Planning and Scheduling of Robotic Welding Processes in the Rolling Stock Industry: A Literature Review

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Abstract. Robotized welding processes in the manufacturing industry play a crucial role in enhancing competitiveness through automation, adaptability, and increased productivity. To optimize welding parameters, modeling approaches have gained significance, enabling users to simulate welding experiments and determine appropriate settings. With the growing need for reduced development phases and costs while maintaining quality standards and production volumes, flexible and robust manufacturing technologies are essential. In this paper, we present a literature review highlighting best practices for welding processes. We address five research questions related to welding techniques, planning models, factors affecting welding processes, and performance indicators. Our findings reveal various models and techniques for planning robot operations, focusing on welding robots. By this review, we contribute to the development of effective strategies for optimizing robotized welding processes, leading to improved efficiency in manufacturing systems.

Keywords: Optimization models, Robot welding process, Welding techniques.

1 Introduction

In manufacturing, robots are widely used to enhance competitiveness by enabling efficient, flexible, and precise operations [1]. In particular, the welding process (WP) is essential in many manufacturing systems. It has been shown to boost production rates by automating, adapting, and enhancing productivity [2–4]. Furthermore, to optimize welding parameters, modeling approaches have become increasingly attractive. Such models are ideal when experimental knowledge is limited, such as with a new type of metal or with unusual welding geometry [5]. Nonetheless, in the rolling stock industry, robotized welding still faces complex challenges demanding innovative solutions. To begin with, complex designs and hidden joint components require advanced programming and precise control of welding processes (WPs). Accessing and welding these joints necessitate inventive approaches to maintain structural integrity. Indeed, streamlined programming and user-friendly interfaces are vital to reduce welding downtime. Secondly, balancing efficiency with weld quality is crucial, requiring careful parameter calibration. Ensuring consistent quality across materials demands vigilant monitoring.

Thirdly, energy efficiency and error reduction are priorities, requiring the orchestration of factors like joint torque and inertia tensors [1]. Another problem is finding an optimal path between two states using mathematical programming techniques or other planning approaches [6]. In addition, due to shorter product lifecycles and the growing need for more product variants, manufacturing companies are under great pressure to reduce the development phase and production costs while maintaining high-quality standards. Due to these trends, flexible and re-configurable manufacturing technologies and models are becoming increasingly important [7].

In this literature review, we explore the models, techniques, factors, and indicators associated with planning and optimizing robotized welding processes (RWPs) in the rolling stock industry. We also provide a unified definition of the robotized welding process (RWP) and its typical features. To conduct the review, an accurate search and screening methodology was followed. Utilizing various sources published in English up to 2023, we defined and answered five research questions: (Q1) What methods are used to plan operations for robotic processes in general? (Q2) Which welding techniques commonly employ welding robots? (Q3) What models and methods have been developed to plan operations for RWPs? (Q4) What indicators are used to measure the efficiency of RWPs? (Q5) What are the main factors, barriers, and challenges affecting RWPs in the rolling stock industry? In what follows, we present our methodology, our findings and our theoretical framework explaining the relations among various elements crucial to RWPs within the rolling stock industry.

2 Methodology

To begin the search, some initial articles were selected to gain a better understanding of different aspects of RWPs in the rolling stock industry. Once the subject under study was clearer, the review was conducted to find the barriers in RWPs and ways to increase their effectiveness. We followed a precise search and screening methodology to ensure that the most relevant papers were included in our analysis. We utilized Web of Science, Engineering Village, Scopus, and ScienceDirect due to their extensive collection of journals and their ability to search for specific keywords or phrases in titles, keywords, and abstracts. We focused on literature in the English language up to August 2023, including books, journal articles, and conference proceedings. We selected three sets of keywords after conducting an initial search using various keyword combinations in different fields. In all of them "welding robots" was searched in the title and keywords, in addition to some other keywords including "welding techniques", "rolling stock industry", "rail industry", and "robot planning" which were searched in the title, keywords, and abstracts. "optimization", "real-time scheduling", "simulation", "industry 4.0", "robot welding process", and then "welding techniques", and "welding robots challenges and barriers" were also searched in different fields. This primary search resulted in 1,995 papers. To ensure the inclusion of only the most relevant papers, titles and abstracts were evaluated. Each article underwent an examination of its content, methodology, and findings. This evaluation aimed to identify articles that directly addressed the research questions and were deemed pertinent to the study. In the next step, introductions and conclusions were screened and, by removing duplicates, 1,617 papers were omitted and 378 remained. Finally, a thorough evaluation of the full-text articles was conducted and by removing irrelevant articles, the choices were narrowed down to 56 papers of which 41 relevant articles remained after further analysis to answer the five research questions provided in the introduction.

