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Intelligent Decision Making and Knowledge Management System for Industry 4.0 Maturity Assessment

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Abstract Achieving a seamless transition to Industry 4.0 requires a holistic, knowledge-driven approach that integrates multiple dimensions of digital transformation. This paper proposes a smart, data-driven ontology-based system that integrates strategic, operational, technological, and cultural dimensions for Industry 4.0 maturity assessment. Built using OWL (Ontology Web Language) for structured knowledge representation and SWRL rules (Semantic Web Rule Language) for intelligent inference, the proposed ontology-based system assesses manufacturing enterprises into five maturity levels: Pre-Adoption, Experimental, Transitional, Integrated, and Transformational. It leverages technical KPIs from SCADA, ERP, IoT, and the industrial real-time data sources to enable automated reasoning and data-driven decision-making. An industrial case study in an automotive manufacturing plant is developed to validate the proposed ontology-based system potentialities and effectiveness in optimizing the industry 4.0 maturity assessement process, maturity levels aggregations and effective insights generation. The results highlight its adaptability across industries, offering a scalable and intelligent solution for Industry 4.0 assessment and adoption. It highlight also its potential to ensure domain-specific digital transformation benchmarking and previous maturity models interoperability.

Keywords Digital Transformation; Assessment model; Rule Based Reasoning, Information Computing, Knowledge Management; Inference Ontology Development; Expert system.

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1. INTRODUCTION

The digital transformation of the industrial sector, driven by Industry 4.0 principles and technologies, has significantly reshaped manufacturing ecosystems [1]. Industry 4.0 integrates cyber-physical systems (CPS), the Internet of Things (IoT), artificial intelligence (AI), big data analytics, cloud computing, and automation to create smart, interconnected factories with real-time decision-making capabilities [2, 3, 4]. These advancements promise increased efficiency, cost reduction and enhanced flexibility in production. However, the transition to Industry 4.0 is complex and requires a structured approach to assess and guide digital transformation efforts effectively.

Existing Industry 4.0 maturity models, such as the ACATECH Industry 4.0 Maturity Index[5], the IMPULS Readiness Model[6], the Singapore Smart Industry Readiness Index[7], and SIMMI 4.0[8], provide structured frameworks to evaluate digital transformation readiness. These models assess dimensions such as technological infrastructure, workforce competencies, data analytics, cybersecurity, and business strategy alignment[9, 10, 11, 12]. While they contribute to understanding digital maturity, they present several limitations. Many of these models lack interoperability, as they define independent dimensions and evaluation criteria, making cross-model integration

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and benchmarking difficult. Additionally, most of these models provide static, descriptive assessments that do not dynamically adapt to emerging technologies, evolving industry demands, or real-time performance data. Their limited decision-support capabilities restrict their ability to offer predictive insights, adaptive recommendations, or automated reasoning for Industry 4.0 adoption. Furthermore, some models predominantly focus on technological aspects, often overlooking strategic, operational, and cultural factors that are crucial for a holistic digital transformation strategy.

To overcome these limitations, this paper proposes a reference inference Ontology for Industry 4.0 Maturity Assessment, a cross-domain, smart knowledge-driven system designed to integrate strategic, operational, technological, and cultural dimensions into a unified assessment framework. Unlike traditional static models, this ontology-based system leverages semantic reasoning and intelligent inference mechanisms to enhance decision-making, ensuring adaptability to evolving Industry 4.0 trends. The ontology formalizes Industry 4.0 knowledge, incorporating key dimensions such as process automation, AI-driven predictive analytics, workforce readiness, cybersecurity, and digital strategy alignment. By utilizing Web Ontology Language Description Logic (OWL DL) for knowledge representation and Semantic Web Rule Language (SWRL) for intelligent inference, the proposed system enables real-time, context-aware assessments that dynamically adjust based on industry-specific requirements and operational data extracted from SCADA, ERP, IoT, and other industrial data sources.

This research contributes to the field by developing a semantically rich inference-driven knowledge representation model that enhances interoperability among existing maturity frameworks. By integrating automated reasoning and data driven decision support, this approach goes beyond static assessments, offering predictive analytics, prescriptive recommendations, and adaptive transformation pathways tailored to an organization's Industry 4.0 readiness level. Furthermore, the system ensures continuous evolution by refining assessment parameters based on real-time industrial performance metrics, sector-specific developments, and emerging technological trends. A case study within an automotive parts manufacturing plant validates the framework, demonstrating its practical application and cross-industry adaptability.

