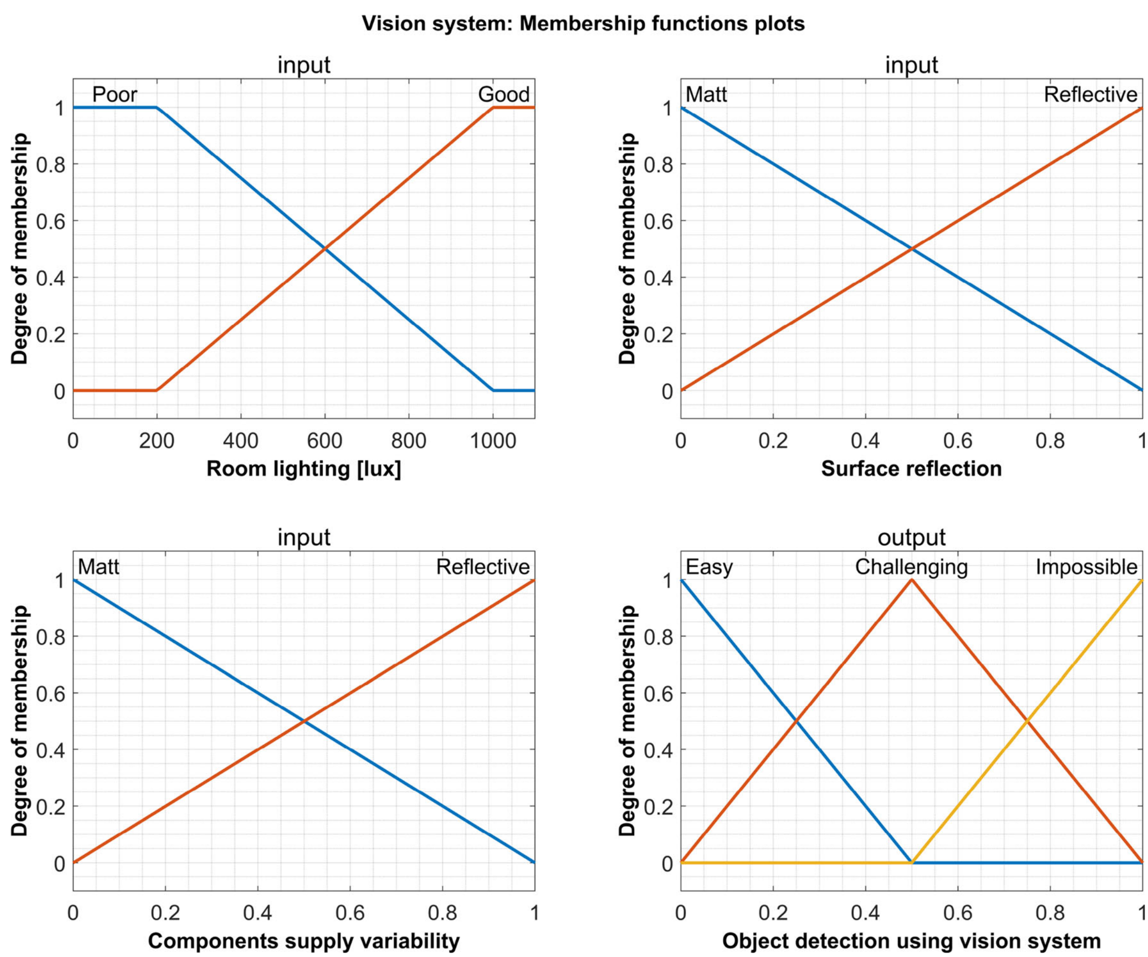


Fig. 4 Fuzzy set and membership functions: input and output representation for "Object detection using vision system"

Table 5 Fuzzy set for "Technical Feasibility" index

Input	Input fuzzy set	Output fuzzy set of Technical Feasibility index
Object detection using	Impossible	H*
	Challenging	H/r
Visual system	Easy	R
Dexterity required	Low	h/R
	Medium	H/r
	High	H*

*A veto rule forces the outcome of the algorithm in order to ensure the accomplishment of the task

