DOI: 10.2195/lj_proc_klein_en_2025_01

A Knowledge-Based Intralogistic System for a Circular Factory

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In the context of circular production, factories must cope with uncertainty arising from the reuse of components with varying availability, quality, and timing. This creates new requirements for intralogistic systems that are both highly flexible and able to adapt to local shifts in transport demand or unforeseen events. We present a novel modular intralogistic system designed to meet these challenges, where autonomous mobile robots can mount self-contained modules to provide on-demand reconfiguration of material-handling capabilities. To ensure semantic interoperability within the circular factory, we further introduce the accompanying ontologies that formalize key concepts and support knowledge-driven decision-making.

[Keywords: intralogistics, material handling, ontology, knowledge modeling, circular factory]

1 INTRODUCTION

In the era of Industry 4.0, data-driven intelligence is a fundamental enabler of autonomous production and decision-making systems. Cyber Physical Production Systems (CPPS), as summarized by [1] and adapted from [2], are networked systems composed of autonomous and cooperative elements that interact in situation-dependent ways across all levels of production. These systems enhance real-time decision-making, enable adaptation to unforeseen conditions, and support continuous evolution over time.

Building on this foundation, the concept of the *circular factory* raises the demands on CPPS beyond those of traditional linear production systems [3]. A circular factory is designed to manufacture the latest product generation using a variable proportion of reused components from previous product generations. This approach, while advancing sustainability and resource efficiency, introduces a high degree of uncertainty into the production process - particularly with respect to the availability, timing, and quality of reused components. As a result, the associated processes and the resources on which they are executed require greater flexibility, robustness, and real-time responsiveness. To address these challenges, CPPS require a shared knowledge representation that enables both horizontal and vertical integration, facilitating system-wide semantic interoperability [4], [5]. A formalized knowledge model is essential for harmonizing the dynamic interactions among physical resources, digital twins, and planning systems.

To realize these objectives, we adopt a robust, modular ontology-based approach that ensures factory-wide interoperability across heterogeneous systems through agreement, agility, and compliance. **Agreement** is established through a shared core ontology that defines fundamental concepts such as products, processes, and resources, serving as a semantic contract for scalable extension and collaboration without information loss. **Agility** is achieved through the modularity of domain-specific sub-ontologies, facilitating adaptability and quality control of workflows while maintaining interoperability. In future work **Compliance** will be ensured by aligning with established standards and by reusing existing ontologies. This reuse-driven strategy accelerates ontology development, minimizes redundancy, and secures interoperability of modeled knowledge both within and beyond the factory ecosystem.

In this paper, we present a novel modular intralogistic system specifically designed to meet the requirements of a circular factory [3]. Alongside, we introduce an ontology that formalizes its key components and interactions. As one of the subsystems of the circular factory, this ontology adheres to our established standards for semantic interoperability, supports flexible system configuration, and enables data-driven decision-making in modular and uncertain production environments. The remainder of this paper is structured as follows. Section 2 reviews related work, followed by a discussion on the knowledge modeling process. Section 3 introduces the intralogistics system, with Section 4

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offering a more detailed view of the embedded manipulator system. Section 5 explores the integration of the proposed ontology into the runtime system of the circular factory. Finally, Section 6 concludes the paper and outlines directions for future work.

2 RELATED WORK

Several ontologies for intralogistics – also referred to as production logistics or internal logistics – have been developed in recent years, differing in their targeted subdomains and in the level of conceptual detail. One of the earlier contributions is the core ontology for logistics proposed by Daniele and Pires [6], which was motivated by the ambiguity of terminology across different stages of the supply chain. Their ontology builds on foundational constructs such as *Activity*, *Actor*, *Physical Resource*, *Location*, and *Time*, providing a shared conceptual basis for representing logistics processes. Complementary to this, Negri et al. [7] introduce a taxonomy of physical components relevant to internal logistics, aligned with the Manufacturing System Ontology (MSO). Their taxonomy defines key concepts such as *Storage*, *Processor*, *Unit Load*, *Operator*, *Transporter*, *Sensor*, *Controller*, *Tool*, and *Fixture*, thereby providing a structured representation of the fundamental building blocks of intralogistic systems. Moving from taxonomies towards reasoning about system capabilities, Elfaham and Epple [8] focus on material flow and logistic capabilities of physical devices, in particular their ability to transport and hand over materials. Their instantiated ontology can be used to examine possible transport pathways and feasible handover positions. Similarly, Ocker et al. [9] propose an approach for providing feasibility feedback during the design phase of intralogistic systems based on a knowledge graph. This involves comparing product specifications with resource capabilities while also verifying reachability. D'Amico et al. [10] present an application study in which an instantiated ontology is used for failure detection in a sorting station, based on a set of rules evaluated at runtime.

