

Article

Knowledge Graph-Based Framework to Support Human-Centered Collaborative Manufacturing in Industry 5.0

László Nagy , János Abonyi  and Tamás Ruppert * 

HUN-REN-PE Complex Systems Monitoring Research Group, Department of Process Engineering, University of Pannonia, 8200 Veszprém, Hungary; nagy.laszlo.92@gmail.com (L.N.); janos@abonyilab.com (J.A.)

* Correspondence: ruppert@abonyilab.com

Abstract: The importance of highly monitored and analyzed processes, linked by information systems such as knowledge graphs, is growing. In addition, the integration of operators has become urgent due to their high costs and from a social point of view. An appropriate framework for implementing the Industry 5.0 approach requires effective data exchange in a highly complex manufacturing network to utilize resources and information. Furthermore, the continuous development of collaboration between human and machine actors is fundamental for industrial cyber-physical systems, as the workforce is one of the most agile and flexible manufacturing resources. This paper introduces the human-centric knowledge graph framework by adapting ontologies and standards to model the operator-related factors such as monitoring movements, working conditions, or collaborating with robots. It also presents graph-based data querying, visualization, and analysis through an industrial case study. The main contribution of this work is a knowledge graph-based framework that focuses on the work performed by the operator, including the evaluation of movements, collaboration with machines, ergonomics, and other conditions. In addition, the use of the framework is demonstrated in a complex use case based on an assembly line, with examples of resource allocation and comprehensive support in terms of the collaboration aspect between shop-floor workers.

Keywords: human-centered; knowledge graph; Industry 5.0; manufacturing ontology; semantic reasoning; operator support



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1. Introduction

The global economy and the developers of MES (Manufacturing Execution System) and ERP (Enterprise Resource Planning) systems face the challenge of enhancing productivity while retaining human labor in the manufacturing sector [1]. With the increasing diversity and complexity of product lifecycle applications, there is a growing need to digitize knowledge related to various aspects of the industry, such as process planning, production, and design. It is suggested that the key drivers for transforming data into knowledge and advancing process automation through interoperable data will involve KGs (knowledge graphs), semantic web technologies, and multi-agent systems [2]. Effective representation and communication of domain knowledge are also vital for smart manufacturing. The primary focus of Industry 4.0 lies in achieving extensive digitization, while Industry 5.0 aims to merge cutting-edge technologies with human involvement, characterized as a value-driven approach rather than a technology-centred approach [3]. Industry 4.0 integrates digital technologies such as IoT, artificial intelligence, big data, and automation into manufacturing processes to improve their efficiency, productivity, and customization. By prioritizing connectivity, data exchange, and smart factories, it establishes a more adaptable and responsive manufacturing setting. Industry 5.0, an emerging concept based on Industry 4.0, reintroduces human-centric methods into manufacturing operations. In contrast to Industry 4.0, which focuses mainly on automation and machine-to-machine communication, Industry 5.0 emphasizes collaboration between humans and machines.

The objective is to take advantage of the distinct strengths of humans and machines, such as creativity, problem-solving, and emotional intelligence, to drive increased levels of innovation, flexibility, and sustainability in manufacturing. Industry 5.0 strives to achieve a harmonious balance between technology and humanity, using advanced technologies while giving priority to human well-being, creativity, and empowerment. Furthermore, there is growing interest in research areas such as industrial humanization [4], sustainability, and resilience [5]. Within the context of Industry 5.0, the importance of a Knowledge Graph (KG) is underscored by its ability to represent and analyze intricate data related to human operators [6].

The networked data structure of this system effectively records essential operator-related elements like ergonomics, working conditions, and machine cooperation in a systematic manner. By utilizing ontologies, a structured understanding of human actions in the manufacturing setting is achieved, guaranteeing compliance with human limitations and abilities. The graph's dynamic query and visualization features support real-time monitoring and flexibility. Consequently, the Knowledge Graph (KG) has become a key instrument for enhancing human-centered approaches in intricate manufacturing environments [7].

The human-centered aspect of the Industry 5.0 idea [3] strives for improved human-machine interaction, envisioning robots integrated with the human mind to collaborate rather than compete [8]. Throughout history, humans have influenced cyberphysical systems (CPSs) significantly, playing a vital role in their establishment and advancement. Consequently, human intelligence stands out as a crucial and predominant element in intelligent manufacturing, aligning with the concept of human-cyber-physical systems (H-CPSs) [9]. To achieve a suitable level of human-machine fusion, the concept of operator 4.0 [10,11] must be assessed. This concept promotes adaptive automation within collaborative human-automation work systems, fostering a socially sustainable manufacturing workforce. A more recent idea, the concept Resilient Operator 5.0 [12], explores improving the resilience of human operators to various workplace factors, thus facilitating the implementation of efficient smart manufacturing systems. Additionally, a proposition is made to model cognitive abilities and task requirements using a human asset administration shell [13]. Ontology models can also help contextualize key performance indicators (KPIs) [14], identify indirect effects or influences, and analyze relationships within a complex network [15]. They can also assist in visually representing KPI themes, developing dashboards [16], and consolidating KPI-related data [17]. Once this relationship with the decision variable is established, it enables responsive development and optimization. The ontologies, semantic tools, and industry standards proposed in this paper can support the development of systems that enhance operators' resilience, flexibility, and efficiency. The primary contribution of this study is the introduction of a framework known as the Human-Centric Knowledge Graph (HCKG), which models elements related to the human operator, such as monitoring movement, work environment, and collaboration with robots, using ontology and standards. The framework is exemplified through an industrial case study and incorporates graph-based data querying, visualization, and analysis. An instance involving a complex wire harness assembly process illustrates instances of resource allocation and comprehensive support for human-machine collaboration. The key innovations and contributions of this paper include the following:

- Suggested the expansion of automation standards like ISA-95, AutomationML, or B2MML to cover human-centric processes and the application of semantic technologies.
- Advocated for a Knowledge Graph (KG)-based approach to bolster human-centered and collaborative manufacturing in Industry 5.0.
- Showcased a replicable industrial case study to validate the concept. Various graph-based analyses utilizing normal, directed, or hypergraphs will be demonstrated, such as resource allocation assessment, KPI evaluation, or identification of diverse collaboration forms between human and machine agents in the assembly process.

This research builds upon a previous conference paper [18], which introduced only a portion of the concept. Initially, Section 2 presents the current state of the field, pinpointing

knowledge gaps and motivations. The core contribution of the paper is outlined in Section 3, where the foundational elements of the HCKG design concept are elaborated. Section 4 outlines a wire harness assembly-based case study to trial the human-centered KG-based design concept. Lastly, the contributions and potential avenues for future research are discussed in Section 5.

2. State-of-the-Art—Knowledge Gap and Motivation

The integration of collaborative robots into manufacturing processes, known as human–robot collaboration (HRC), represents a significant advancement in Industry 4.0. Unlike traditional industrial robots that are confined to isolated cells, collaborative robots are designed to work alongside humans, using embedded interaction, sensing, and safety technologies. This enables a hybrid production environment where human and robot resources are dynamically allocated to optimize productivity, flexibility, and reconfigurability. HRC environments aim to overcome the limitations of manual and robotic assembly lines by providing a novel approach to task allocation and execution that improves overall manufacturing efficiency and adaptability [19].

Cyber-Physical Production Systems (CPPS) integrate physical processes with digital technologies to optimize production processes. These systems enable seamless communication between physical components and digital systems, fostering an adaptive and intelligent manufacturing environment that is capable of self-optimization and autonomous decision-making. Information management of emerging industry trends requires an effective solution, such as KGs, that uses a graph-based data model to capture knowledge in application scenarios that involve integrating, managing, and extracting value from diverse data sources, even on a large scale [20]. Semantic technologies such as ontologies, graph databases, semantic analytics, and reasoning provide an efficient way to process large amounts of data from multiple sources by making the entire data set transparent and accessible [21,22]. Semantic networks and graph-based analytics are recommended to handle process information using linked data features. Knowledge graph (KG) techniques are capable of extracting data from structured, semi-structured, or unstructured sources and then incorporating this information into a graph-based knowledge representation [23]. To improve operator working conditions, various monitoring systems, such as sensor networks, can be utilized to monitor operator movements and physical states, enabling the assessment of performance metrics [24,25]. In the process of ontology engineering, systematically adapting ontologies to different production systems and factory settings requires a thorough initial requirements analysis to ensure deep understanding [26]. Existing ontologies are meticulously assessed to facilitate reuse and adaptation through a modular design. Emphasizing granularity and maintaining consistent naming conventions requires thorough documentation. Seamless integration with existing factory data sources is carefully coordinated, and an iterative refinement strategy, supported by expert input and real-world tests, is integrated [1]. Utilizing specialized software and tools, along with adherence to standards like the OWL (Web Ontology Language) and the RDF (Resource Description Framework), coupled with stringent governance, guarantees compatibility and systematic updates. A knowledge reasoning framework has been suggested, using semantic data to improve real-time data processing in a smart factory setting [27]. A machine learning semantic layer has been introduced to complement augmented reality solutions in the industry, providing an intelligent layer [28]. Operators in an Industry 5.0 environment should be able to interact effortlessly with industrial assets while dealing with more complex assets. To achieve this development objective, a generic semantics-based task-oriented dialogue system framework like KIDE4I (Knowledge-driven Dialogue framEwork for Industry) can offer a solution to reduce cognitive load [29].

The use of international standards can improve the quality of information systems by facilitating the interoperability of the software tools used. ISA-95 [30] is one of the essential standards in the field of integration of enterprise control systems and serves as a widely used basis for designing Industry 4.0 [31], IIoT (Industrial Internet of Things) [1] or smart

factories [32] related to MES and MOM (Manufacturing Operations Management). To create a semantically integrated design concept, the production capability and personnel models of the ISA-95 standard are recommended as a basis for modeling.