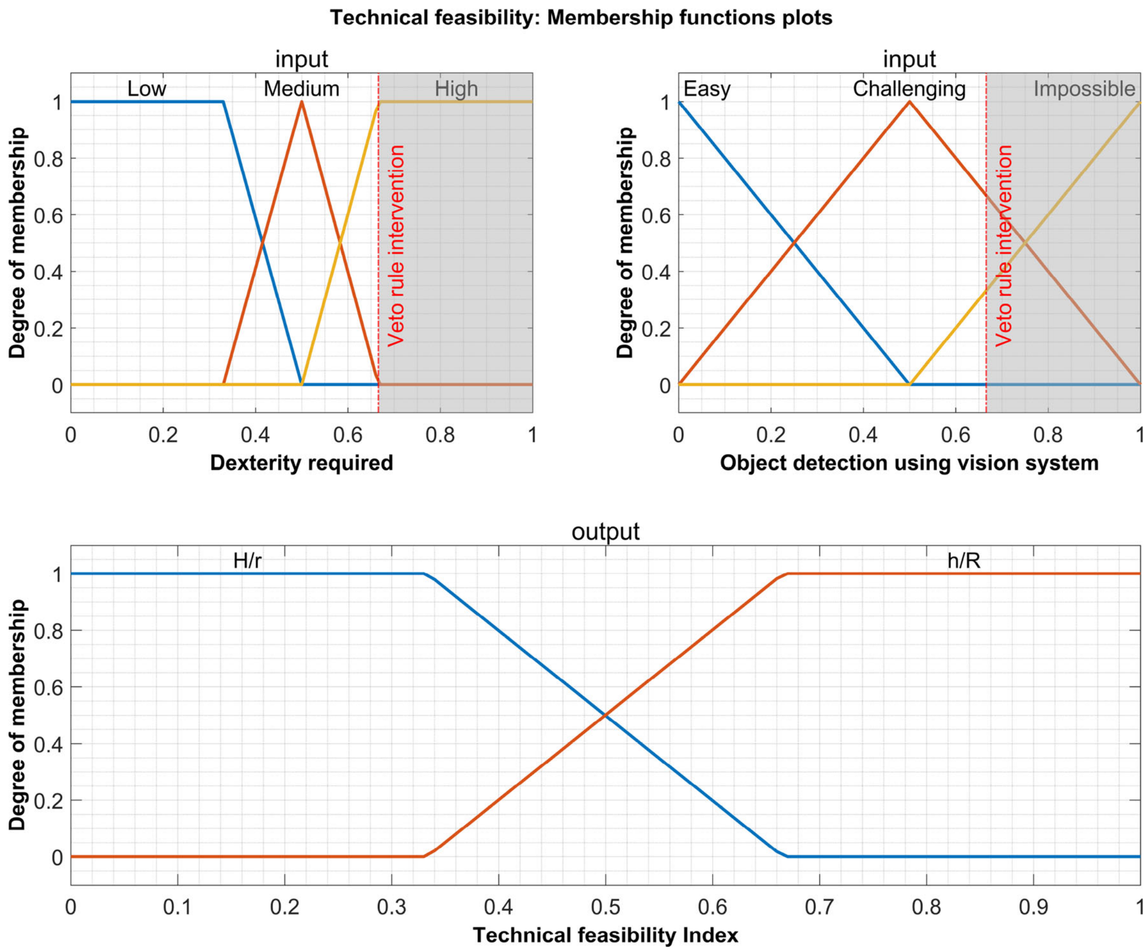


Fig. 5 Fuzzy set and membership functions: input and output representation for "Technical Feasibility index"

Table 6 Fuzzy set for "Cognitive load" index

Input	Input fuzzy set	Output fuzzy set of Cognitive load index
CLAM	Very Low	H
	Low	H/r
	Moderate	h/R
	High	R
Δtime	Negative	H/r
	Zero	h/R
	Positive	R

Table 7 Fuzzy set for "Cost & Quality" index

Input	Input fuzzy set	Output fuzzy set of Cost and Quality index
TSRE	Low	H
	Medium	h/R
	High	R
Quality	Low	R
	Medium	h/R
	High	H