The ontology introduced in this work differs from previous approaches in that it is tailored specifically to the requirements of the circular factory, with the goal of capturing its inherently interdisciplinary nature across multiple domains. Within this context, our knowledge modeling process is designed to support cross-project knowledge sharing, represent cross-domain concepts and relationships, and enable knowledge-driven decision-making at scale. Ultimately, this facilitates the systematic reuse of components and thereby contributes to greater sustainability.

3 INTRALOGISTIC SYSTEM

The intralogistic system plays a central role in picking, transporting, and manipulating products and components on the circular factory shop floor. Since the material flow of both new and reused components is inherently uncertain and may require on-the-fly adjustments based on the outcomes of disassembly or diagnostic processes, the system

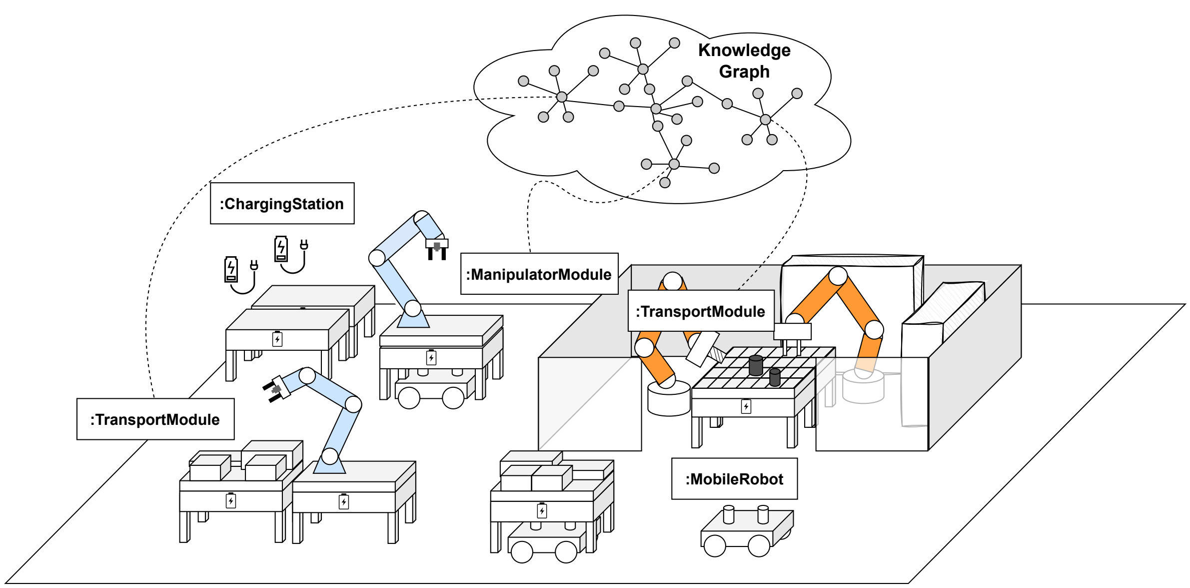

Figure 1: Overview of the intralogistic system for a circular factory: Mobile robots equipped with interchangeable modules navigate the shop floor to enable flexible transport and material handling operations.

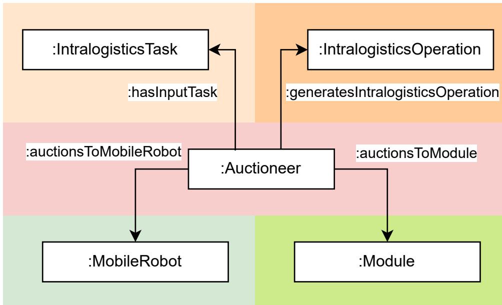

Figure 2: Overview of the intralogistic system

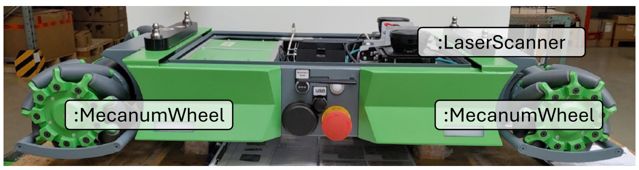

Figure 3: A MobileRobot equipped with two LaserScanner and MecanumWheels which allow omnidirectional motions.

must be highly adaptable and flexible [11]. Figure 1 provides an overview on the proposed system.