B2MML is an implementation of IEC/ISO 62264 [33] to provide a freely available XML for manufacturing companies [34]. B2MML standard elements are recommended for the development of problem-specific ontologies, such as the concept of collaborative assembly workstations [35], where semantic technologies are used to improve interoperability with external legacy systems such as ERP and MES. AutomationML [36] aims to standardize the exchange of data in the engineering process of production systems. In an AutomationML environment, the IEC 62264-2 personnel model [37] provides a method to model the operator in a production process with the following elements: personnel class, personnel class property, person and person property. AutomationML is also recommended as an exchange file format as a step toward automated job design based on optimized resource allocation [38].

Another important point to consider is that human-centric Cyber-Physical Production Systems (CPPSs) in smart factories and active collaboration between humans and machines have introduced an ontological framework known as the PSP ontology (Problem, Solution, Problem-Solver Ontology) [39]. The research focused on integrating the three main concepts of “Problem-Solving Semantically Profile”, “Problem-Solver Profile”, and “Solution Profile”. In addition to the semantic representation and reasoning of these core concepts, the study introduced the contingency vector, competence and autonomy vectors, and the solution maturity index for CPPS [39]. Moreover, due to the insufficient operator-based models, particularly in decision-making aspects [40], it is recommended to incorporate the human operator model into the shop floor control system. Enhancing human-machine interaction through ontologies is recommended. To prioritize human well-being while ensuring production efficiency, the development of a human-centred intelligent environment requires the consideration of various factors. There is a high demand for identifying suitable factors to evaluate human-robot collaboration and ergonomic conditions for factory workers [41]. A comprehensive framework is required to evaluate Human-Machine Interfaces (HMI) and Human-Robot Interactions (HRI) in collaborative manufacturing settings [42]. A comprehensive systematic review [15] categorized the measures, indicators, and quality factors used in the HRI literature using a methodical approach. The indicators are grouped into categories relevant to industry 5.0 research, including physical ergonomics (safety, physical workload, job design), cognitive ergonomics (mental workload, awareness), performance (efficiency, effectiveness), and user experience satisfaction/hedonomics (emotional responses, acceptance, attitudes, trust) [15]. In the field of ontology engineering, especially within the Industry 4.0 framework, a structured series of methodical procedures is adhered to [43]. Initially, a comprehensive analysis of requirements is performed to grasp the diverse points of view of stakeholders and establish the goals, extent, and requirements of the ontologies [44]. Before embarking on any new development, existing ontological resources are evaluated for potential repurposing, focusing on efficiency and the integration of well-established concepts. Throughout the development phase, specialized tools are utilized to define essential elements such as classes, relationships, and axioms. A thorough assessment process, involving expert evaluations and automated validations, ensures alignment with recognized standards and specifications. Elaborate documentation is generated that elucidates the structure and operation of the ontology to enhance comprehension and stakeholder participation. The final result is incorporated into the Industry 4.0 setting and, acknowledging the evolving nature of industrial domains, undergoes regular reviews and improvements to maintain relevance and efficiency [45].

In summary, the knowledge gaps in a semantic framework to support collaborative and ergonomic manufacturing include the need for effective human-centered design integration [46], comprehensive manufacturing ontologies [47], robust semantic reasoning techniques [48], and advanced operator support tools [49]. Addressing these gaps requires overcoming challenges related to data integration, data quality, real-time analytics, and scalability in KG-based frameworks [50]. The motivation of this paper is to propose a

semantic-based framework for human-centric manufacturing and to present an industry-related case study of KG utilization. In the following section, the concept of HCKG design is presented after discussing the motivation for this research.

3. Human-Centered Knowledge Graph-Based Concept towards Collaboration in Manufacturing

This section delves into the primary contribution of this paper, which is the design concept of the Human-Centered Knowledge Graph (HCKG). Section 3.1 explores the activity model associated with the management of manufacturing operations. Section 3.2 describes the different human–robot collaboration scenarios and the key essential performance indicators of a human-centric assembly process. Lastly, Section 3.3 details the framework of the HCKG concept. The objective of the HCKG design concept is to establish a framework to monitor and control human–machine collaboration, improve resilience and agility, and improve working conditions for operators. The knowledge graph incorporates monitored data concerning the operator’s activities, the environment, as well as all robots and equipment within the manufacturing space. Through the analysis of the collected knowledge graph data, collaboration can be enhanced, work instructions can be customized for the operator, and any modifications can be adaptively managed. Figure 1 illustrates the integration approach of the HCKG concept. In the initial segment, the Production Process element represents the intricate production environment encompassing all human–machine resources, processes, activities, and interactions. The Monitoring System element interacts with the production process, collecting historical and real-time data using sensors and IoT devices. Furthermore, the schema element offers semantic tools to establish a contextualized data model, while the meta-information element contains meta-information, such as industry standards, to ensure reusability. In knowledge graphs, Metal pertains to data about the data itself, providing details such as its source or properties, whereas Scheme defines the structure, properties, and relationships within the graph, organizing and standardizing the data model. The initial segment comprises a variety of structured and unstructured data sources that require preprocessing.

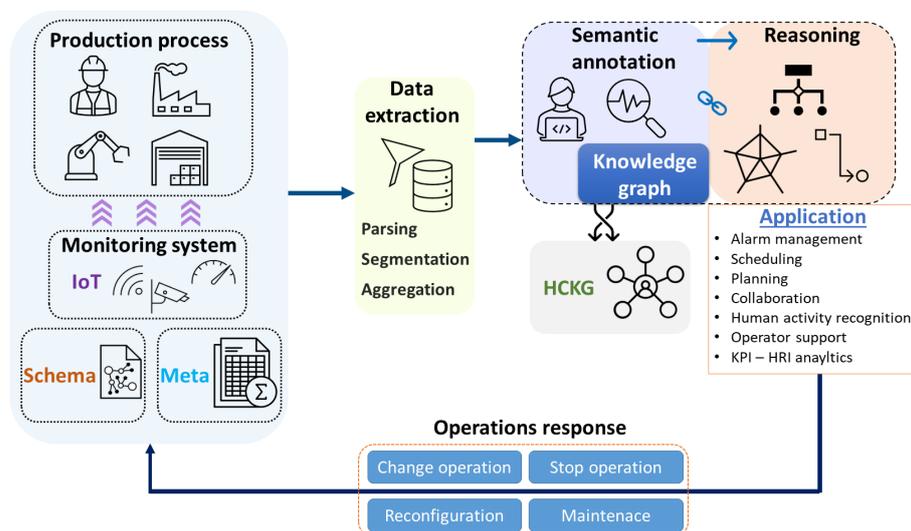


Figure 1. Integration of the HCKG design concept connected to the production process, using five segments.

Therefore, the second part involves procedures such as parsing, segmenting, and consolidating data, which constitute the Data Extraction component. The goal of data extraction is to recognize and retrieve pertinent information from unstructured or semi-structured data sources of the initial part and to transform it into a structured form for analysis and optimization. The third section encompasses the Semantic Annotation and Reasoning components, which leverage semantic modeling and data analysis in a complex

KG. The Semantic Annotation module constructs the KG utilizing the schema, metadata, and extracted data. This process entails the appending of metadata, standardized labels, or tags to entities and relationships within the KG, such as industry-specific terms or concepts from a particular domain. Within knowledge graphs, “metadata” refers to semantic details that delineate the attributes, context, and connections of the data, thereby enhancing comprehension and interpretation of the underlying information. It enables applications to recognize and classify diverse entities more precisely within the KG by furnishing additional context and facilitating more accurate categorization and identification within the data model. The HCKG module signifies the human-centric KG aspect of the established semantic network, which may encompass the entire KG or only the portion relevant to shop floor workers, depending on the specific scenario. This section is elaborated further in Appendix A and the case study in Section 4.2. The Reasoning component enhances the semantic information for the subsequent segment, the component Application . The reasoning process relies on the concept that the interrelations and links among various entities in the KG can be leveraged to derive logical inferences and form novel predictions. In the realm of analytics and optimization, semantic reasoning plays a crucial role in uncovering patterns, correlations, and causal connections between entities within the KG. Through the application of semantic reasoning, patterns and correlations among various data points can be identified, such as determining which machines are likely to cause delays on a specific production line. By engaging in reasoning across the KG, the application can determine the most efficient sequence of steps in the production process to minimize waste and improve efficiency. Human-centric KG applications can assist in managing alarms, scheduling operations or personnel, optimizing human–machine interactions, recognizing human activities, or analyzing performance metrics. This topic is further elaborated in Section 4.3 through a case study. The outcome of the application, along with the analysis results, leads to the operation response (fifth segment), which is then directed to the production process component. Examples of responses include change operation , stop operation , reconfiguration , or maintenance .

3.1. Manufacturing Operations Management

This section delves into an expanded MOM activity model, illustrated in Figure 2, where the components can be categorized based on the timing of their occurrence during the execution of the task. Although this aspect of the methodology has been previously documented by the authors in a conference paper [18], the inclusion of the associated MOMs here aims to enhance the comprehension of the HCKG framework. The temporal perspective of the general activity model concerning pre-, during, post-, and reference data is also emphasized [51]. Moreover, the supplementary modules for extending the standard activity model of MOM [52] are depicted in brown below.

The MOM approach is designed to provide a detailed insight into the mechanisms linked to the operator’s role in a general manufacturing task, while also emphasizing the characteristics of the additional monitoring and support framework components. The generic activity model is segmented into four sections based on a temporal perspective, indicated by green labels in the diagram, and is evaluated and deliberated upon in a similar manner. The Reference Data encompasses all the details regarding individual operators, including their skills, capabilities, and expertise in specific domains. The Resource and Definition Management segments of the MOM system compile this data and establish the foundational information for the subsequent operational segments of the model. As an expansion of the reference data segment, the Control and Optimization component is suggested, where the integration of machine learning or artificial intelligence solutions can enhance the ongoing manufacturing processes.