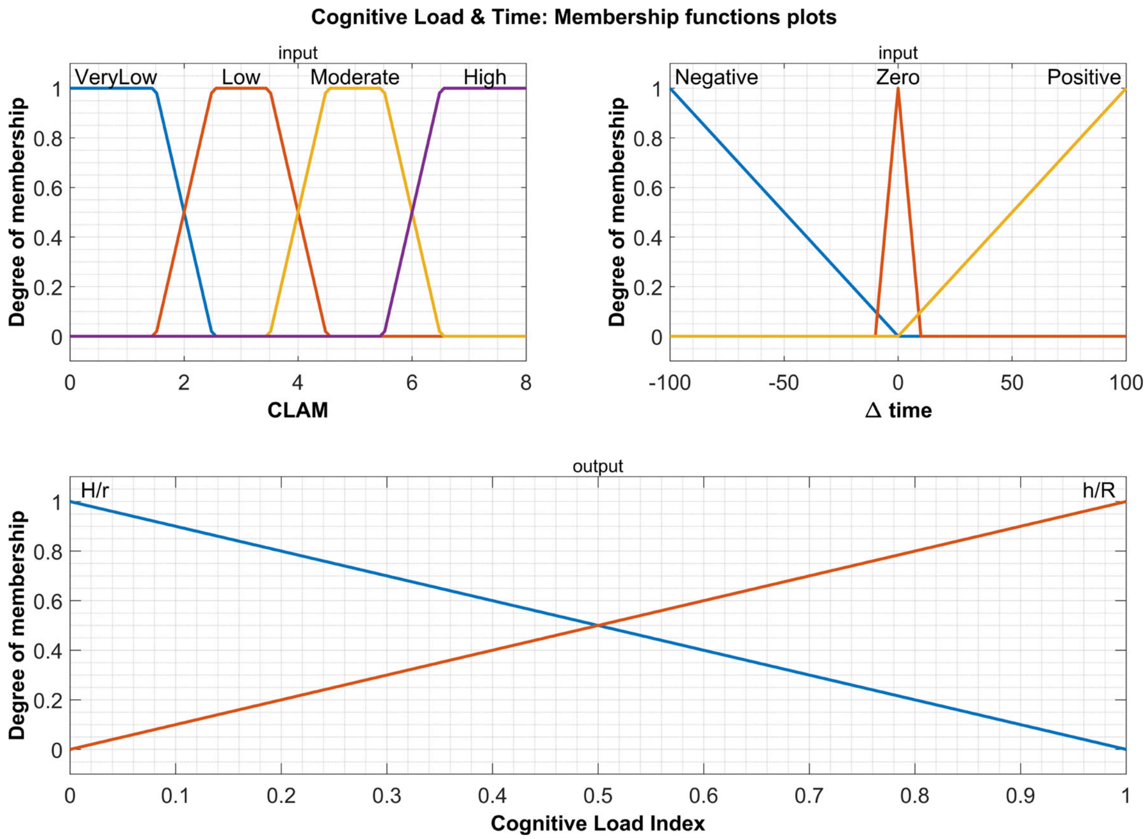


Fig. 6 Fuzzy set and membership functions: input and output representation for Cognitive load index section

- Exclusive: one or more results of the indicator analysis indicate that the task in question must necessarily be performed by a specific operator. If this operator is not available during the execution of the task, it cannot be replaced.
- Collaborative (HRC): the analysis of indicators returns the need to have the same task performed by different operators, for different reasons. During the execution of the task, both workers must be available.
- Collaborative (hrc): the analysis of the indicators does not force the operators to collaborate but advises it for an optimal management of the resources.
- Commutative: the analysis of indicators presents only assignment preferences. Optimal resource management is achieved if the activity is completed by the indicated operator but, if not available, the non-preferred operator would also be adequate.

Combining the evaluation results, the following options are provided: human-only execution (H), robot-only execution (R), human-preferred execution (H/r), robot-preferred execution (h/R), human-robot collaboration mandatory (HRC), and human–robot collaboration suggested (hrc). Figure 8 shows the inputs and outputs of the FI “Task assignment”.

Practical application

To test the task assignment technique, the assembly process of a two-stage snow plough mill (see Fig. 9) was used. Due to the limited production numbers of the factory where it is carried out, the assembly in question is not automated but relies solely on human power. Observation of the actual manual work during assembly provided the basis for the process description. The processing time was recorded in order to compare the manufacturing process with the simulated process. Several considerations are possible when evaluating the fully manual process: an overhead crane is required due to the heavy parts that need to be handled, the shape of the blades and their bending process are dangerous and arc welding poses additional safety risks. The above aspects suggest that there are several activities that could be carried out with the help of the robot. Nonetheless, in the case study, many activities require a high-level dexterity, so human involvement is necessary. The process can be divided into 9 main phases and 23 tasks. The phases are sequences of tasks that must be performed in a precise order according to the diagram in Fig. 10. Phases arranged in parallel can be performed in any order as long as the previous phase is completed before the