The remainder of this paper is structured as follows. The next section reviews the existing Industry 4.0 maturity models, analyzing their methodologies, strengths, and limitations. This is followed by a detailed presentation of the proposed ontology-based approach, including its conceptual design, integration principles, and knowledge representation framework. The subsequent section discusses the intelligent decision-making framework, outlining the inference mechanisms and data-driven analytics that enhance maturity assessment. The results and validation section evaluates the effectiveness of the proposed system through a real-world case study from automotive industry. Finally, the conclusion summarizes key findings and outlines future research directions.

2. RELATED WORK

2.1. Industry 4.0 Readiness and Maturity Assessment Models

The assessment of Industry 4.0 readiness and maturity has been already explored through various frameworks and models [13] each emphasizing different aspects of technological adoption, organizational preparedness, and sector-specific transformation. While these models provide valuable insights, they exhibit limitations in terms of cross-industry adaptability, holistic integration, and decision-support capabilities. These challenges highlight the need for a more interoperable, intelligent, and dynamic approach to Industry 4.0 maturity assessment.

One of the most widely recognized models, the ACATECH Industry 4.0 Maturity Index [5], proposes a structured six-level framework that integrates both technological and organizational aspects. Despite its comprehensive theoretical foundation, it lacks empirical validation across diverse industries and does not provide concrete implementation guidelines tailored to different business scales. Similarly, the IMPULS Industry 4.0 Readiness Model [6] is a sector-specific tool developed for the German manufacturing industry. While it delivers a practical evaluation aligned with industrial needs, its strong manufacturing focus limits its broader applicability to sectors such as logistics, healthcare, and services.

The Singapore Smart Industry Readiness Index (SIRI) [7] introduces a multidimensional evaluation framework covering 16 key dimensions across three pillars: process, technology, and organization. This broad-spectrum approach enhances its cross-sector applicability; however, it lacks granularity in sector-specific transformation pathways and does not define a clear mechanism for progressing from one maturity level to another. In contrast, the 6Ps Maturity Model for SMEs [14] specifically addresses the digital transformation challenges faced by small and medium-sized enterprises (SMEs). Although it effectively accounts for financial and resource constraints, its applicability to larger corporations and high-tech industries remains limited.

For organizations prioritizing IoT adoption, the Integrated IoT Capability Maturity Model [15] provides a five-stage framework consolidating IoT competencies from various assessment models. However, its strong IoT-centric perspective [16] neglects broader Industry 4.0 transformation factors such as workforce readiness, cybersecurity, and organizational change management. Similarly, SIMMI 4.0 [8] emphasizes digitalization and IT integration, but its technical focus overlooks critical cultural and human factors, posing a challenge for organizations seeking a balanced digital transformation strategy.

A more extensive framework, the Industry 4.0 Readiness and Maturity Model [17], evaluates readiness across nine dimensions, including leadership, governance, and innovation. While its comprehensive scope provides an in-depth assessment, its complexity makes implementation challenging, particularly for SMEs lacking the required expertise. Likewise, the Maturity Model for Smart Manufacturing [18] follows a modular structure to enhance adaptability across various manufacturing environments, yet its scalability to large enterprises or non-manufacturing sectors remains unverified.

Finally, the Categorical Framework of Manufacturing [19] integrates intelligence, automation, and operational processes into a structured multi-level system. Despite its well-defined structure, it lacks practical validation and does not offer actionable insights to guide organizations through their transformation journey.