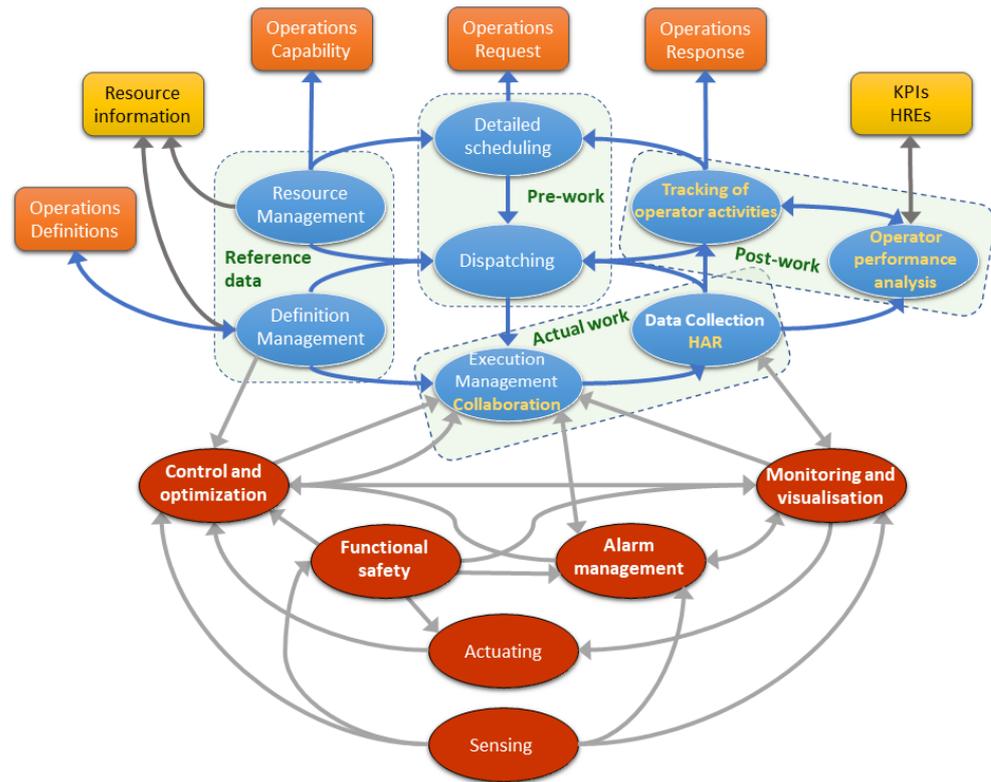


Figure 2. Activity model of manufacturing operations management from an operator-centric point of view [18].

The following section in Figure 2 represents the Pre-work phase, where Detailed Scheduling is employed based on the Operation Request, and Dispatching tasks are carried out. These actions ensure that all operators receive proper instructions, are efficiently scheduled, and are assigned tasks accordingly. The actual work segment of the MOM delineates the ongoing activities managed by Execution Management, while concurrently conducting Data Collection. Some elements centered on humans are integrated (marked in yellow text), such as Collaboration or the utilization of Human Activity Recognition (HAR) sensor technologies. To enhance real-time operator assistance, additional components like Alarm management, Monitoring and visualization are included as supplementary features. An intelligent monitoring system can gather data from various manufacturing parameters such as temperature, noise, or vibration, and display it graphically in real-time, issuing alerts in case of anomalies.

In the post-work phase of the task, monitoring of operator activities is carried out to derive an operational response for the MOM. Additionally, the evaluation of operator performance is utilized, serving as the foundation for Key Performance Indicators (KPIs) and Human Resource Effectiveness (HRE), which are crucial components in the Knowledge Graph (KG) used to establish adaptable and resilient conditions for the operators. The expansion modules of the activity model are intricately linked to the KG through semantic technologies. The advancement of intelligent cyber-physical systems establishes an environment where each aspect of the intricate manufacturing system, involving humans and machines, is effectively supervised, and the information systems are compatible. The vital components of the extended MOM model, viewed from the shop floor perspective, include Operator Performance Analysis, HAR, and Monitoring, which plays a key role in KPI and metric evaluation. A thorough examination of operator performance can support skill-based matching and the development of skill clusters. With the growing need for adaptable production lines, conventional assembly lines might be substituted by self-sufficient workstations, referred to as skill clusters, with mobile robots transitioning between them. In

addition, skill clusters should be furnished with collaborative robots capable of working safely and reliably alongside operators.

3.2. Human–Robot Collaboration and Key Performance Indicators

This section delves into the various categories of workstations and collaboration scenarios that are of significance within the context of the case study under consideration. In addition, a concise summary of the primary performance metrics related to human-centered, ergonomic, and human–robot collaboration is provided. Depending on whether the actors involved are human or robotic, different types of workstations can be identified: manual, collaborative, and automatic [53]. Within a collaborative workstation setup, further categorization is established based on the nature of the interaction between human and robot actors during work tasks, aiming to yield a more comprehensive case study. Figure 3 illustrates three different types of collaboration [42,54]:

1. Separate work: Human and robot tasks are kept apart, and they do not share workspaces, tools, or workpieces.
2. Sequential collaboration: Although the human and robot actors are in a shared process flow of a workpiece, tasks are completed in succession. The workspaces, tools, and workpieces may be shared, but the tasks are strictly serialized such that any sharing is temporally separated.
3. Simultaneous collaboration: Human and robot tasks are executed concurrently and, moreover, may involve working on different parts of the same workpiece but are focused on achieving separate task goals.
4. Supportive collaboration: Humans and robots work together on the same piece of work to complete a common task.

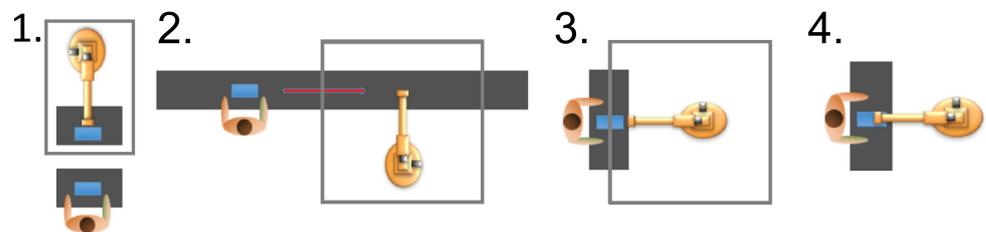


Figure 3. Separate (1.), sequential (2.), simultaneous (3.), and supportive (4.) types of human–robot collaborations [42].

The key performance indicators (KPIs) focused on human factors are outlined in Table 1 across six distinct categories: time behavior, physical measures, HR physical measures, efficiency, effectiveness, and ergonomics. Furthermore, the Operator 4.0 typologies [46] have been incorporated into these KPIs in the second column, illustrating the potential to facilitate the establishment of a harmonious relationship between humans and automation. A study that assesses the quality of human–robot interaction [15] has been partially referenced, although it does not offer a comprehensive overview of the subject matter. Additionally, a paper on ontology-driven KPI metamodeling [14] has been taken into account in this case study, focusing on a semantic technology perspective.

Table 1. The categorized human-centric KPIs for the case study.

KPI Description	Operator 4.0 Type
Time behavior category	
Average time to complete task	Analytical operator
Collaboration time—Type-3 and Type-4	Collaborative operator
Functional delays	Analytical operator
Human operation time	Analytical operator
Interaction time	Collaborative operator

Table 1. Cont.

KPI Description	Operator 4.0 Type
Response time	Collaborative operator
Robot functional delay	Collaborative operator
Robot operation time	Collaborative operator
Task completion time	Analytical operator
Total assembly time	Analytical operator
Total operation time	Analytical operator
Physiological measures category	
Biosignals (temperature, tactile, etc.)	Healthy operator
Ergonomics improvement	Healthy operator
Muscle activity	Healthy operator
Ocular behavior	Healthy operator
HR physical measures category	
Avg./min. length between a human hand and a robot hand	Collaborative operator
Human–robot distance	Collaborative operator
Efficiency category	
Availability	Collaborative operator
Average robot velocity	Collaborative operator
Concurrent activity	Collaborative operator
Degree of collaboration	Collaborative operator
Layout efficiency	Analytical operator
Effectiveness category	
Accuracy	Analytical operator
Interaction accuracy	Collaborative operator
Level of assignment	Collaborative operator
Level of interaction	Collaborative operator
Overall equipment effectiveness	Analytical operator
Real-time human fault	Analytical operator
Real-time robot fault	Collaborative operator
Ergonomics—environmental category	
Environmental condition—noise	Healthy operator
Environmental condition—humidity	Healthy operator
Environmental condition—temperature	Healthy operator
Environmental condition—gases	Healthy operator

3.3. Design Structure of the HCKG Concept

This section outlines the methodology and presents a summary of the proposed development framework in a block format, as illustrated in Figure 4. The main objective is to integrate the human-centric KG block within a sophisticated industrial setting. The framework comprises five distinct blocks (or sections), commencing with the metadata sources from a business or industrial network and culminating in the application that leverages the information to generate value.

The meta block includes essential data to characterize the business processes and describable elements of a plant, such as material or information flows, starting from the foundational level. Markup languages and standards like B2MML (Business To Manufacturing Markup Language), AutomationML, or ISA-95 establish the initial framework for handling and overseeing the diverse data sources and processes within a complex network. It is advisable to expand existing standards such as ISA-95. A critical aspect of industrial progress involves utilizing standardized models, which facilitate the seamless integration of a new design concept into a production system and enhance the adaptability of existing methodologies, thereby making the learning curve for technical aspects more dynamic. The next component is the Schema and PPR block, representing the three descriptive on-

tologies within an Industry 4.0 setting. The product, process, and resource ontologies can comprehensively depict the entire network in a semantic format. Various assets, whether physical or human attributes, characteristics, and specific values, are structured as ontology axioms (individuals) and classified into classes. Furthermore, semantic properties, rules, and queries support interoperability and the depiction of relationships, such as actors' capabilities, the sequence of manufacturing activities, or resource allocation. PPR-based modeling aligns with AutomationML and serves as a method for establishing knowledge-driven mappings of products, processes, and resources in assembly automation [55]. The primary advantage of PPR-based modeling lies in facilitating the management of engineering datasets' mappings and connecting product attributes to manufacturing processes and resources. Moreover, knowledge-driven PPR mapping can aid in dynamically configuring and analyzing assembly automation systems [56]. The IoT Block comprises monitoring devices and sensors for conducting observations, along with HAR, which are essential inputs for the higher-level human-centric block—a pivotal component. Additionally, IoT devices form a complex system that necessitates separate management due to the diversity of smart devices and sensors. The so-called VAR ontology encompasses three key elements: tangible assets, intangible assets, and dynamic status.