3 Results

3.1 Findings on (Q1): What methods are used to plan operations for robotic processes in general?

Increasingly, robots are being deployed for tasks demanding precision, e.g., welding, painting, and adhesive applications [8]. Robots are also used to move heavy or fragile items throughout production facilities. When equipped with advanced sensors, robots can carry inspection and quality control tasks, e.g., inspect for defects and ensure products comply with strict quality standards [9]. They are regarded as a significant presence in society since they are progressively replacing humans in fundamental and hazardous tasks such as handling chemicals or working in extreme environments [10]. As industrial automation evolves, robots have contributed to collaborative tasks alongside human labor, emphasizing their adaptability and versatility [10].

This diverse use of robots in industry has prompted the need for effective planning and operation methods. One prominent model for planning robot operations is the task planning model [11]. It is used when an autonomous robot plans a sequence of high-level actions to accomplish a specific task. Another approach is motion planning, which focuses on generating collision-free paths for robots to execute their tasks [12]. Robot deployment in practical applications relies heavily on motion planning [13]. Hanheide et al. [14] introduced two approaches for robotic process planning: classical AI planning and decision-theoretic planning. Classical AI planning is a quicker approach, but it cannot factor in multiple possible outcomes, unreliable observations, or multiple possible open-world situations, resulting in a linear plan that will succeed only when all the previous actions in the plan are completed. As opposed to classical AI planning, decision-theoretic planning produces a policy to maximize the probability of success based on any belief state the robot may reach during plan execution, considering the probabilities of every possible action outcome in those states [14]. Automating manufacturing processes is another approach which aims at minimizing the time it takes to complete a task [4]. A robot's cycle time is determined by the distance traversed by the joints in its manipulators, which is influenced by the sequence of the task points visited by its end-effector [15]. Hence, the integration of efficient robotic task execution and planning methods plays an essential role in enhancing productivity and precision within modern industrial settings.

3.2 Findings on (Q2): Which welding techniques commonly employ welding robots?

Welding is a manufacturing process that involves joining materials (e.g., metals or thermoplastics) together by melting their edges and fusing them into a single piece. This process is used to create a strong and permanent bond between the materials, and it is widely used in industries such as construction, automotive, and manufacturing.

Two of the commonly used welding techniques in the industry are resistance spot welding (RSW) and arc welding (AW). RSW is a fusion process using electrical resistance and force to generate thermal energy and join metal sheets [16]. Manufacturers in the automotive industry use RSW assembly lines extensively to construct the body of the vehicles [17]. Compared to other joining welding, RSW is a predominant joining technology because of its relatively high mechanical strength, low cost, and high automation capabilities [18]. Spot welding robots are used to join metal sheets efficiently with welding guns, connecting the power supply to the welding points. RSW robots work by generating heat between 1,000Amp to 100,000Amp [19]. Excessive heat, however, causes weld spatter that may cause defective welds, and damage surrounding equipment or sheet surfaces, requiring costly repairs. Moreover, industrial welding can also be affected by misaligned components, or by the condition of the sheet surface [18]. During AW, electricity is applied to create an arc between an electrode and conductive base metals. In the RWP, AW robots are programmed to perform all types of AW [16]. For AW robots, a vital stage in the WP involves cleaning the gun nozzle after a specific duration of welding. Typically, the gun must be taken from the robotic cell to the cleaning station which is located outside the cell. A standard AW robot station comprises elements such as a robot system, gantry system, positioner system, and welding system. The robot is equipped with a welding torch that matches the welding needs of the work cell, in accordance with the specific WP requirements [20]. In the WP, key parameters such as electro force, electrode contact, surface diameter, squeeze time, and weld current are interdependent, with minor adjustments in one affecting the others. The diameter of the electrode contact surface is particularly crucial, impacting electrode force. Additionally, factors like base and average voltage, peak voltage, light intensity, precise edge localization, heat transfer, and arc characteristics are essential in determining welding quality [18].