Assessment Model	**Ref**	**Country**	**Core Methodology**	**Key Strengths**	**Limitations**
ACATECH Industry 4.0 Maturity Index	[5]	Germany	Six-level maturity framework integrating technology and organizational aspects.	Comprehensive structure, strong focus on adaptability.	Limited empirical validation across multiple industries.
IMPULS Industry 4.0 Readiness	[6]	Germany	Sector-focused readiness tool with practical assessment metrics.	Easy to implement within German manufacturing.	Not widely applicable outside manufacturing.
Singapore Smart Industry Readiness Index	[7]	Singapore	Multi-dimensional assessment with 16 factors across process, technology, and organization.	Holistic coverage of transformation requirements.	Lacks depth in sector-specific maturity pathways.
6Ps Maturity Model for SMEs	[14]	Italy	SME-focused framework addressing six key dimensions.	Tailored for small businesses, considers SME challenges.	Limited validation for larger organizations.
Integrated IoT Capability Maturity Model	[15]	Netherlands	Five-stage model integrating IoT capability dimensions.	Strong focus on IoT ecosystem integration.	Narrow applicability; does not address broader Industry 4.0.
SIMMI 4.0	[8]	Germany	Digitalization-focused maturity model for IT and operational alignment.	Well-structured IT-centric framework.	Underemphasizes cultural and workforce transformation.
Industry 4.0 Readiness and Maturity Model	[17]	Austria	Comprehensive framework covering governance, leadership, and technological transformation.	Strong strategic perspective, inclusive of multiple organizational factors.	Complexity may make adoption difficult for SMEs.
Maturity Model for Smart Manufacturing	[18]	Turkey / Cyprus	Modular approach adaptable to different manufacturing contexts.	Flexible, allows gradual Industry 4.0 adoption.	Limited validation for scalability in larger organizations.
Categorical Framework of Manufacturing	[19]	United Kingdom	Multi-level structure integrating intelligence, automation, and operational processes.	Clear categorization of manufacturing intelligence levels.	Limited practical examples for real-world adoption.

Table 1. Comparison of the existing Industry 4.0 assessment models.

2.2. Inference ontologies for Industry 4.0 Maturity Assessment

Despite offering diverse perspectives, the existing Industry 4.0 maturity models share several key limitations. One of the main issues is the lack of interoperability [1, 13]. Most models operate independently, with limited mechanisms for integrating their assessments with other frameworks or decision-support systems. This isolation creates challenges for organizations that struggle to compare results across different models, primarily due to inconsistent terminologies, assessment criteria, and maturity scales[20, 23, 24]. Another limitation is the restricted decision-support capabilities of these models. Most models are designed as diagnostic tools, focusing primarily on classification rather than providing actionable recommendations [25, 26, 27]. They do not take advantage of real-time data, predictive analytics, or intelligent reasoning to guide decision-making processes.

Furthermore, these models fail to provide deep insights. They do not leverage advanced AI-driven techniques or knowledge representation methods to generate in-depth, actionable insights. As a result, they lack the ability to dynamically update assessments based on evolving industry trends, real-time performance metrics, or emerging technological advancements. Additionally, many models are constrained by their sector-specific focus [20]. Tailored to particular industries or company sizes, these models have limited applicability across sectors. There is a need for a more flexible, adaptable, and scalable approach to address the diverse transformation needs of organizations operating in various industrial environments.

To overcome these challenges, an ontology-based approach offers a promising solution. By harmonizing existing Industry 4.0 maturity models, an ontology can enable semantic interoperability, smart data-driven analytics, and intelligent decision-making[21, 22]. By formalizing key concepts, relationships, and assessment criteria in a structured, machine-readable format, an ontology can serve as a unified knowledge representation model. This would allow organizations to integrate multiple maturity models within a single interoperable framework, improving comparability and coherence across different assessment methodologies.

Moreover, an ontology-based system can leverage smart data-driven reasoning to generate predictive insights and dynamically adapt assessment criteria based on real-time industry data and emerging trends. This enhances decision support by providing intelligent, context-aware recommendations tailored to an organization's specific Industry 4.0 maturity level. The system's adaptability is another key advantage, as it can continuously refine assessment parameters in response to technological advancements, regulatory changes, and best practices.

Developing an ontology-based Industry 4.0 maturity assessment system not only addresses the interoperability challenges of existing models but also transforms traditional static assessments into intelligent, knowledge-driven decision-support tools, enabling organizations to achieve sustainable, strategic, and data-driven digital transformation.

3. THE PROPOSED SMART INDUSTRY 4.0 MATURITY ASSESSEMENT SYSTEM

The proposed ontology-based approach enables a structured, data-driven, and intelligent evaluation of Industry 4.0 maturity for industrial companies. It leverages an inference ontology developed in OWL, supported by SWRL rules, to automate the assessment process.