Building blocks	Elements of the different building blocks			
Application	KPI - HRI	Integrated collaboration evaluator	Simulator for integrated uncertainty	Scheduling
Human-centric	Monitoring ontology	Evaluating ontology	Operator support ontology	
IoT	Sensors	Observation	HAR	
Schema PPR	Product ontology	Process ontology	Resource ontology	
Meta	B2MML	AutomationML	ISA-95	

Figure 4. Theoretical structure of the proposed human-centered knowledge graph-based design concept [30].

The human-centric block includes the monitoring, evaluation, and operator support ontologies, with the goal of gathering and analyzing relevant information related to the production process, collaboration, human activities, or working conditions in the factory. Its primary aim is to keep the operator informed and assist them in various aspects such as ergonomics and collaboration. In a setting where humans and robots work together, feedback is crucial not only from the control or machine perspective but also from the human perspective, focusing on real ergonomic features, process parameters, and other input from the operator. Operators on the factory floor can offer valuable insights for the MOM's Operations Response, which should be integrated into the semantic-based data management system supporting CI/CD (Continuous Integration and Continuous Delivery) practices. The application block encompasses all the valuable information that the HCKG can provide for tasks like scheduling, resource allocation, enhancing KPIs and HRI factors, assessing collaboration aspects, or conducting simulations. The end user, whether a process engineer, factory worker, or production manager, is primarily interested in this segment as it delivers the final outcome of the semantic-based analysis. The application block can aid in exploring integrated uncertainty through simulations and assessing collaboration or business processes. Furthermore, scheduling and allocations can be optimized based on the performance metrics obtained. Other issues like the cybersecurity of large infrastructures,

which are not covered here, are likely to remain significant challenges in the foreseeable future. Subsequently, a case study demonstrating the application of the proposed KG framework is presented following the discussion on the KG design concept.

4. Human-Centered Knowledge Graph Representation for a Wire Harness Assembly Process

This section illustrates the implementation of the HCKG approach elaborated in Section 3. Initially, a case study specific to the industry is outlined in Section 4.1. The establishment and organization of the generated KG are thoroughly examined in Section 4.2. Lastly, Section 4.3 demonstrates the visualization and examination of the production data.

4.1. Wire Harness Assembly-Based Case Study

A recent study on research and development [57] emphasized the importance of exploring collaborative robots in wire harness assembly. The authors of this study also delved into the analysis and design of Intelligent Collaborative Manufacturing Spaces (ICMS) using a hypergraph-based approach similar to a referenced benchmark [58]. The wire harness assembly sector served as the inspiration for the case study discussed in this paper. Specifically, the case study focused on the manufacturing processes of a multinational wire harness assembly plant. Detailed information cannot be disclosed due to confidentiality policies; however, the proposed methodology is continually undergoing validation with manufacturing experts. Figure 5 illustrates the factory floor layout, featuring a coordinate system that establishes a grid for assigning operators and production resources like robots and machinery. The case study incorporates a real-time location system (RTLS) that monitors the whereabouts of assembly workers and assets. The X and Y axes on the shop floor correspond to potential RTLS-based positions. Distances required for material handling and transportation can be determined from the grid. Furthermore, the shop floor is divided into 18 distinct areas, for instance, ST_11, which can accommodate workstations.

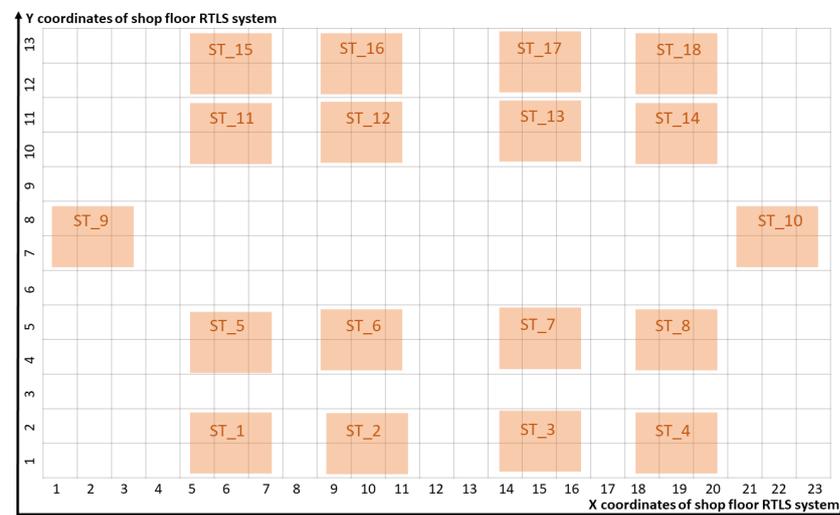


Figure 5. The grid layout of the benchmark shop floor.

A dual production system comprising batch and traditional production was specified, and the workflow is depicted in Figure 6, which is derived from an actual wire harness industry assembly line. This process involves two assembly lines that share tasks and resources. The components of these lines are detailed in Table 2. The shop floor includes two storage areas, multiple buffers, crimping stations, and assembly stations. The second group of components encompasses human-machine agents, which can be operators or robots, as well as production line assets, such as machines, tools, screwdrivers, and the AGV (Automated Guided Vehicle). Additionally, specific capabilities are necessary to perform designated tasks, along with sensor components, to oversee the collaborative environment.

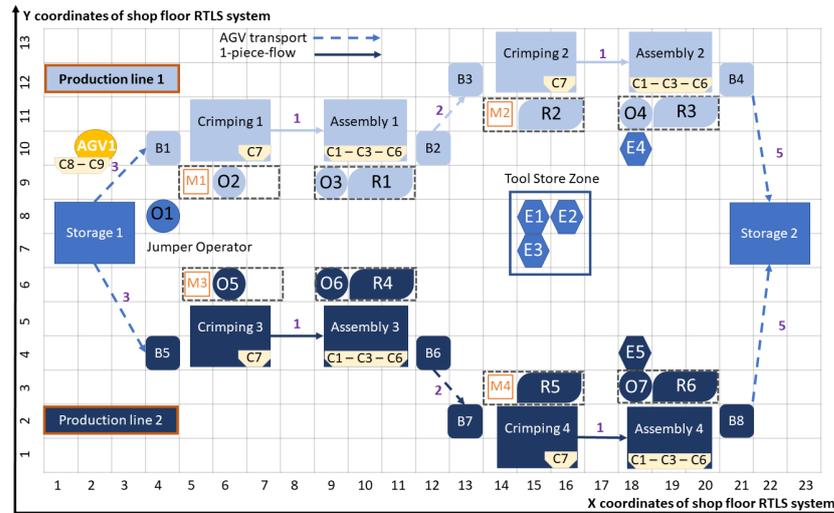


Figure 6. The process flow of the wire harness assembly line benchmark.

Table 2. The elements of the wire harness assembly lines.

Work sections of the production lines	
Storage	[K1, K2]
Buffer	[B1, B2, B3, B4, B5, B6, B7, B8]
Crimping stations	[Crimping 1, Crimping 2, Crimping 3, Crimping 4]
Assembly stations	[Assembly 1, Assembly 2, Assembly 3, Assembly 4]
Human–machine members and assets	
Operators	[O1, O2, O3, O4, O5, O6, O7]
Robots	[R1, R2, R3, R4, R5, R6]
AGV	[AGV1]
Machines	[M1, M2, M3, M4]
Tools	[E1, E2, E3, E4, E5]
Capabilities	[C1, C3, C6, C7, C8, C9]

A detailed list of activity types for this benchmark problem can be found in Appendix A in Table A2, encompassing categories such as the crimping process, assembly process, or material handling, along with the definitions of the outcomes associated with these activity types. It is crucial not only to define the activity types but also their results for effective process tracking and collaboration. A more comprehensive overview of the wire harness assembly benchmark is presented in Appendix B, where each activity type of the intricate industrial process is outlined in Table A1, followed by detailed descriptions of the sequence of activities in Tables A3 and A4 of the Appendix B, as highlighted in this study. In addition to the main elements listed in Table 2, other attributes of the elements include the following Capabilities necessary for carrying out specific activities: C1—insertion and laying of parts (cabling), C3—terminal handling, C6—terminal screwing, C7—crimp machine operation, C8—loading or unloading of the AGV, and C9—workpiece transport on the shop floor. Moreover, there are specialized tools, some of which are shared across the process, namely E1—wiring tool, E2—hose tool, and E3–E5—screwdrivers. Additionally, various unique Machines (M) are allocated to different Crimping Stations, while Tools (E) are considered communal assets within Assembly Stations.

In Figure 6, the brighter-colored elements represent Production line 1, while the darker ones represent Production line 2. Shared assets and resources are visualized in the middle. Material handling steps during production are indicated with arrows, which can be carried out as a one-piece-flow by operators or through an AGV-based transport

system. Additionally, the distances over which materials are moved are marked with purple numbers. The process flow, illustrated in Figure 6, begins at Storage 1, where the operator known as jumper O1 loads AGV1 (using capability C8) with a batch, which is then transferred by AGV1 to either Crimping station 1 or 3 (using capability C9), where the unloading is performed by operator O2 or O5 into the local buffers B1 or B5. The subsequent steps are identical on both production lines, with the continuation of the process description focusing on Production line 1. As per the production plan, operator O2 carries out crimping-related activities listed in Table A2 that necessitate capability C7. Furthermore, machine M1 is utilized during these crimping activities. Subsequently, operator O2 transfers the workpiece to operator O3 at Assembly station 1 (one-piece-flow). Operator O3 and robot R1 collaborate, carrying out activities related to capabilities C1, C3, and C6. Additionally, tools E1–3 are employed during the activity steps at Assembly station 1. At the conclusion of the process, operator O3 places the workpiece into buffer B2. Upon the completion of a full batch, the same operator loads AGV1, which transports the batch of cables to the subsequent buffer, B3. Subsequently, robot R2 unloads the buffer and performs activities related to capability C7 and machine M2 at Crimping station 2. Following this, robot R2 transfers the workpiece (one-piece-flow) to operator O4 at the subsequent station, Assembly station 2. At the final workstation of Production line 1, operator O4 and robot R3 collaborate to carry out activities requiring capabilities C1, C3, and C6. At the end of the assembly line, operator O4 places the workpieces into buffer B4. Upon completion of a full batch, the same operator loads AGV1, which delivers the products to their final destination, Storage 2.