3.3 Findings on (Q3): What models and methods have been developed to plan operations for RWPs?

The methods found in the literature encompass two planning levels, tactical (low-level) and operational (high-level). Tactical decision planning defines strategies to reach mid-term goals based on the most precise data available. This helps organizations adapt and improve their strategies to match the changing world around them [21]. Path planning for RWPs is a mid-term strategy since the robot is programmed to follow a specific path for each task. The welding path may be determined ahead of time by a person or an algorithm and remains in use for an extended period. However, operational decision planning involves short-term, day-to-day decision-making processes, such as scheduling [22]. It aims to efficiently allocate resources and plan tasks to ensure smooth daily operations. Unlike tactical planning, operational planning occurs either just before or during the execution of services. For RWPs, task scheduling revolves around addressing challenges related to the use of robots in the WP [8].

Path planning (low-level). Path planning plays a pivotal role in the realm of robotics and automation, particularly as robots and automated systems can increase the speed of operation to reduce production timelines [23]. In various industrial settings, the order a manipulator robot visits a set of welding points and returns to the starting point is known as the path. It significantly affects the total cycle time for completing the task. The goal of path planning is to find the optimal path and sequence that minimizes the execution time of the assigned task. Organizations analyze and optimize their paths or sequences of actions to achieve specific weekly or monthly objectives. Path planning addresses two key challenges: (1) determining how the robot can recognize a safe distance between the obstacles to reach its destination without a collision, and (2) devising a way to navigate between these obstacles in the shortest possible path while avoiding collisions [10].

These challenges can be tackled with methods extending from the traveling salesperson problem (TSP), a famous combinatorial optimization problem where one must visit a set of cities exactly once and return to the starting city. In the case of robotic processes, the objective is to minimize time instead of distance by finding a path enabling the robot to pass through the given points in minimal time [24]. In particular, path planning focuses on optimizing both the welding path for AW robots and total welding deformation. Deformation is an important problem in AW. Since it has much greater heat input than RSW, it introduces greater deformation. The authors used an approximate method named particle swarm optimization for this biobjective path planning problem and the simulation results show the effectiveness of this approach [2]. Welding robot task planning is another crucial aspect in this process. The path length and cycle time of welding robots are important factors to consider when tasks are planned [25]. In addition, to extend the collision avoidance problem, some moving obstacles (e.g., two mobile robots in a welding cell) must follow a predefined motion. To solve this problem, one can define new obstacles at each time step corresponding to the positions of the moving obstacles at that point in time. For rectangular obstacles, the binary constraints format must be the same as for linear obstacles. At each step, obstacles change their coordinates according to their predefined motion [6].

Scheduling (high-level). Scheduling involves allocating resources within a defined timeframe to achieve a set of tasks [26]. Job shop scheduling and flow shop scheduling are two different scheduling approaches used in production and manufacturing to optimize the allocation of resources and the sequencing of jobs or tasks. A flow shop is a manufacturing layout where machines are set up in a sequential order. Orders are processed on an initial machine, passed through several intermediate machines, and eventually completed on a final machine [26]. In a job shop approach, order processing can follow any sequence. Typically, there are m machines and n jobs to be processed, where each machine can do one to k operations [26]. Generally, scheduling deals with immediate issues and entails detailed scheduling of welding robot activities or daily task planning of this robot. The need to ensure that tasks are done on time highlights the importance of the scheduling role. Within a dynamic environment, orders come from both client representatives and manufacturing facilities. The responsibility for determining the most suitable timing to process these orders, along with the management of proactive tasks such as the review of production orders and monitoring inventory levels, falls upon the individual or software responsible for scheduling [27].