On the most abstract level, see Figure 2, the system consists of a fleet of MobileRobots that can freely navigate the shop floor. These robots can mount different types of self-contained Modules, either to reposition the modules within the factory or to extend their own capabilities for carrying out various material handling processes. On a control level, and aligned with the concepts of the *Core Ontology* introduced in [12], IntralogisticsTasks generated by the production control system are auctioned by an Auctioneer. The auction process results in executable IntralogisticOperations, which define the concrete actions to be performed. The following subsections examine these concepts in greater detail.

At the time of writing, the accompanying ontologies are still under active development. The ontologies referenced in this paper are publicly accessible and include the circular factory *Core Ontology* [1], the *Intralogistics Ontology* [2] and the *Manipulation System Ontology* [3].

3.1 Mobile Robots and Modules

The core:Resources of the proposed intralogistic system reflect the high degree of flexibility and adaptability required in the circular factory. We distinguish between two types of resources: MobileRobots and Modules. A detailed view of the corresponding ontology elements is shown in Figure 4.

In our demonstration factory, we employ a fleet of homogeneous autonomous MobileRobots. Each robot is equipped with MecanumWheels for omnidirectional movement and multiple LaserScanners for localization and navigation using SLAM techniques. An exemplary instance is shown in Figure 3. Through the use of ModuleAdapters, MobileRobots can mount Modules. These modules are tool-like, self-contained units that can operate independently but require a MobileRobot for transportation. Once mounted, a Module co-moves with its carrier, thereby extending the robot's capability.

Modules enhance the system's capabilities on demand and enable the flexible execution of a wide range of material-handling tasks. At the current stage of development, we distinguish between two types of Modules: the TransportModule and the ManipulatorModule. The TransportModule acts as a passive carrier that facilitates the relocation of items between different stations while acting as a flexible component buffer, whereas the ManipulatorModule provides grasping and handling functionality when required. In addition, a ChargingStation is included in the infrastructure to provide the necessary capability for recharging the individual module batteries.

Aligned with [12], each of the core:Resources relate to a specific set of capabilities. The MobileRobot exposes both a MoveSelfCapability and a MoveCapability while the ManipulatorModule has a ManipulationCapability.

3.2 Tasks and Operations

In the context of the circular factory, a core:Task is generally defined as a production step that takes one or more components as input and produces one or more components as output [12]. For the intralogistic system, tasks generated by the production planning and control system are represented as IntralogisticsTasks, as illustrated in Figure 5. An IntralogisticsTask is characterized by the following elements:

- the PickupLocation, a core:Location where the core:Component must be collected.
- the TargetLocation, a core:Location where the core:Component should be moved to.
- a time window for the pickup, bounded by the EarliestPickupTime and the LatestPickUpTime.

[1] https://w3id.org/circularfactory/Core
[2] https://w3id.org/circularfactory/IntralogisticSystem
[3] https://w3id.org/circularfactory/ManipulationSystem