3.1. The proposed Approach Workflow

This methodology ensures comprehensive integration of diverse data sources, structured aggregation of maturity levels, and reasoning capabilities that provide actionable insights. The assessment process follows a systematic workflow consisting of seven key steps, as presented in figure 1 :

Step 1: Data Collection and Integration
The assessment process begins with collecting relevant data from multiple sources that reflect different aspects of Industry 4.0 maturity. These sources include:

- **Enterprise systems** such as ERP (Enterprise Resource Planning) and MES (Manufacturing Execution Systems), which provide structured data on strategic planning, investment levels, process automation, and production efficiency.
- **Operational technologies**, including IoT (Internet of Things) devices and networked sensors, which generate real-time information on machine connectivity, automation levels, and system integration.
- **Human resource inputs**, obtained from workforce surveys and interviews, capturing qualitative aspects such as leadership commitment, digital competencies, and organizational culture.
- **External industry and regulatory reports**, which provide benchmarks and contextual factors influencing Industry 4.0 adoption.

These data sources are mapped to the ontology, ensuring a structured and semantically enriched representation of the company's maturity level across the four dimensions, as in figure 2: **Strategic, Technological, Operational, and Cultural**. The ontology formalizes relationships between entities, enabling interoperability and intelligent processing.

Step 2: Individual Criteria Assessment Using Ontology Inference Rules
Once data is integrated into the ontology, the assessment process evaluates each of the 21 criteria using predefined SWRL rules. These rules allow for automated reasoning, inferring the maturity level of each criterion based on the collected data. Each rule processes relevant attributes and applies logical conditions to determine a maturity level. For example, a rule may assess the presence of a digital strategy, the degree of IoT adoption, or the extent of workforce training efforts. The inference engine classifies the company's state for each criterion, assigning a maturity score that aligns with predefined thresholds. The formalized evaluation ensures consistency and repeatability, eliminating subjectivity in the assessment process. The use of ontology-based reasoning also enhances the adaptability of the framework, allowing it to accommodate evolving Industry 4.0 requirements.

Step 3: Sub-Dimension Score Aggregation The next step aggregates the maturity scores of individual criteria to compute scores at the sub-dimension level. This aggregation is achieved using a weighted averaging approach:

$$S_{SD} = \frac{\sum_{i=1}^{n} S_{Ci}}{n}$$

where:

- S_{SD} is the maturity score of the sub-dimension.
- S_{Ci} represents the maturity score of the i-th criterion.
- n is the number of criteria in that sub-dimension.

To enhance the objectivity of decision-making, weight assignments could be done with multi-criteria decision-making techniques like the Analytical Hierarchy Process (AHP)[30]. These approaches would allow for more consistent, evidence-based assessments, removing biases that could potentially influence the evaluations.

Step 4 : Dimension Score Aggregation Once sub-dimension scores are obtained, the next step aggregates them into dimension-level maturity scores. This is accomplished using a weighted sum approach, considering the relative importance of each sub-dimension:

$$S_D = \sum_{j=1}^{m} w_j S_{SD_j}$$

where:

- S_D is the overall score of a given dimension.
- S_{SD_j} is the score of the j-th sub-dimension.