To address current scheduling challenges, the robotic welding cell has evolved into an essential component. The effective deployment of these cells has introduced a range of intricate challenges, notably encompassing scheduling problems focused on finding the most efficient utilization of expensive equipment [28]. In comprehensive production scheduling, the key aim is to plan all tasks efficiently, especially at workstations within a manufacturing cell, in order to reduce task time or manufacturing expenses [8]. Analyzing the scheduling of tasks carried out by robots involves a well-defined procedure. It considers factors like robot movements, task requirements, and potential collisions between the robot and workstation elements within a manufacturing cell [21]. Production scheduling with robotic workstations is then referred to as “production scheduling” while scheduling of lower-level work is “task-level planning” [8].

Other methods. Models and techniques were also developed to address the planning challenges specific to welding robots. One important model is the weld sequence planning model [29]. This model aims to determine the optimal welding parameters, such as welding speed, current, and voltage, to achieve high-quality welds. Considering the number of constraints, experimental investigation of the optimal process parameters is time-consuming and expensive. Regression analysis, graphical methods, and response surface methodology are common methods used to determine WP parameters [30–32].

3.4 Findings on (Q4): What indicators are used to measure the efficiency of RWPs?

Efficiency in the context of WPs refers to the ability to achieve the desired welding results with minimal waste of resources, such as time, energy, materials, and labor. It is a measure of how well a welding operation utilizes these resources to join materials effectively and reliably. Efficiency in welding robots is evaluated through various performance indicators that gauge their productivity and effectiveness.

One of the crucial measures in RWPs is cycle time. To increase efficiency, industries should aim for shorter cycle times [25], since they reflect the ability to produce more welds in less time, ultimately leading to cost savings and improved productivity. It encompasses the total duration a welding robot takes to complete a welding operation, including positioning, welding, and post-welding tasks [33]. Welding speed, measured in units of length per time, also plays a significant role. Increased welding speeds contribute to improved efficiency by reducing the time needed for each weld. Another vital indicator is weld quality, which encompasses factors such as strength, penetration, absence of defects, and adherence to specifications. High quality welds are more efficient and reliable. Welding downtime, the period when the robot is not operational due to maintenance or setup should be minimized to enhance output. Welding utilization, measuring the percentage of active welding time compared to the total available time, indicates efficient use of the robot's resources. Energy consumption and error rates are additional indicators, where lower energy consumption and error rates signify improved efficiency and accuracy. Robot energy consumption is generally affected by joint torque and links' inertia tensors [34]. Moreover, to produce a part, many spot welds are needed [35]. Generally, the weld's dimensions, like its diameter and thickness, determine the appropriate welding tool. These parameters are key to deciding which tasks the welding robots take on, particularly with a range of guns and tools to choose from [36]. By analyzing these performance indicators, WPs can be continually optimized and improved.

To evaluate the entire robotic production process workflow, one can use indicators aiming at reducing time and costs, e.g., the estimated minimum workflow completion time, the total task execution time, and the data transmission costs [37]. In addition, minimizing the makespan via a proactive task scheduling approach could lead to higher resource utilization and reduced costs. Consequently, the individual or software in charge of planning must holistically factor in technical and financial indicators to make informed decisions and optimize the overall system performance. Task scheduling plays a pivotal role in ensuring the efficient functioning of workflow. A well-planned task scheduling strategy can minimize the execution time, accommodate requirements under various constraints, enhance resources utilization, and lead to reductions in energy consumption and costs [38].