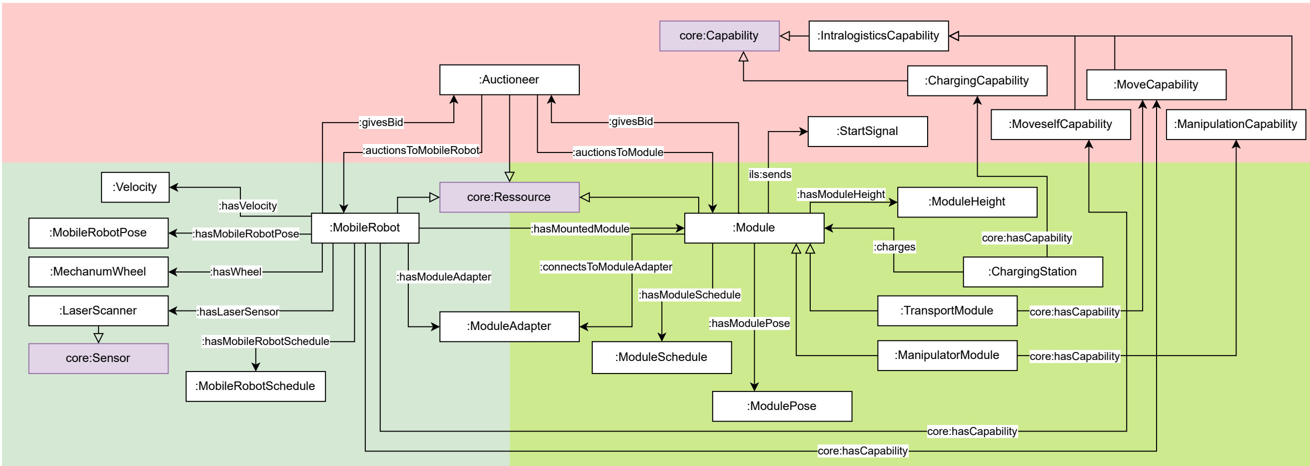

Figure 4: Intralogistic resources and their capabilities

- the LatestDeliveryTime, representing the latest acceptable time by which the core:Component should arrive at its TargetLocation.

An IntralogisticsTask represents a high-level specification of what needs to be achieved in terms of material flow, without prescribing how it is to be executed. Since such tasks are too abstract to be directly allocated to specific core:Resources, they must be decomposed into smaller units. For this purpose, we define the IntralogisticsAtomicTask, a sub-concept of core:AtomicTask. These atomic tasks represent the minimal, resource-allocatable subtasks that together fulfill an IntralogisticsTask. In the current development state, we distinguish between four different IntralogisticsAtomicTask, namely a ManipulationTask, a MoveTask, a MoveSelfTask and a ChargingTask, Each IntralogisticsAtomicTask is further characterized by:

- a TaskStatus, indicating its current execution state,
- an EarliestStartTime, specifying when execution may begin, and
- a LatestFinishTime, defining the deadline for completion.

core:Operations represent the concrete execution of a task on a specific core:Resource, see [12]. In the intralogistic system, the translation from a task to an operation is managed by the Auctioneer, which creates a corresponding IntralogisticsOperation once a task has been successfully allocated to a core:Resource. Each IntralogisticsOperation is characterized by, see Figure 6:

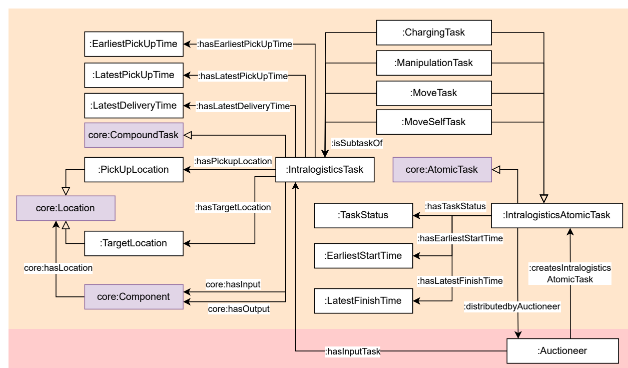

Figure 5: The structure of an IntralogisticsTask

- a PlannedStartTime, the timestamp at which the core:Resource is scheduled to begin the operation,
- a PlannedFinishTime, the expected time of completion, and
- the OperationStatus, specifying its current execution state of the operation.

3.3 Capability Matchmaking and Auctioneer

The Auctioneer serves as the central coordination mechanism of the intralogistic system. Its primary function is to mediate between high-level compound tasks originating from factory planning and the heterogeneous resources that carry them out. As described in [13], intralogistics control operates across multiple layers. The auctioneer bridges these layers by recursively decomposing IntralogisticsTasks into IntralogisticsAtomicTasks and subsequently transforming them into executable IntralogisticsOperations that are as-