Furthermore, it is important to mention that this case study also includes different types of sensors, the purpose of which is to make observations about each activity, human, and machine of the production line, as well as to monitor the working conditions. These groups of sensors are camera systems, RTLS, robot-embedded sensor data, machine-embedded sensor data, environmental sensors, and human body sensors.

All three categories of workstations are included in this instance focusing on collaborative work. Crimping Station 1 and 3 are characterized as manual workstations, while Crimping Station 2 and 4 are classified as automatic workstations. The research features four collaborative workstations, denoted as Assembly stations 1–4. The specific case study on harness assembly delves into collaboration types 3 and 4. An illustration of concurrent and supportive collaboration is shown in Figure 7. In this simplified scenario, four distinct outcomes are observed, corresponding to the tasks executed by the entities Robot 3 and Operator 4. For instances Result 28 and 31, where both human and robot actors engage in similar activities on the same product, they engage in supportive collaborations aimed at achieving the same assembly result. On the contrary, Result 29 and 30 involve different activities, with human and robot actors operating on the same product simultaneously but pursuing different objectives. The idle period occurs when Robot 3 must wait for Operator 4 to complete their task, as they share the same workstation.

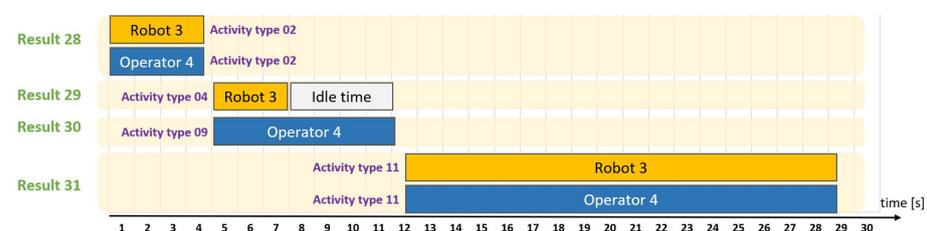


Figure 7. Gantt chart of collaboration scenarios.

4.2. Development of the Industry-Specific Human-Centered Knowledge Graph

A section of the KG that has been utilized in the case study discussed in Section 4.1 is depicted in Figure 8, excluding the distinct data properties of the ontology classes. The structural illustration in Figure 8 is segmented into six sets of ontology classes since the KG comprises multiple sub-ontologies. Moreover, the object properties, representing relationships among classes, are indicated on the arrows.

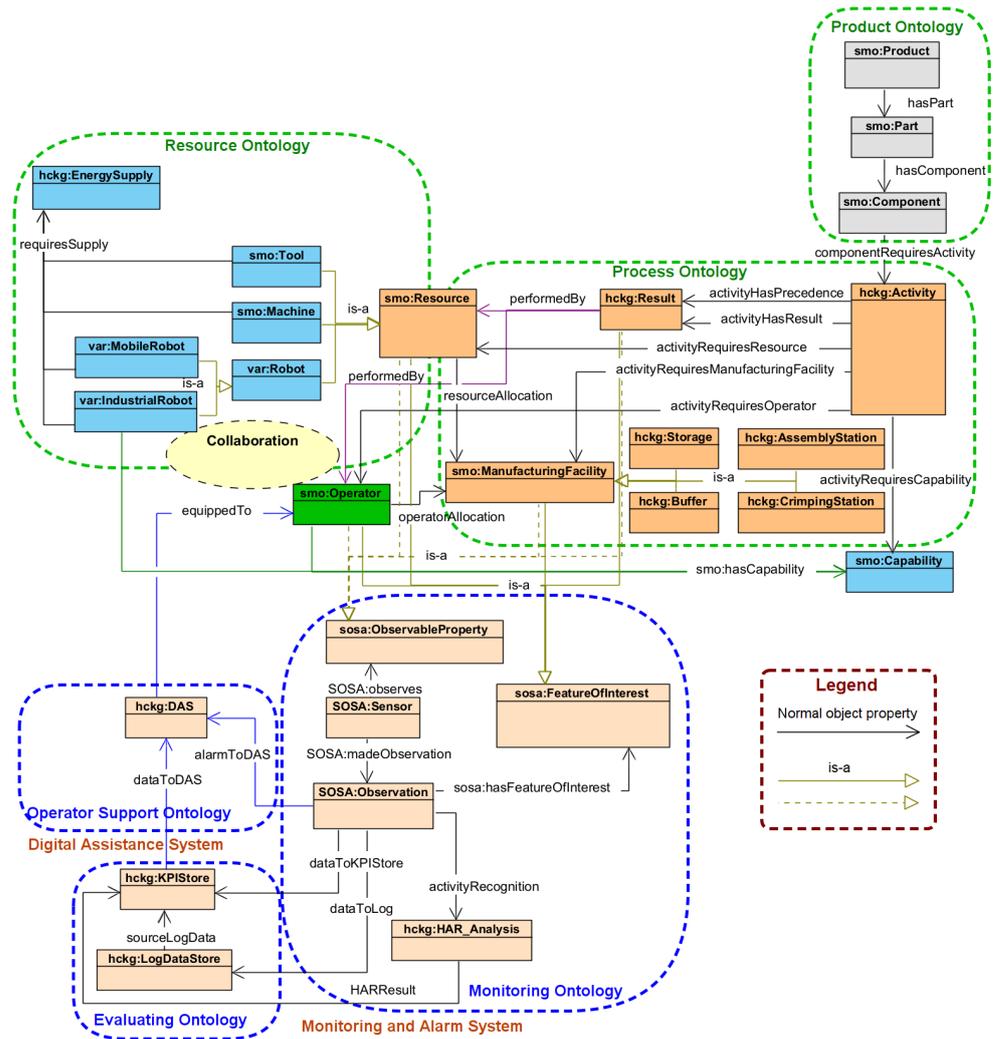


Figure 8. Partial structural diagram of the developed wire harness assembly-specific KG.

Prefixes indicating adapted namespaces from other industry-specific ontologies are included in the names of the ontology classes. The following list summarises these prefixes and the ontologies used:

- smo—Smart Manufacturing Ontology [59]: An ontology to model I4.0 production lines and smart factories based on RAMI 4.0. It highlights the sequence of processes and machines required for a produced workpiece.
- SOSA—Sensor, Observation, Sample, and Actuator ontology [60]: For modeling the interactions between the entities involved in terms of observation, actuation, and sampling. Together with SSN (Semantic Sensor Network), it can be used to describe sensors and their observations, the involved procedures, the studied features of interest, the samples used to do so, the feature’s properties being observed or sampled, as well as actuators and the activities they trigger [61].
- var ontology [35]: A core ontology for data exchange in a semantic-oriented framework to support adaptive, interactive, assistive, and collaborative assembly workplaces.
- hckg—Human-Centric Knowledge Graph: The authors created a set of classes and properties to model the wire harness assembly-based case study semantically.

The product ontology includes three categories: product, part, and component. The complexity of this domain, previously addressed by the authors in [62], is not further explored here. The Process ontology is composed of the subsequent categories: Activity, Result, and ManufacturingFacility, which encompasses additional subclasses like Storage, Buffer, AssemblyStation, CrimpingStation, and Capability. The primary category in the

Resource ontology is Resource, which includes various subclasses such as Tool, Machine, and Robot. The Robot category is further divided into MobileRobot and IndustrialRobot. The EnergySupply category is also part of the resource ontology. The Operator category, a central element of the human-centered HC, is highlighted in green at the center of the HC structure in Figure 8. The operator category, which semantically characterizes the processes and impacts related to personnel on the shop floor, is associated with six distinct object properties. The Monitoring ontology comprises three categories: Sensor, Observation, and HAR_Analysis, storing the semantic model of sensor devices, their measurements, observation, and human activity recognition. The Evaluating ontology contains two categories: KPIStore and LogDataStore, designed to handle data from the aforementioned three categories. Lastly, in the Operator Support Ontology, the DAS category defines the digital assistance system. Considering that the categories Operator and Activity are pivotal in the KG, Tables 3 and 4 provide details on the corresponding object properties.

Table 3. Object properties of the Activity class.

hckg:Activity	
component Requires Activity	Connects individuals from the component and activity classes and provides information about the required activity to assemble a specific component on the wire harness.
activity Has Precedence	Since the assembly procedure requires a specific sequence, certain activities must be finished before another can be started. This is known as the precedence criteria.
activity Has Result	Describes the intended result of a particular activity. In the case of collaboration, several activity individuals may be connected to the same result individual.
activity Requires Resource	Interlinks Tool, Machine, or Robot individuals to an activity as a resource requirement.
activity Requires—Manufacturing Facility	Workstation requirement of an activity. Connects activity individuals with the ManufacturingFacility individuals such as Storage, Buffer, AssemblyStation, or CrimpingStation.
activity Requires Operator	Connects operator individuals to an activity as a personnel requirement.
activity Requires Capability	Describes the capability requirement of a specific assembly activity, which has to be conducted by an Operator or IndustrialRobot.