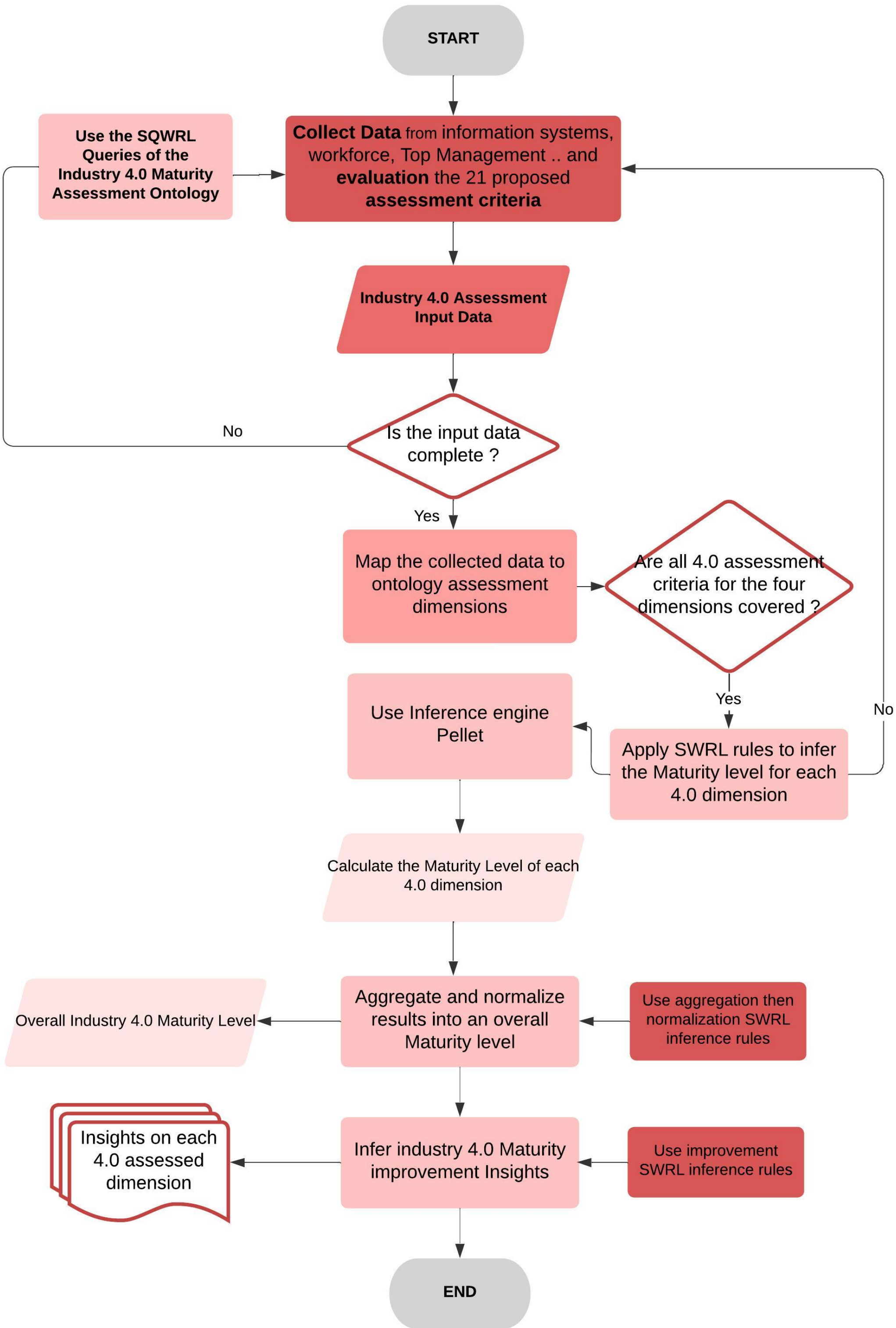

Figure 1. The logigram of the proposed approach

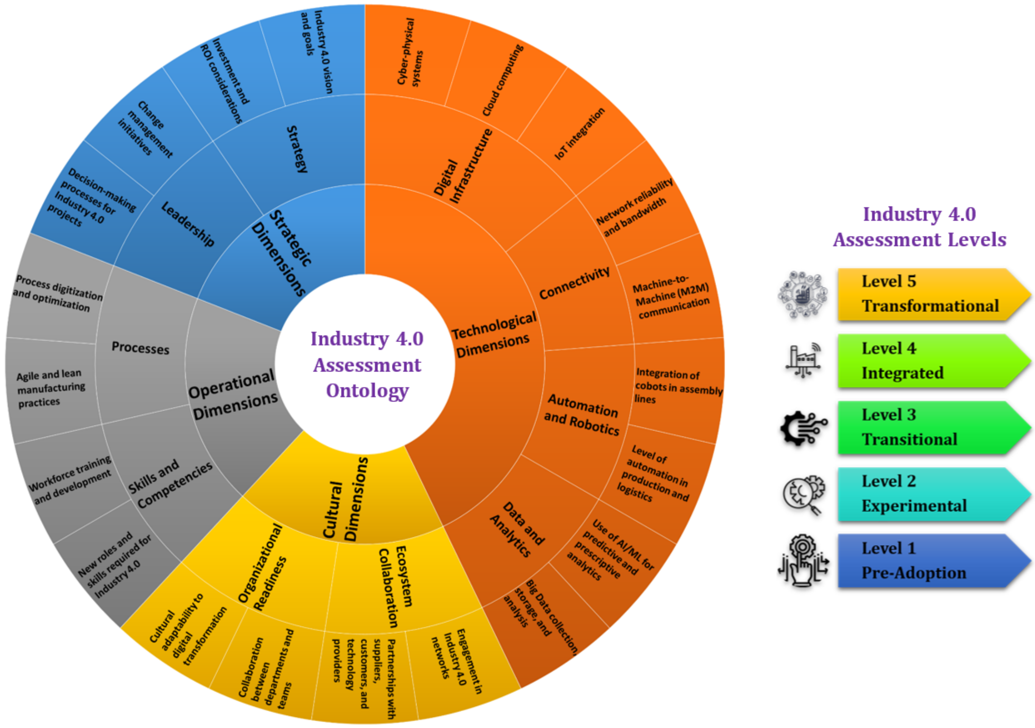

Figure 2. The assessment dimensions of the Industry 4.0 Maturity Assessment Model.

- w_j is the weight assigned to each sub-dimension, ensuring that $\sum w_j = 1$.

Weights can be determined based on empirical studies, expert opinions, or industry-specific factors.

Step 5 : Overall Maturity Score Calculation The final Industry 4.0 maturity score is derived by aggregating the four dimension scores, each weighted according to its cross-domain significance:

$$S_{Overall} = \sum_{k=1}^{4} w_k S_{D_k}$$

where:

- $S_{Overall}$ is the final maturity score of the company.
- w_k is the assigned weight of each dimension (Strategic, Technological, Operational, Cultural).
- S_{D_k} is the maturity score of each corresponding dimension.

This final score provides a holistic view of the company's Industry 4.0 maturity, integrating strategic alignment, technological adoption, operational efficiency, and cultural adaptability. The aggregation model ensures that the final score reflects both technical and organizational aspects of digital transformation.

Step 6 : Normalization for Cross-Company Benchmarking

To facilitate meaningful comparisons between companies within the same industrial sector, the final maturity score is normalized to a standard range of [0,1]. This ensures that variations due to sector-specific factors do not skew the assessment results.

$$S_{Normalized} = \frac{S_{Overall} - S_{Min}}{S_{Max} - S_{Min}}$$

where:

- $S_{Normalized}$ is the adjusted maturity score.
- $S_{Overall}$ is the computed maturity score of the company.
- S_{Min} and S_{Max} represent the lowest and highest maturity scores within the same industrial sector.

This normalization process enables objective benchmarking, allowing companies to assess their relative standing within the industry and identify areas for improvement.

Step 7: Insights Generation and Decision Support