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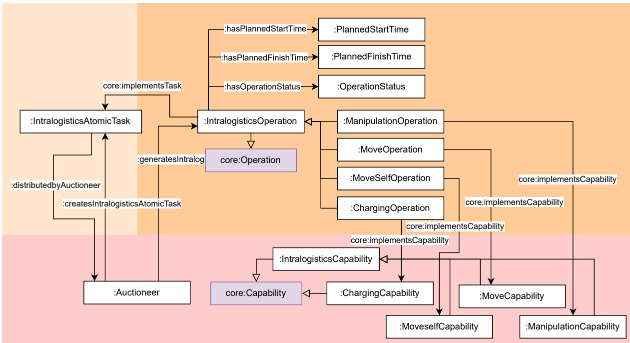

Figure 6: The structure of IntralogisticsOperations and their relations to IntralogisticsCapability

signed to specific core:Resource. This approach is suitable for the circular factory, as it allows the best robots and modules for a task to be found quickly and efficiently by calculating their ability to perform a task in a decentralized manner. The task decomposition is achieved through a dynamic, auction-based allocation process. The auctioneer performs three key functions:

1. It queries the knowledge graph to identify eligible resources that possess the required capabilities.
2. It generates candidate operations by simulating feasible start and finish times.
3. It compares bids from the candidate resources and selects a winner to execute the operation.

Once a winning bid is selected, the corresponding IntralogisticsOperation is instantiated, annotated with its planned start and finish times, and marked as planned. All competing candidate operations are discarded, ensuring a one-to-one mapping between each IntralogisticsAtomicTask and its assigned IntralogisticsOperation.

The current auctioneer approach, an adapted form of the TEPSSI algorithm by [14], uses multi-stage sequential auctions tailored to the interdependent nature of the IntralogisticsAtomicTasks. ManipulatorModules first bid to perform pick operations. Secondly, TransportModules bid to carry out the delivery, including reloaction to the pick site, waiting for the manipulator to finish, and subsequently transporting the product to the target location. Finally, MobileRobots bid to integrate the movement of these modules into their schedules, using schedule-insertion heuristics to minimize the makespan while avoiding conflicts. This mechanism ensures temporal and spatial coordination among all resources. Movements are planned just-in-time, allowing robots and modules to dynamically form collaborative teams around each IntralogisticTask and dissolve after execution.

4 Manipulator Module

Within the modular intralogistic system, the ManipulatorModule extends the system's capabilities beyond transportation and buffering by enabling the active handling of components. While the MobileRobots provide mobility to all Modules and the TransportModule ensures buffering and relocation, many tasks in the circular factory require grasping, repositioning, or orienting components – capabilities that only the ManipulatorModule provides. A key strength lies in its versatility: it can operate as a mobile unit, mounted on a MobileRobot to perform manipulation tasks throughout the shop floor, or used as a stationary pick-and-place robot at fixed locations. This dual mode enables flexible system design, efficient resource usage, and a highly automated material flow.

The *manipulation system* refers to the broader functional concept that integrates the module's hardware, control logic, sensors, environmental representations, and the learning-based grasp software. Figure 7 illustrates this system. In the following sections, we provide technical details on its two main components: the Manipulator (Section 4.1), responsible for executing actions in the environment, and the GraspLearningSystem (Section 4.2), which handles data processing, learning, and action prediction.

4.1 Manipulator

The Manipulator, visualized in Figure 8, consists of the physical components and control logic to enable seamless execution of actions and data recording. The physical components of the manipulator encompass a RobotArm, equipped with a parallel jaw RobotGripper, which delivers proprioceptive data, including the joint configurations of the RobotArmState and the current GripperPose. To enable the capability of 6-DOF grasping, the GripperPose comprises Position and Orientation parameters, as well as the GripperAperture, i.e., the separation of the gripper fingers.

To capture exteroceptive observations, i.e., information about the environment, the Manipulator is equipped with one or more RobotSensors. A common example is a mounted RGB-D camera, which captures both depth and color information of the environment. These images are then transformed into structured SensorData, making it possible to trace where the data came from and to share it consistently across different systems.