Table 4. Object properties of the Operator class.

smo:Operator	
activity Requires Operator	It provides information about a certain operator involved in certain activities.
operator Allocation	Semantically connects operators with Manufacturing Facility individuals such as Storage, Buffer, AssemblyStation, or CrimpingStation. It provides information on where the operator performs his/her work.
performed By	Connects Results with Operators and shows which operator was involved in which result(s).
equipped To	Describes the usage of devices from the Digital Assistance System by operators.

Table 4. Cont.

smo:Operator	
is-a SOSA: Observable Property	Semantically connects the properties, which are monitored by sensors with operators and shows how personnel are monitored.
is-a SOSA: Feature Of Interest	Main class of the feature of interest of the SOSA:Observation
smo:hasCapability	Shows which capabilities require a specific operator.

In addition, some of the key features of the use of semantic technologies and graph analysis from a human-centered approach are presented in Table 5 [63]. These analytics can help to better monitor and understand the HRE [64] and KPI [65] factors. In addition, Table 5 provides an example of its application for each network metric.

Table 5. KG metrics and analytical features.

Network Metrics	Analytical Features of KGs
Centrality computation	Which are the critical objects in the network?
	Detect the most significant influencing factors in the operator's environment.
Similarities between nodes and edges	How similar are two objects based on their properties and how are they connected to other objects?
	Solve allocation problems concerning operators and resources.
Flows and paths	What is the shortest, cheapest, or quickest way to perform a process step?
	Optimise the shop floor layout to best match operator needs.
Cycles	Are there any cycles in the graph? If so, where are they?
	Analyze tasks allocated to humans and machines in a collaborative work environment
Network communities	What communities can be found in the production network?
	Facilitate the design of human-machine collaboration or cell formation.

Once the use case-specific knowledge graph has been established and the necessary data have been imported into the semantic network, the subsequent stage involves formulating queries and examining the outcomes. Consequently, the subsequent subsection delves into the examples of graph-based knowledge analyses that were utilized.

4.3. Discussion on KG-Based Analytics of the Use Case

Initially, Figure 9 shows the graphical representation of the complete knowledge graph (KG) related to the wire harness assembly case study. This visual depiction serves as a means to validate the manufacturing process. The complete network is illustrated on the left side, encompassing all properties and entities within the KG, while a more detailed view is presented on the right side. The orange node corresponds to the equipment *E5* and includes various associated data properties like locationID (18-4), equipmentCondition (86), equipmentID (*E5*), equipmentName (screwdriver C), and equipmentType (screwdriver).

All the SPARQL queries that have been developed are accessible on our website at <https://github.com/abonyilab/HCKG> (accessed on 14 March 2024). The initial instance of a SPARQL query-based data mapping, as referenced in [66], is illustrated in Figure 10. The left section of Figure 10 shows a graphical representation of the query, where four distinct rules are outlined to achieve the intended result. This particular example aims to identify RobotAssets categorized as IndustrialRobot s and seeks to present three associated data elements: Location , EnergySupply , and ManufacturingFacility. On the right side of Figure 10, a graphical representation of the result of the query is provided. Robot

assets classified as IndustrialRobot s are depicted as orange nodes, each necessitating an EnergySupply referred to as g2 (electricity). Each IndustrialRobot node is linked to the corresponding workstation node (ManufacturingFacility), which represents various assembly stations, illustrated in purple in this scenario. Lastly, the location data attributes of the robots are denoted by blue nodes (indicating the robots require two zones on the shop floor). This type of visual examination can aid in exploring dependencies concerning specific assets.

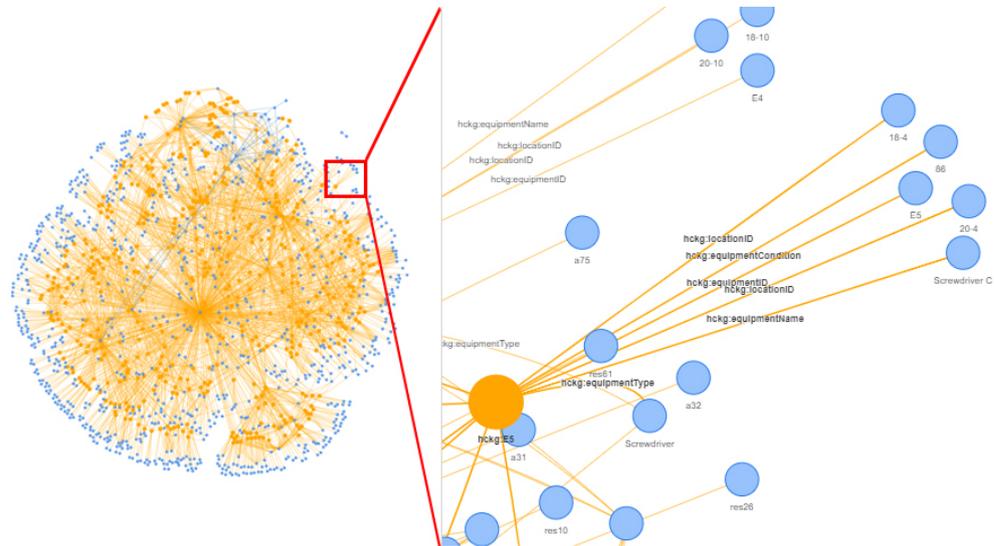


Figure 9. Visualization of the entire KG of this case study (on the left-hand side) and some of the data properties of equipment E5 (on the right-hand side—zoom into the red rectangle).

The resulting graph in Figure 11 illustrates the connections between Actors (operators or robots) and the Capability entities they are linked to. This illustration can be utilized for a visual examination of production capability. In Figure 11, it is evident that the majority of actors possess the capability C8 (AGV loading/unloading). Moreover, robots are limited to a maximum of two capabilities, whereas operators can concurrently possess up to four capabilities.

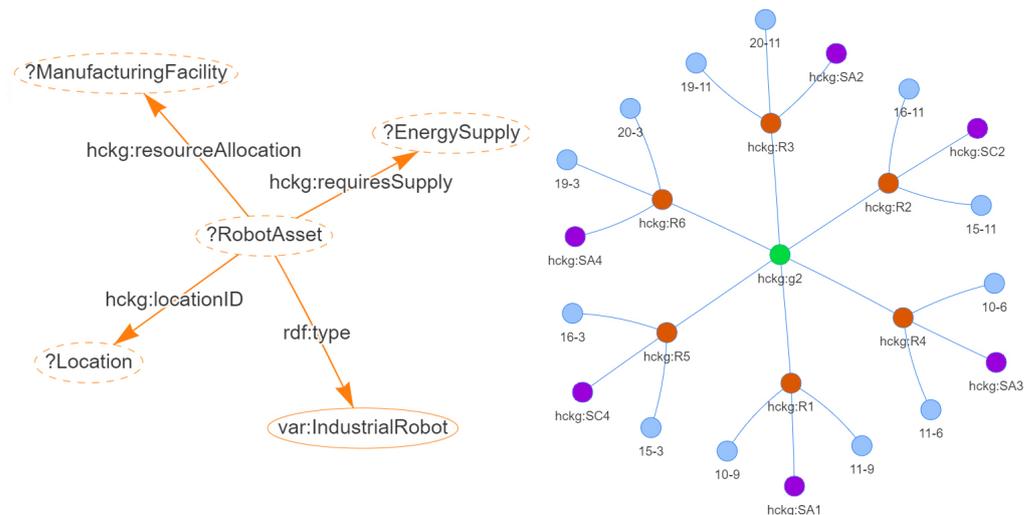


Figure 10. Visualization of the RobotAsset query (on the left-hand side) and the graph visualization of the result (on the right-hand side).

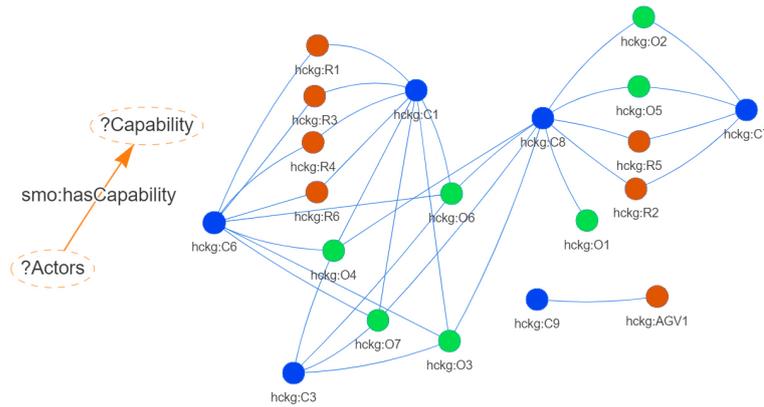


Figure 11. Visualization of the Actors-Capability query (on the left-hand side) and the graph visualization of the result (on the right-hand side).

A more intricate data query aimed at identifying sensor alerts transmitted to DAS devices is outlined in Figure 12. Initially, the KG is streamlined to include only the sensor, observation, and observed nodes, which are then refined to encompass sensor instances categorized under type names starting with “env” or “body”, denoting environmental or body sensors. Subsequently, additional data are integrated into the dataset, specifying attributes such as observationValue, warningLimit, and alarmLimit. A subsequent filter is employed to isolate instances where the observationValue exceeds the warningLimit. The output comprises a compilation of the DAS device name, the message content, and the device’s location. On the right-hand side of Figure 12, a graphical representation showcases only the most pertinent segment of the query outcome. Here, the purple nodes symbolize the sensor’s location, the red nodes depict the message relayed to the DAS, and the green nodes correspond to the specific operator integrated into the DAS device, such as Smart Glass. Notably, in the graph located in the lower right corner of the figure, the locations of the observation sensor and the DAS device coincide, indicating that they are body sensors.