Table 8 Information sheet for snow plough mill assembly

TASK	Niosh index	Safety Risk	Required dexterity	Room lighting [lx]	Surface reflection	Components supply variability	CLAM	timeH [s]	timeR [s]	TSRE	Required quality
Components and workstation setup	0.4	2	0.5	1000	0	1	1	1200	1320	0.956	0
Base and headstock placement	5	12	0	1000	0	0	4.31	180	120	0.944	0.5
External disc positioning	5	12	0	1000	1	0	4.31	355	230	0.923	0.5
Inner cross positioning	5	12	0	1000	0	0	4.31	220	200	0.889	0.5
Outer cross positioning	5	12	0	1000	0	0	4.31	220	200	0.778	0.5
Internal blades bending	0.3	2	1	1000	0.5	1	2.66	900	900	0.889	0
Brackets bending	0.25	2	1	1000	1	1	2.66	240	240	0.778	0
Inner blades assembly	0.3	2	0	1000	0.5	0.5	4.79	520	1040	0.929	0
Brackets positioning for blades attachment	0.25	25	1	1000	0	1	4.31	280	520	0.858	1
Brackets welding for blades attachment	0.1	25	0	1000	1	0	6.23	700	450	0.889	1
Outer disc and headstock welding	0.1	25	0	1000	1	0.5	6.23	200	200	0.833	1
Outer disc brackets positioning and welding	0.25	25	1	1000	1	0	6.23	810	660	0.667	1
External disc brackets bending	0.25	2	1	1000	1	1	2.66	360	360	0.833	0
Outer blades bending	0.3	2	1	1000	0.5	1	2.66	900	900	0,667	0

Table 8 continued

TASK	Niosh index	Safety Risk	Required dexterity	Room lighting [lx]	Surface reflection	Components supply variability	CLAM	timeH [s]	timeR [s]	TSRE	Required quality
Outer blades assembly	0.3	2	0	1000	0.5	0.5	4.79	520	520	0.75	0
Welding	0.1	25	0	1000	1	0	6.23	3880	2520	0.333	1
Central cross supports bending	0.25	2	1	1000	1	1	2.66	600	600	0.667	0
Footprint template picking	5	2	1	1000	1	1	2.66	600	150	0.333	0
Central cross brackets assembly	0.25	25	1	1000	0	0.5	4.79	1840	1800	0.8	1
Grinding	0.1	25	0.5	1000	0	0	3.3	770	540	0.75	0.5
Spacers assembly	0.85	25	1	1000	0	1	4.79	700	740	0.667	1
Outer ring assembly	0.85	2	0	1000	0	0	4.79	160	150	0.5	0
Footprint template removing	5	25	0	1000	0	0	4.31	180	60	0	0