Enabled by the captured Data, the GraspLearningSystem (see Section 4.2) generates physically grounded actions, either as a grasp pose or an entire trajectory. In the case of grasp pose prediction, a MotionPlanner computes a trajectory from the current GripperPose to

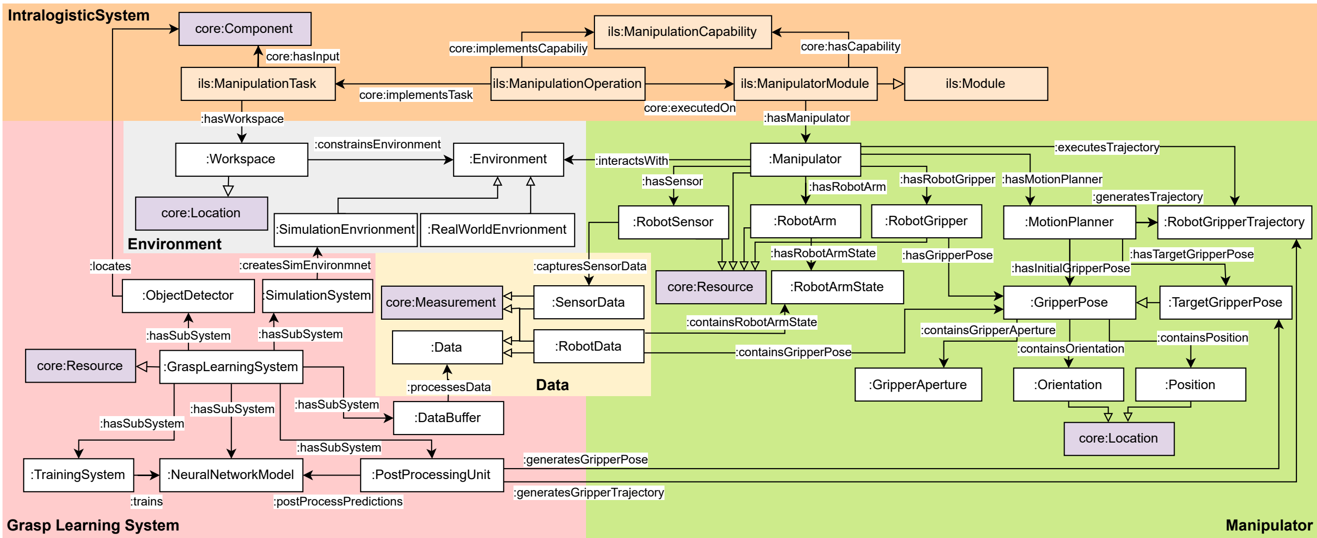

Figure 7: The structure of a learning-based manipulation system integrates with the intralogistic system (ils).

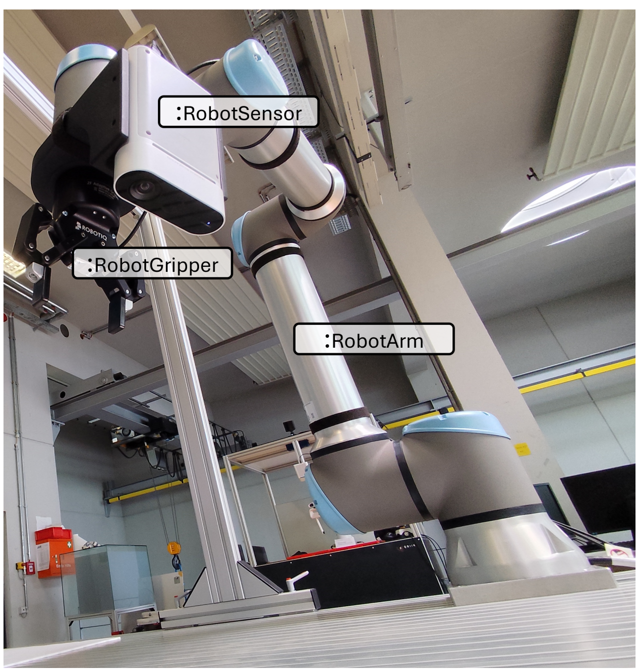

Figure 8: The physical components of an instance of the Manipulator including a RobotArm, a RobotSensor, in this case an RGB-D camera, and a RobotGripper, in this case a parallel jaw gripper.

the TargetGripperPose. Given the current configuration of the RobotArmState and the GripperPose, a control module executes the given trajectory. Subsequent changes to the environment are captured by the RobotSensors, establishing a closed-loop and interpretable data flow between the components of the Manipulator and the GraspLearningSystem.

The developed ontology facilitates both modeling manipulators from RealWorldEnvironments, as well as SimulationEnvironments, as the basic components and control loop are similar in both.