Beyond numerical assessment, the ontology-based approach enables automated insights generation through SWRL-based reasoning. These rules analyze the maturity scores and generate recommendations tailored to the company's strengths and weaknesses. For instance, if a company's technological maturity is significantly lower than its strategic maturity, the system may recommend prioritizing investments in infrastructure, connectivity, and data analytics. If operational maturity is lagging, recommendations may focus on process optimization and workforce upskilling. This reasoning capability enhances decision-making by providing targeted recommendations rather than generic assessments. It also enables dynamic adaptation to evolving industry conditions, ensuring continuous improvement in digital transformation efforts.

3.2. The smart data-driven approach potentialities

The proposed ontology-based Industry 4.0 maturity assessment framework offers a structured, intelligent, and data-driven evaluation of an organization's digital transformation progress. By leveraging ontology reasoning, multi-source data integration, and hierarchical aggregation, the system ensures a comprehensive and objective assessment and ensure a set of potentialities :

- **Formal Knowledge Representation:** The ontology provides a rich, machine-readable model of Industry 4.0 concepts, enabling the structured capture of dependencies, hierarchies, and contextual relationships.
- **Interoperability and Integration:** Designed to align with existing enterprise systems (SCADA, ERP, MES), the ontology facilitates seamless data exchange and ensures compatibility with industry standards.
- **Automated Inference and Decision Support:** Through SWRL rules and reasoning mechanisms, the framework dynamically infers maturity levels, reducing manual assessment efforts and enhancing objectivity.
- **Comparability and Benchmarking:** The normalization of key performance indicators (KPIs) enables meaningful cross-company and cross-sector benchmarking, fostering industry-wide insights.
- **Scalability and Adaptability:** The modular structure allows for domain-specific extensions, making it adaptable to various industrial contexts and emerging technological trends.