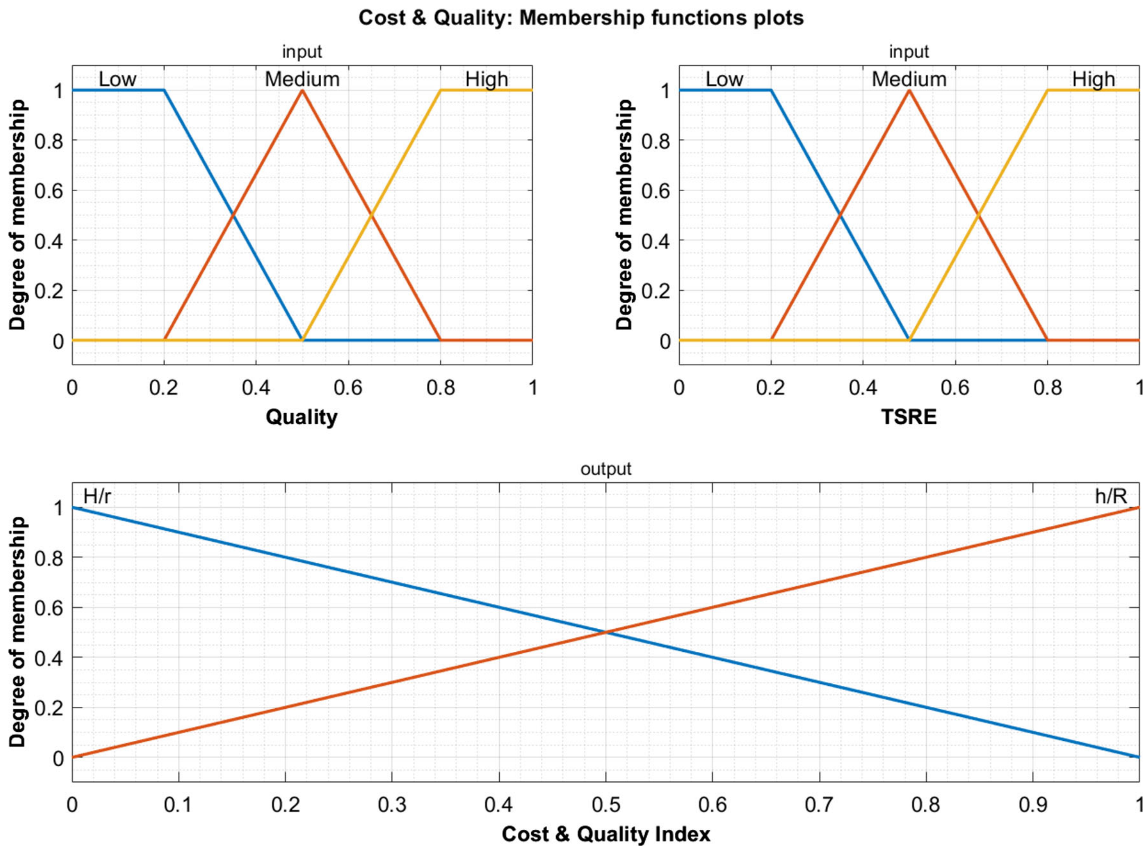


Fig. 7 Fuzzy set and membership functions: input and output representation for "Cost and Quality index"

next one is started. Table 8 represent the information sheet used for the case study.

Tasks assessment in snow plough mill assembly process

After completing the conceptual analysis of the process, which includes its partition into phases and tasks, it is important to evaluate them using the criteria outlined in the proper section. The crisp values used in the first FIS to extract the scores for the four categories analysed are discussed in the following paragraphs.

Ergonomics and safety assessment

Niosh index has been calculated according to the formulation provided by Waters et al. (1993). Regarding the safety risk assessment, the amount of mass moved and the use of sharp or potentially harmful tools defined the severity of the possible damage. Using the risk-matrix reported in Fig. 2, the level of safety risk for each subtask was identified:

- the movement of parts that could cause potentially fatal injuries to humans (due to pinching or cutting of human limbs), or the usage of tools that could cause burns or other injuries to humans (welders, grinders, etc.) are classified as hazardous (25);
- large but non-critical masses are moderately hazardous (12);
- activities with an acceptable operational risk are classified as not hazardous (2).

Technical feasibility assessment

The technical feasibility was assessed according to the criteria described above, evaluating the environmental factors of the place where the assembly is carried out and the requirements for each sub-activity. In order to determine the working conditions of the vision system, the illuminance value of the working area was measured: this value complies with the standard in force (UNI-EN 12464) which foresees a value between 200 and 1000 lx for mechanical assembly processes. The position and orientation of the workpieces are influenced by the design of the work cell and the feeding mode. In the case study, the values were assigned according to the following criteria:

- maximum variability (1) when picking from loose parts;