Overall, this manipulator ontology systematically models the physical state of the robot, control logic, and perception history, thereby supporting task execution such as object picking, placement, and real-time adaptation in dynamic intralogistic environments. At the same time, we emphasize seamless integration with learning-based software components as a key contribution of this ontology, facilitating a structured information flow from sensor observations to neural inference and continuous lifelong learning, which will be detailed in Section 4.2.

4.2 Grasp Learning System

The GraspLearningSystem is responsible for data processing, continual learning, inference, real-time decision making and action predictions. It leverages learned grasping strategies to infer adaptive grasp poses or trajectories, while also quantifying uncertainty in real-time [15], [16]. In the following, we outline its role in grasp prediction, execution, and training, and its interaction with the Manipulator.

SensorData is collected in a DataBuffer, where it may be pre-processed through labeling, filtering, weighting, or augmentation, depending on the concrete learning system. During training, this data is used by a TrainingSystem that trains NeuralNetworkModels. To ensure safety during training and evaluation, the GraspLearningSystem may employ a SimulationEnvironment, which mirrors the structure of the RealWorldEnvironment, ensuring seamless transfer between simulated and physical execution.

During inference, the NeuralNetworkModule predicts gripper poses or trajectories based on current SensorData. The raw predictions are post-processed, e.g., through scaling or coordinate frame transformations, before being executed by the Manipulator.

To support object-centric grasping, an ObjectDetector locates target components within a Workspace. The workspace acts both as a bounding box for perception and as a spatial constraint for manipulation, defining the Environment in which the manipulator operates.

The proposed model is agnostic to a specific learning paradigms. It can be applied to open-loop grasp prediction, where the grasp poses are inferred from a single observation, as well as to closed-loop control strategies, such as receding horizon control, a strategy commonly used in state-of-the-art diffusion policies [17]. By incorporating historical proprioceptive data into the control loop, the modeled system further supports lifelong learning. This is reinforced by the inclusion of a SimulationEnvironment, which allows for safe exploration during online learning.

5 Integration into Runtime System

A central component of the circular factory is the ontology-based knowledge backbone. It integrates the semantic representation of products, processes, resources, tasks, capabilities, and operations with data storage and research data management, thereby enabling efficient knowledge access in the presence of uncertainty and supporting validated inference directly on the shop floor [5]. Within this framework, intralogistics plays a particularly crucial role, as it forms the connective layer between otherwise heterogeneous resources and processes. By coordinating the flow of materials, components, and products across different stations, the intralogistics system ensures that production steps remain synchronized and that flexibility and adaptability are maintained even under uncertain conditions.

The semantic alignment within the circular factory enables the explicit capture of instance specific relations between processes, resources, and products. This creates a foundation for future AI-driven decision support systems, which can exploit these structured relations to derive higher-level optimizations, detect inefficiencies, or suggest alternative resource allocations in real time. In this way, the ontology not only supports current runtime integration but also opens pathways for predictive and adaptive control strategies that improve resilience and efficiency of factory operations.

6 Conclusion and Future Work

In this work, we introduced the concept of a modular intralogistic system tailored to the requirements of a circular factory, which is characterized by high variability and uncertainty of components. Central to our approach is the flexible combination of mobile robots with mountable modules. Acting as versatile tools, these modules can be deployed either statically or dynamically across the shop floor, unlocking new potential for highly adaptable and resource-efficient material flow. At the control level, the system supports a semantic auctioneer that bridges high-level tasks and heterogeneous resources through multi-stage sequential bidding. This mechanism enables dynamic resource coalitions, ensures temporal and spatial synchronization of distributed agents, and provides scalability by allowing additional resources or tasks to be integrated without structural changes.

To ensure interoperability and seamless integration within the circular factory, we introduced an ontology for the proposed intralogistic system and its embedded manipulation system. The manipulation system ontology is designed as a standalone component, enabling integration not only within intralogistics but also as a potential building block within other systems inside the factory. Looking ahead, we aim to further extend the ontology to cover complete flows of operations and to support failure handling in case of unpredicted events. While in the current development phase, we prioritize ontology alignment inside the circular factory, future versions will focus aligning the ontology with widely adopted standards, such as the Semantic Sensor Network Ontology, to enhance reusability and cross-domain interoperability beyond the circular factory.

Funding

This work is funded by the German Research Foundation (DFG) - SFB 1574 – 471687386.

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