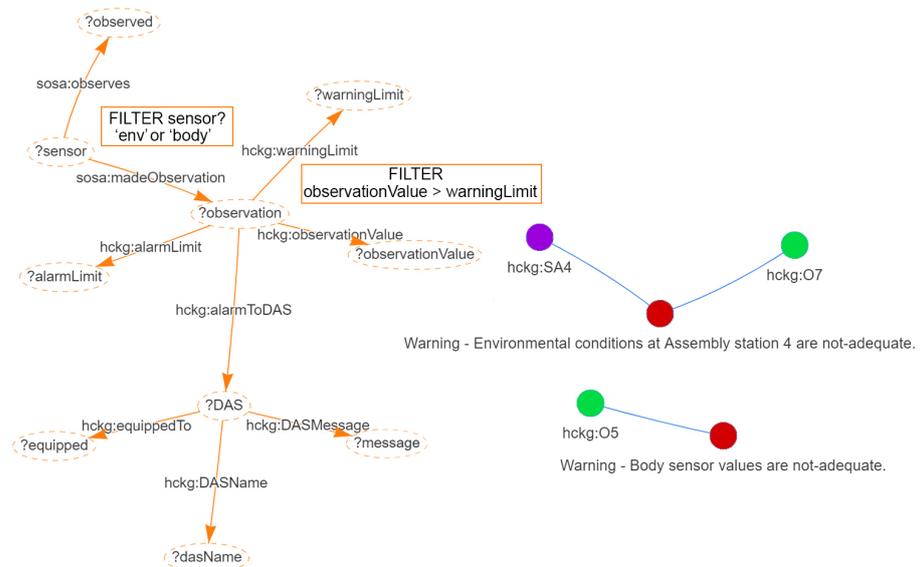


Figure 12. Visualization of the sensor-observation-DAS query (on the left-hand side) and a graph visualization of the result (on the right-hand side).

In the context of Operator 7 (O7) and Robots 6–7 (R6 – R7) collaborating at Assembly Station 4, as depicted in Figures 13 and 14 illustrates the application of the time KPI for human–machine collaboration. The graph in Figure 14 displays the total duration of supportive collaboration (type 4). Notably, O7 dedicated more time to collaborative

The directed edges represent different object properties of the KG, namely:

- done—activityHasResult object property: shows the result condition of a specific activity if the assembly task is performed.
- prec.—activityHasPrecedence object property: represents the precedence criteria of an activity that has to be carried out before the specific activity can be started.
- perform—performedBy object property: describes the human or robot actor that performs the activity.

The tasks and outcomes that serve as a foundation for analyzing the process flow, where the order of steps and conditions can be traced from tasks *a75* to *a83*, are presented on the left side of Figure 15. An expanded visualization, which includes the perform connections indicating that a human or robotic agent has performed a specific task, is shown on the right side of the same figure. Examining the inbound and outbound connections of a directed graph [67] enables the identification of clusters [68] within the network. By applying this approach, it can be inferred that if a result node has multiple completed incoming connections, it has been carried out through a collaborative effort involving actors of type-4 support, as indicated in the instances of tasks *a77* – *a78* and *a81* – *a82*. In such scenarios, the actors are required to wait for the completion of the same outcome (priority is given) before commencing different tasks simultaneously on the same work item.

According to the precedence graph, when two or more activity nodes are assigned the same precedence (prec. edge) but lead to different outcomes (done edge), it indicates a type-3 concurrent collaboration. In Figure 15, it is evident that activities *a79* and *a80* are executed simultaneously after receiving the same precedence (res63), yet they generate distinct results upon completion (res64 and res65). The outcome of this section is a conceptual dashboard, shown in Figure 16, where the percentages indicate the levels of operator competence and robot health. The findings from the previous query, along with the KPIs in Section 3.2, can serve as data sources for smart glasses, shop floor dashboards, the DAS, or other intelligent devices.

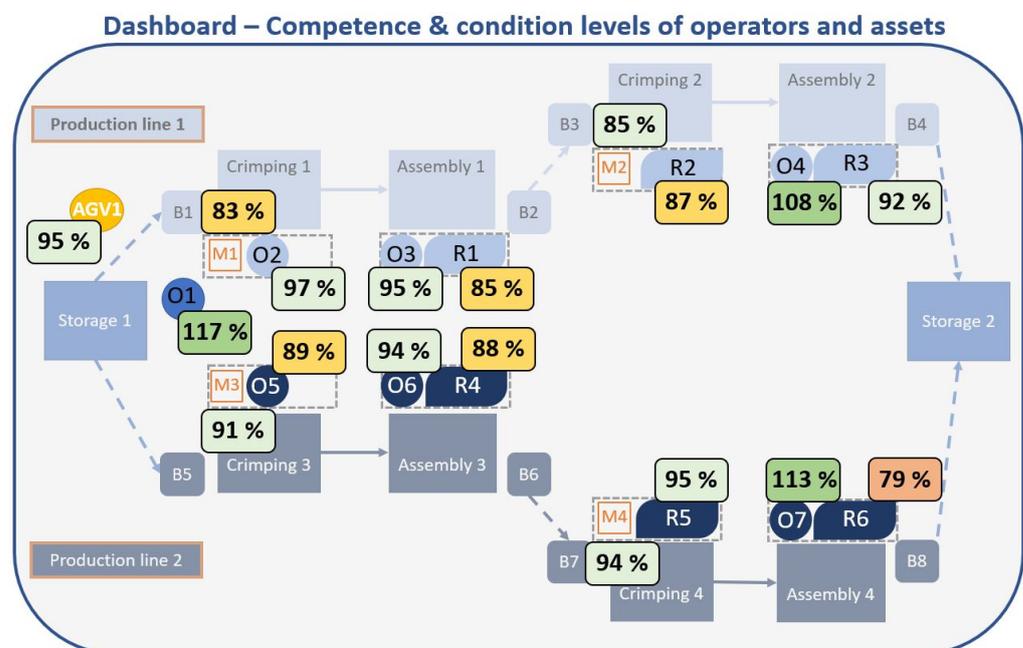


Figure 16. Conceptual dashboard for human-centric manufacturing—competence and condition levels of operators and assets.

5. Conclusions and Future Work

This article introduces the design idea of a Human-Centred Knowledge Graph (HCKG) that is based on industry norms and semantic technologies related to Industry 5.0 advance-

ments. A block structure is presented as an enhanced version of the MOM model and the development framework. The study thoroughly considers the tasks performed by operators, encompassing movement assessment, collaboration with machines, work sequences, and ergonomic aspects. It is also emphasized that the integration of activity recognition technologies can enrich the valuable data within a knowledge graph in a smart factory setting. The issue of insufficient operator monitoring and assistance is discussed in the context of existing industry standards, advocating for a new human-centric approach to contemporary manufacturing practices. In the coming factories that use knowledge graphs, the data collection and knowledge exploration processes will be automated, thereby facilitating the creation of human digital twins and the adoption of Industry 5.0 technologies.

Our objective was to summarize current methods and tools for semantic development and to introduce a concept for creating standard models of human-centered collaboration, illustrated through an industrial case study. The key contributions of this paper are as follows.

- Emphasized the importance of incorporating human factors into cyber-physical systems.
- Proposed an expansion of automation standards (ISA-95, AutomationML, B2MML) to include human-related processes and demonstrated the use of semantic technologies.
- The concept was validated through a replicable industrial case study. Various graph-based analyses were conducted using different types of graphs such as normal, directed, or hypergraphs, including resource allocation analysis, KPI evaluation, and the integration of a DAS.
- The application based on HCKG facilitated the identification of various forms of collaboration between human and machine actors in the assembly process.
- Furthermore, a conceptual design was put forward for a human-centric manufacturing dashboard.

Future research will focus on enhancing the design of human-machine and human-human collaboration in manufacturing by implementing the HCKG concept in an intelligent environment. Several areas for improvement should be considered in future studies. One aspect is the incorporation of additional functionalities within the application block, such as an uncertainty simulator, a collaboration assessment tool, or an intelligent scheduling mechanism. Moreover, integrating HCKG into a digital twin and implementing closed-loop optimization and decision support could further strengthen the proposed approach. Lastly, it is crucial to encompass the entire HCKG pipeline and establish automated data retrieval within the shop floor and the semantic network.

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Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The related dataset is freely and fully available on the website of the authors: <https://github.com/abonyilab/HCKG> (accessed on 14 March 2024).

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A. Applied Methodologies and Software Tools

Figure A1 shows several processing stages of a data pipeline based on a study [69] that aims to create KGs for the automation industry. In addition, an end-to-end digital twin pipeline [70] has been taken into account.

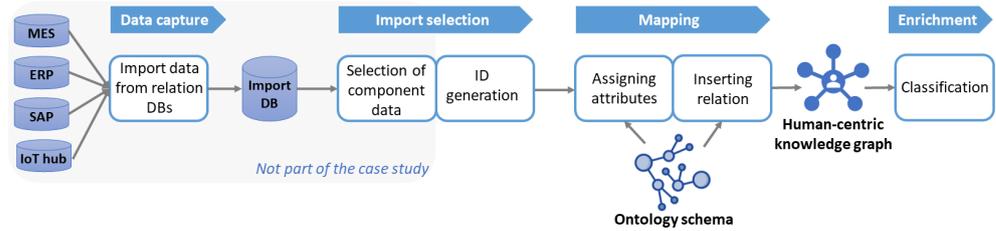


Figure A1. Knowledge graph pipeline based on [69].

It is beyond the scope of this paper to discuss the data acquisition and import selection parts of the pipeline. Only the KG, the ontology creation, the data queries, the mapping, and the data enrichment and visualization will be discussed. The phases, the methods used, and the different software stages of the industrial case study presented are shown in Figure A2.

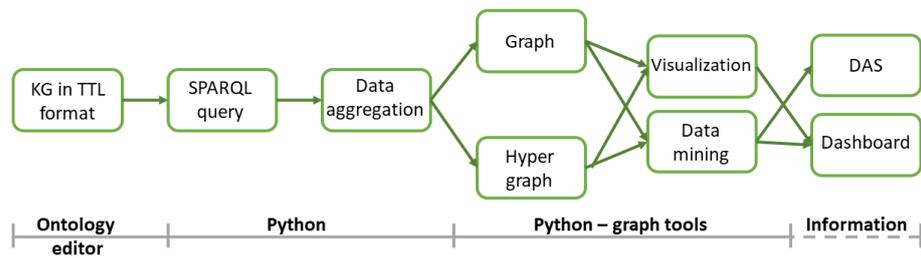


Figure A2. The steps of the applied method.