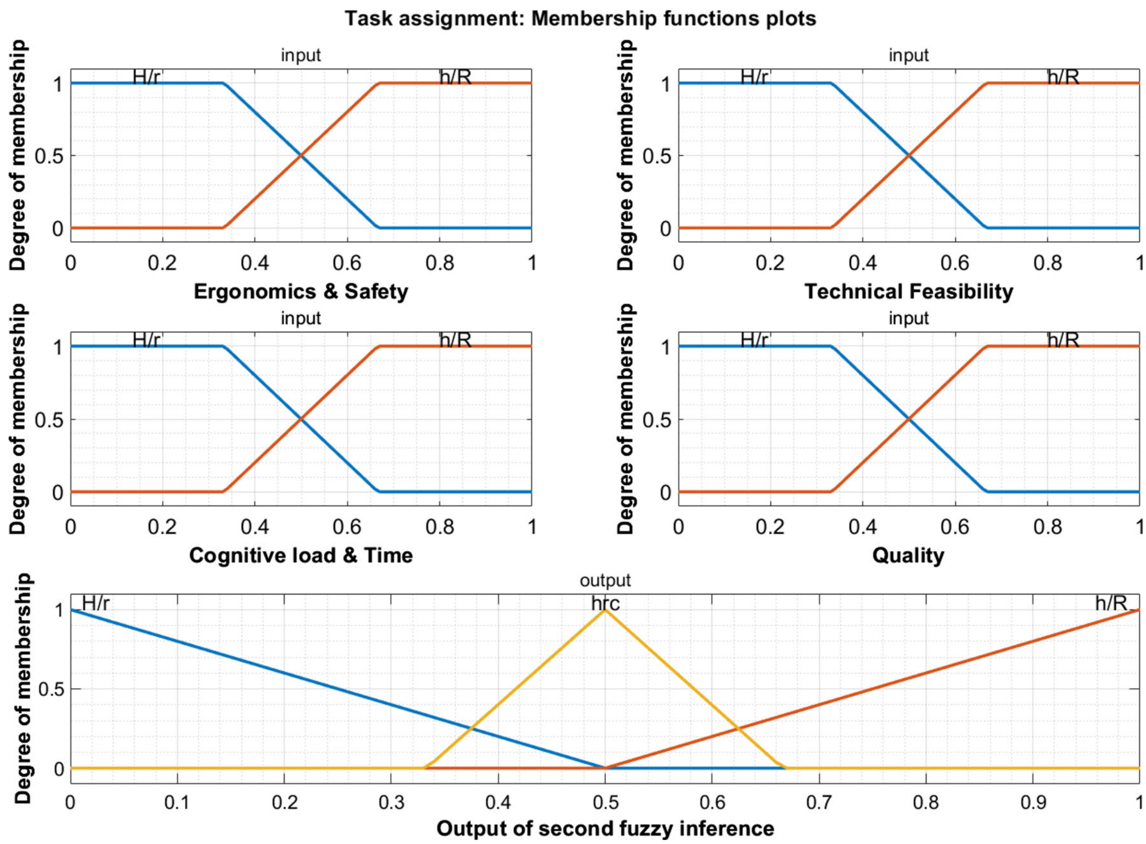


Fig. 8 Fuzzy set and membership functions: input and output representation for "Final Assignment"

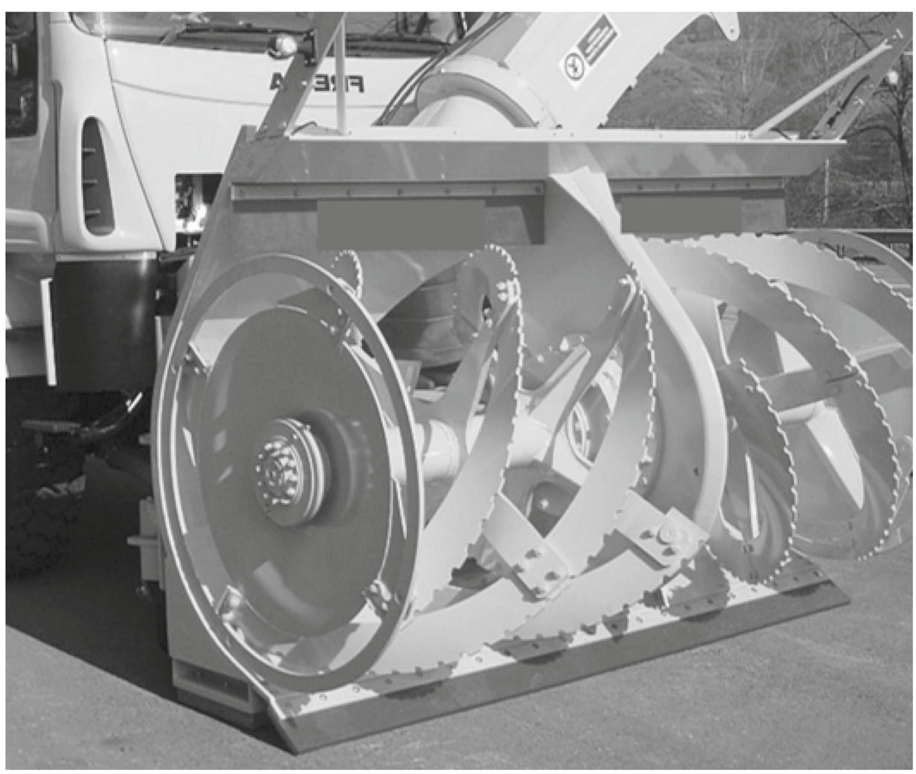
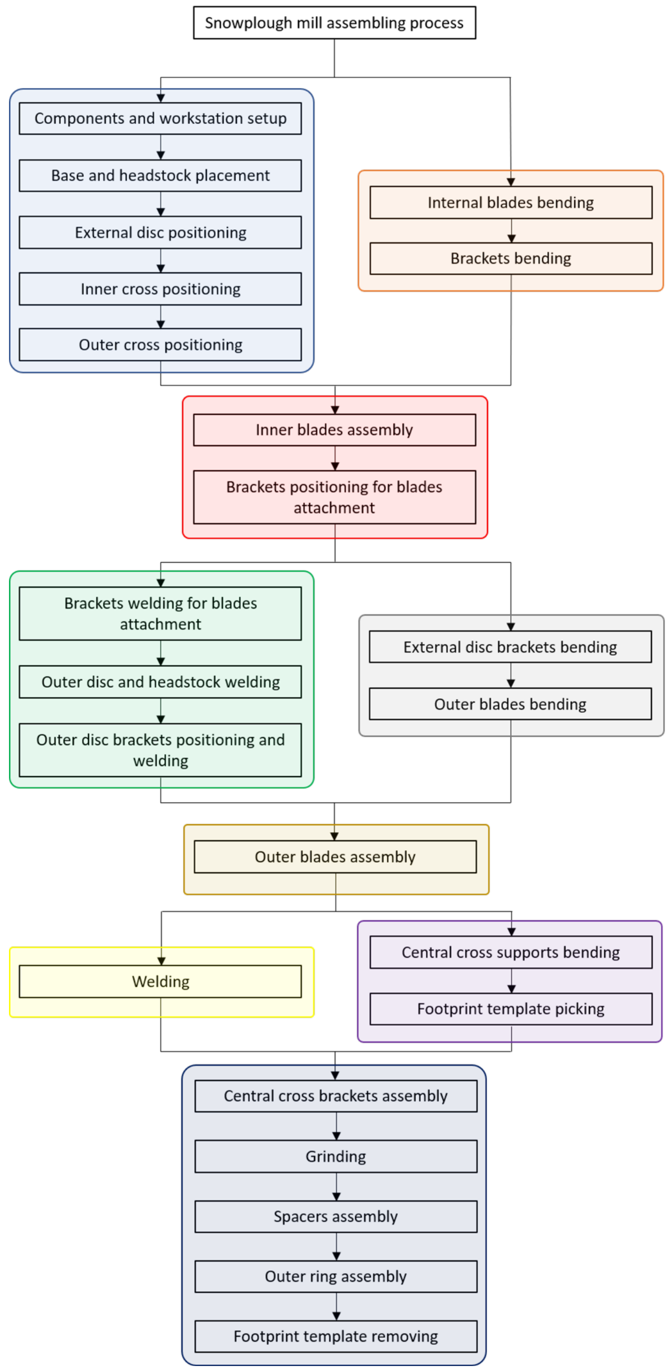