3.5 Findings on (Q5): What are the main factors, barriers, and challenges affecting RWPs in the rolling stock industry?

RWPs in the rolling stock industry face several factors, barriers, and challenges that impact their effectiveness and implementation. One significant factor is the complex nature of structures such as locomotives and railcars. They have intricate designs with varying shapes, sizes, and materials, which pose challenges for robotized welding systems. Joint accessibility is another barrier in the rolling stock industry. Many welding joints are located in areas that are difficult to access, either due to their location, orientation, or limited space. As welded joints cannot be moved easily from point to point, it is crucial that the robot avoids colliding with the workpiece whilst moving between welded joints [25]. This presents a challenge for robotized welding systems, as they must be capable of reaching and welding these joints accurately. Failure to access and weld these joints properly can result in welding defects or compromise the overall productivity of the WP. Programming and set-up time for welding robots can be time-consuming, particularly when dealing with compound train structures. Optimizing the programming and setup process is crucial to minimize downtime and maximize productivity. Streamlining these processes through advanced programming techniques and user-friendly interfaces can help overcome this challenge. As for scheduling challenges, the diversity and complexity of resources and services in rolling stock systems heightens the difficulty of defining and modeling the problem which are essential requirements for effective scheduling [39]. Moreover, aligning resources and tasks presents a significant research challenge. Advancements in WP optimization, include the use of the Taguchi method as presented by Esme [40] who applies it to the optimization of welding parameters and a thorough assessment of their influence on tensile shear strength. Similarly, Thakur and Nandedkar [41] adopt the Taguchi method to investigate the impact of process parameters on the tensile shear strength of austenitic weld parts. These findings collectively underscore the importance of employing effective methodologies and techniques to achieve optimal outcomes in WPs.

4 A Theoretical Framework

In Fig. 1, we introduce a theoretical framework that explains the relationships among various elements crucial to RWPs within the rolling stock industry. This framework features how related factors, such as the industry's unique challenges and characteristics, significantly influence the decisions made at the operational and tactical levels. These two levels of planning in turn determine the selection and sequencing of welding tasks, which must address complexities like joint accessibility. The bridge between planning and execution is provided by modeling, encompassing task planning models, motion planning, and weld sequence planning. These models provide essential guidance for welding robots, ensuring tasks are carried out accurately and safely. Finally, performance indicators are integral to assessing efficiency, encompassing metrics like cycle time, welding speed, quality, and energy consumption. The framework also incorporates a dynamic feedback loop, allowing for real-time adjustments when problems or changes are observed, thus ensuring that robotized welding remains agile, efficient, and competitive in the ever-evolving rolling stock industry. It offers a view of the sophisticated web of factors, planning, modeling, and performance assessment that characterizes robotized welding in the rolling stock industry. This dynamic approach recognizes the industry's evolving nature and the need for continuous adaptation to maintain efficiency, making it an invaluable tool for researchers and practitioners in this critical field.

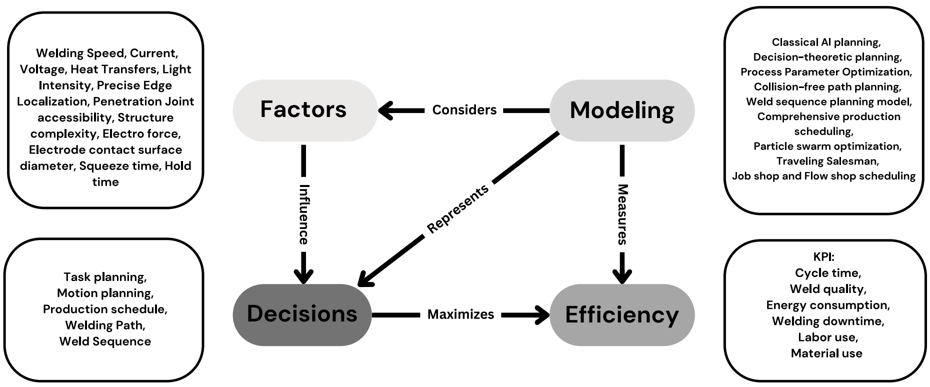

Fig. 1. Framework for planning and scheduling robotic WPs in the rolling stock industry

5 Conclusion

This literature review provides insights into the planning and optimization of robotized WPs in the rolling stock industry and addresses key questions, revealing planning models, parameter optimization, and performance indicators. Challenges like complex structures and joint access are recognized. Our methodology ensured the meticulous extraction of relevant insights from diverse sources. This study furthers our comprehension of how robotized welding optimally contributes to manufacturing efficiency and elevated quality standards. In future work, researchers can investigate the development of advanced machine learning algorithms, cloud computing, and artificial intelligence techniques to further improve the performance of welding robots. Additionally, future studies can focus on developing more efficient simulation models by leveraging advances in computational power and data analytics.

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