Before processing the TTL file in a Python 3.12.3 environment using Pyvis (a Python library for visualizing networks) [71] and KGLab [72,73], the sub-ontologies and the whole KG were developed using Protégé [74]. Either Protégé or KGLab can be used to import data into the ontology skeleton and to create axioms and properties in Python. For each data query, SPARQL language has been used [66]; moreover, Pyvis offers a graphical representation. Having mapped the semantic data, it was further aggregated in Python to obtain data-enriched graphs for analysis. Normal, directed, or hypergraphs can also be used for graph-based visualization of KG data. Finally, as a concept (denoted by a dashed line in Figure A2), the key information, generated charts, statements, or messages can be displayed on dashboards and DAS devices, or fill any other elements of the application block with data, as previously presented in Figure 4.

Appendix B. Assembly Activities of the Wire Harness Production Benchmark

Table A1. Description of the different activity types throughout the wire harness assembly benchmark.

Activity Type ID	Description of the Activity Type
t1	Point-to-point wiring on a chassis
t2	Laying in a U-channel
t3	Laying a flat cable
t4	Laying wire(s) onto the harness jig
t5	Laying one end of a cable connector onto a harness jig
t6	Spot-tying onto a cable and cutting it with a pair of scissors
t7	Lacing activity
t8	Lacing activity
t9	Inserting into a tube or sleeve
t10	Attachment of a wire terminal
t11	Screw fastening of a wire terminal
t12	Screw-and-nut fastening of a wire terminal
t13	Circular connector
t14	Rectangular connector
t15	Clip installation

Table A1. *Cont.*

Activity Type ID	Description of the Activity Type
t16	Loading of the AGV
t17	Transportation
t18	Manual handling of a wire from a buffer
t19	Positioning of a crimp into a vise
t20	Inserting a wire into a crimp
t21	Starting a machine
t22	Crimping
t23	Manual handling of a semi-finished product
t24	Handover of a semi-finished product
t25	Positioning of a crimp into a fixture
t26	Manual handling of a semi-finished product into a buffer
t27	Unloading of the AGV

Table A2. The activity types in the wire harness assembly process and their results.

Crimping Process	
t18	Manual handling of a wire from a buffer Result: One piece of wire is moved to the crimping station from the buffer.
t19	Positioning of a crimp into a vise Result: Crimp is positioned into a vise.
t20	Inserting a wire into a crimp Result: Wire is inserted into a crimp.
t21	Starting a machine Result: Machine is running.
t22	Crimping Result: Crimping is finished.
t23	Manual handling of a semi-finished product Result: Semi-finished product is removed from the vise.
t24	Handover of a semi-finished product Result: Semi-finished product is moved to another station.
Assembly process	
t2	Laying in a U-channel Result: U-channel is laid in the right assembly zone.
t4	Laying wire(s) onto a harness jig Result: Wire(s) is (are) laid correctly onto a harness jig.
t9	Insertion into a tube or sleeve Result: Tube is inserted into the correct sleeve.
t11	Fastening of the terminal with screws Result: Terminal screws are fastened.
t25	Positioning of a crimp into a fixture Result: Crimp is correctly positioned into the fixture.
t26	Manual handling of a semi-finished product into a buffer Result: Semi-finished product is placed into the buffer.
Material handling	
t16	Loading of the AGV Result: Parts are loaded on to the rack of the AGV.
t17	Transportation by an AGV Result: AGV moved the position from the source to its destination
t27	Unloading of the AGV Result: Parts are unloaded from the rack of the AGV.

Table A3. The sequence of activities as well as the results of the proposed wire harness assembly benchmark and their details—Part 1.

Activity ID	Activity Type ID	Result ID	Result Type ID	Process Step	Number of Process Steps
a1	t16	res1	res_type_16	Storage 1—AGV1	1
a2	t17	res2	res_type_17	Storage 1—Buffer1	1
a3	t27	res3	res_type_27	AGV1—Buffer1	1
a4	t18	res4	res_type_18	Buffer1—Crimping1	Batch size
a5	t19	res5	res_type_19	Crimping1	Batch size
a6	t20	res6	res_type_20	Crimping1	Batch size
a7	t21	res7	res_type_21	Crimping1	Batch size
a8	t22	res8	res_type_22	Crimping1	Batch size
a9	t23	res9	res_type_23	Crimping1	Batch size
a10	t24	res10	res_type_24	Crimping1—Assembly1	Batch size
a11	t24	res10	res_type_24	Crimping1—Assembly1	Batch size
a12	t25	res11	res_type_25	Assembly1	Batch size
a13	t02	res12	res_type_02	Assembly1	Batch size
a14	t02	res12	res_type_02	Assembly1	Batch size
a15	t04	res13	res_type_04	Assembly1	Batch size
a16	t04	res13	res_type_04	Assembly1	Batch size
a17	t09	res14	res_type_09	Assembly1	Batch size
a18	t09	res14	res_type_09	Assembly1	Batch size
a19	t11	res15	res_type_11	Assembly1	Batch size
a20	t11	res15	res_type_11	Assembly1	Batch size
a21	t26	res16	res_type_26	Assembly1—Buffer2	Batch size
a22	t16	res17	res_type_16	Buffer2—AGV1	1
a23	t17	res18	res_type_17	Buffer2—Buffer3	1
a24	t27	res19	res_type_27	AGV1—Buffer3	1
a25	t18	res20	res_type_18	Buffer3—Crimping2	Batch size
a26	t19	res21	res_type_19	Crimping2	Batch size
a27	t20	res22	res_type_20	Crimping2	Batch size
a28	t21	res23	res_type_21	Crimping2	Batch size
a29	t22	res24	res_type_22	Crimping2	Batch size
a30	t23	res25	res_type_23	Crimping2	Batch size
a31	t24	res26	res_type_24	Crimping2—Assembly2	Batch size
a32	t24	res26	res_type_24	Crimping2—Assembly2	Batch size
a33	t25	res27	res_type_25	Assembly2	Batch size
a34	t02	res28	res_type_02	Assembly2	Batch size
a35	t02	res28	res_type_02	Assembly2	Batch size
a36	t04	res29	res_type_04	Assembly2	Batch size
a37	t09	res30	res_type_09	Assembly2	Batch size
a38	t11	res31	res_type_11	Assembly2	Batch size
a39	t11	res31	res_type_11	Assembly2	Batch size
a40	t26	res32	res_type_26	Assembly2—Buffer4	Batch size
a41	t16	res33	res_type_16	Buffer4—AGV1	1
a42	t17	res34	res_type_17	Buffer4—Buffer9	1
a43	t27	res35	res_type_27	AGV1—Storage 2	1
a44	t16	res36	res_type_16	Storage 1—AGV1	1
a45	t17	res37	res_type_17	Storage 1—Buffer5	1
a46	t27	res38	res_type_27	AGV1—Buffer5	1
a47	t18	res39	res_type_18	Buffer5—Crimping3	Batch size
a48	t19	res40	res_type_19	Crimping3	Batch size
a49	t20	res41	res_type_20	Crimping3	Batch size
a50	t21	res42	res_type_21	Crimping3	Batch size
a51	t22	res43	res_type_22	Crimping3	Batch size
a52	t23	res44	res_type_23	Crimping3	Batch size
a53	t24	res45	res_type_24	Crimping3—Assembly3	Batch size
a54	t24	res45	res_type_24	Crimping3—Assembly3	Batch size
a55	t25	res46	res_type_25	Assembly3	Batch size
a56	t02	res47	res_type_02	Assembly3	Batch size
a57	t02	res47	res_type_02	Assembly3	Batch size
a58	t04	res48	res_type_04	Assembly3	Batch size
a59	t04	res48	res_type_04	Assembly3	Batch size
a60	t09	res49	res_type_09	Assembly3	Batch size
a61	t09	res49	res_type_09	Assembly3	Batch size
a62	t11	res50	res_type_11	Assembly3	Batch size
a63	t11	res50	res_type_11	Assembly3	Batch size
a64	t26	res51	res_type_26	Assembly3—Buffer6	Batch size
a65	t16	res52	res_type_16	Buffer6—AGV1	1
a66	t17	res53	res_type_17	Buffer6—Buffer7	1
a67	t27	res54	res_type_27	AGV1—Buffer7	1
a68	t18	res55	res_type_18	Buffer7—Crimping4	Batch size
a69	t19	res56	res_type_19	Crimping4	Batch size
a70	t20	res57	res_type_20	Crimping4	Batch size
a71	t21	res58	res_type_21	Crimping4	Batch size
a72	t22	res59	res_type_22	Crimping4	Batch size
a73	t23	res60	res_type_23	Crimping4	Batch size

Table A4. The sequence of activities as well as the results of the proposed wire harness assembly benchmark and their details—Part 2.

Activity ID	Activity Type ID	Result ID	Result Type ID	Process Step	Number of Process Steps
a74	t24	res61	res_type_24	Crimping4—Assembly4	Batch size
a75	t24	res61	res_type_24	Crimping4—Assembly4	Batch size
a76	t25	res62	res_type_25	Assembly4	Batch size
a77	t02	res63	res_type_02	Assembly4	Batch size
a78	t02	res63	res_type_02	Assembly4	Batch size
a79	t04	res64	res_type_04	Assembly4	Batch size
a80	t09	res65	res_type_09	Assembly4	Batch size
a81	t11	res66	res_type_11	Assembly4	Batch size
a82	t11	res66	res_type_11	Assembly4	Batch size
a83	t26	res67	res_type_26	Assembly4—Buffer8	Batch size
a84	t16	res68	res_type_16	Buffer8—AGV1	1
a85	t17	res69	res_type_17	Buffer8—Buffer9	1
a86	t27	res70	res_type_27	AGV1—Storage 2	1

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