Fig. 9 Snow plough mill whose assembly is considered as case study

Fig. 10 Snow plough mill assembly workflow



- minimum variability (0) when using jigs and automated equipment for part positioning;
- otherwise, bulky parts are allocated to dedicated work areas with relatively constant position and orientation (0.5).

The surface finish value is assigned in relation to the materials of the parts, their surface roughness, and their dimensions:

- large metal surfaces are more prone to light reflection (1);
- smaller parts with burnished surfaces or a rough finish are considered non-reflective (0).

Processing the above inputs with FI allows determining the level of difficulty in part detection. This result is post-processed in combination with the required dexterity to determine the technical feasibility of the task. The required dexterity is considered:

Table 9 FISs crisp output values and final assignment

TASK	Cost and quality	Cognitive load	Technical feasibility	Ergonomics and safety	Final assignment
Components and workstation setup	H/r (0.33)	h/R (0.57)	H/r (0.38)	h/R (0.67)	hrc (0.47)
Base and headstock placement	R (1)	h/R (0.66)	h/R (0.55)	h/R (0.67)	R (1)
External disc positioning	R (1)	h/R (0.66)	h/R (0.55)	h/R (0.67)	R (1)
Inner cross positioning	R (1)	h/R (0.66)	h/R (0.59)	h/R (0.67)	R (1)
Outer cross positioning	R (1)	h/R (0.66)	h/R (0.59)	h/R (0.66)	R (1)
Internal blades bending	H/r (0.33)	H (0)	H/r (0.33)	h/R (0.67)	H (0)
Brackets bending	H/r (0.33)	H (0)	H/r (0.33)	h/R (0.66)	H (0)
Inner blades assembly	H/r (0.33)	h/R (0.66)	h/R (0.58)	h/R (0.67)	hrc (0.65)
Brackets positioning for blades attachment	R (1)	H (0)	h/R (0.53)	H/r (0.33)	HRC (0.50)
Brackets welding for blades attachment	R (1)	h/R (0.66)	R (1)	H/r (0.33)	R (1)
Outer disc and headstock welding	R (1)	h/R (0.66)	R (1)	H/r (0.33)	R (1)
Outer disc brackets positioning and welding	R (1)	H (0)	R (1)	H/r (0.37)	HRC (0.50)
External disc brackets bending	H/r (0.33)	H (0)	H/r (0.33)	h/R (0.67)	H (0)
Outer blades bending	H/r (0.33)	H (0)	H/r (0.33)	h/R (0.62)	H (0)
Outer blades assembly	H/r (0.33)	h/R (0.66)	h/R (0.67)	h/R (0.66)	h/R (0.66)
Welding	R (1)	h/R (0.66)	R (1)	H/r (0.37)	R (1)
Central cross supports bending	H/r (0.33)	H (0)	H/r (0.33)	h/R (0.62)	H (0)
Footprint template picking	R (1)	H (0)	h/R (0.63)	h/R (0.62)	HRC (0.50)
Central cross brackets assembly	R (1)	H (0)	h/R (0.66)	H/r (0,33)	HRC (0.50)
Grinding	R (1)	h/R (0.57)	h/R (0.54)	h/R (0.66)	R (1)
Spacers assembly	R (1)	H (0)	h/R (0.64)	H/r (0.37)	HRC (0.50)
Outer ring assembly	H/r (0.33)	h/R (0.66)	h/R (0.64)	h/R (0.67)	h/R (0.66)
Footprint template removing	R (1)	h/R (0.66)	h/R (0.61)	h/R (0.67)	R (1)

- low (0) when the task can be completed easily with the proper tool;
- medium (0.5) when the task can be completed with a single tool, but requires extra effort;
- high (1) when tasks require complicated movements and/or several tools to be completed;

Cognitive load assessment

Following the guidance provided by Thorvald et al. (2019), CLAM values were calculated. The duration of the task is significant for this evaluation because of the time pressure that pushes the human operator to concentrate more to perform the task faster. The task is more stressful because the human compares himself with the robot.

Cost and quality assessment

The task allocation procedure must prevent possible production problems and organise the process in the best possible way. In assessing costs, it was considered appropriate not to judge the operator solely on the timing of task execution; in order to give more value to the activities performed by humans, it was considered appropriate to judge the possible costs arising from tasks performed incorrectly that force the addition of unscheduled processing steps in order to finish the job correctly. In particular, the possibility of performing a task with the wrong schedule (TSRE) defines this decision basis. The quality requirements are 0 for picking up and handling objects, 0.5 for guided assembly and positioning activities for subsequent technological operations, 1 for welding and other activities with functionality purposes.

Results and discussions

The values reported in Table 9 indicate in a quantitative way the level of suitability of the operator for the given assignment.

The numerical values vary on a continuous scale from 0 to 1 to distinguish the assignment types described in the output section. When the index assumes the value of 0 or 1 it means that the task must be assigned the task categorically to the human or to the robot. Conversely, values close to 0 indicate tasks that are more suitable to be performed by a human, close to 1 by a robot. The value 0.5 expresses the collaborative task, where the label HRC specifies that collaboration is necessary while hrc that collaboration is suggested. The final assignment is influenced by the type of membership function used and the imposition of veto rules. The algorithm was set up in this study to ensure equality for each of the four indicators. It would be possible to adjust the form of the membership functions in the last FI assessment or to assign a weight to the rules governing the FI, to emphasize the relevance of one indicator over the others. The results of the suggested classification are consistent with the specifications and requirements and are easy to interpret. What is more important, from the viewpoint of the process scheduler, is that when the suitability level is different from 1 or 0, it is possible to choose a different assignment. This research demonstrates the feasibility of successfully implementing a task classification algorithm that meets both regulatory standards and the flexibility required in manufacturing environments. The application can be executed indifferently during the task planning phase, or dynamically when production has started.

Conclusion

The study defines a set of evaluation criteria, their metrics and proposes a method for task classification in assembly work cell. The new task classification approach uses FIS to maximise the assets of both the human and robot working in the team. The feasibility assessment, implemented in the paper, is based on formal definition of criteria, derived by a combination of existing regulations about safety and ergonomics and industrial requirements of quality, productivity and cost efficiency. Furthermore, the proposed methodology allows the introduction of new or modified assessing indexes whenever required by technology advancement. Several evaluation parameters are analyzed, involving difficulty in determining the assessing rule. The scalability of the number of parameters is therefore the major limitation of the method as is in general for every FIS. For this reason, the choice of rules follows a simplified approach for which the single parameters are evaluated individually and, only afterwards, the results are used as input for the final assignment. The generalized version of this algorithm provides a strong basis for task assignment in a wide range of industrial applications with ambiguous scenarios. As a result of the flexibility of assigning the same duty to multiple players, ambiguities may arise (Zhu & Zhou, 2006). To overcome this issue, the tool's robustness could be improved by the support of artificial intelligence (AI) allowing the machine to recognize human actions. Furthermore, AI could be also used as an aid to predict more precisely the levels for the criteria. The current study can lead to further research, such as comparing its effect on production performance in a human-robot collaborative factory.

Declarations

Conflict of interest There are no conflicts of interest to declare.

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