By structuring Industry 4.0 assessment within an ontology-driven framework, organizations can systematically measure, compare, and enhance their digital transformation strategies, ensuring informed decision-making and continuous improvement.

4. THE DEVELOPED INDUSTRY 4.0 MATURITY ASSESSMENT ONTOLOGY-BASED SYSTEM

4.1. The ontology development methodology

The Industry 4.0 Maturity Assessment Ontology serves as the foundation for a structured, intelligent, and automated evaluation of an organization's digital transformation progress. The ontology-driven approach ensures a standardized, interoperable, and inference-enabled assessment, allowing for dynamic knowledge representation and reasoning. Key objectives of the ontology include:

- **Standardization:** Establishing a well-defined, structured model to categorize and assess Industry 4.0 maturity in a consistent and comparable manner across industries.

- **Automated Inference:** Utilizing SWRL rules and ontology-based reasoning to derive implicit insights, identify maturity gaps, and generate improvement recommendations.
- **Decision Support:** Linking Industry 4.0 maturity criteria with strategic actions to facilitate targeted decision-making and transformation roadmaps.
- **Adaptability:** Accommodating emerging technologies and evolving Industry 4.0 paradigms through scalable and modular knowledge structures.
- **Cross-Functional Alignment:** Providing a shared semantic framework to ensure clear communication across departments, stakeholders, and industrial ecosystems.
- **Data-Driven Insights:** Enabling benchmarking and continuous improvement through the integration of real-time industrial data from SCADA, ERP, IoT, and MES systems.

The ontology, presented in figure 3, is developed using OWL DL (Web Ontology Language Description Logic) [31, 29] within Protégé[21], ensuring both expressiveness and computational efficiency. The Pellet reasoner [32]is used for advanced SWRL rule-based inference, allowing for automated classification of Industry 4.0 maturity levels.

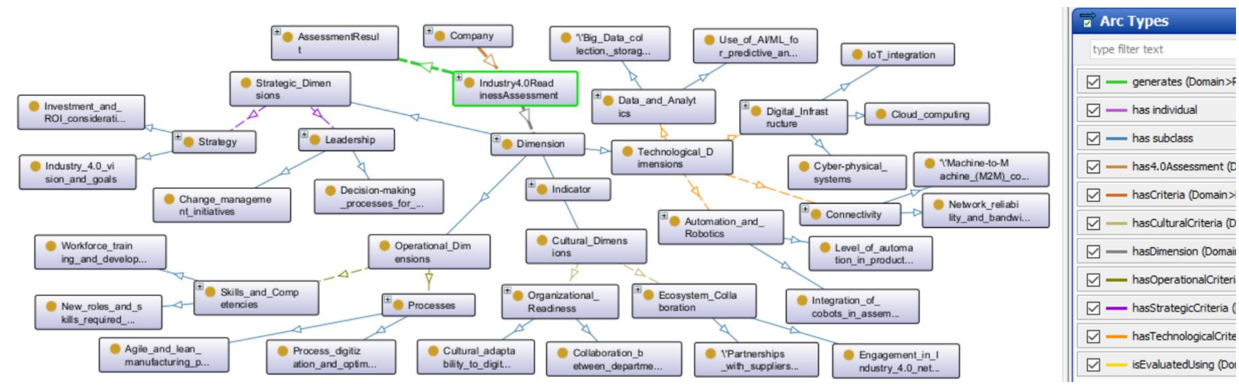

Figure 3. The proposed Industry 4.0 Maturity Assessment Ontology developed in OWL using Protégé 5.

To ensure the ontology's completeness and validity, its development is based on a systematic review of existing Industry 4.0 maturity models and frameworks, including:

- ACATECH Industry 4.0 Maturity Index [5]
- IMPULS Industry 4.0 Readiness Model [6]
- Singapore Smart Industry Readiness Index (SIRI) [7]
- 6Ps Maturity Model for SMEs [14]
- SIMMI 4.0 [8]
- Reference Architecture Model for Industry 4.0 (RAMI 4.0) [28]
- Empirical case studies, expert interviews, and reports from leading manufacturers.

By integrating these models, the ontology ensures a comprehensive representation of the key dimensions, criteria, and indicators necessary for a holistic Industry 4.0 assessment.
OWL DL is chosen over other knowledge representation languages due to its semantic richness, reasoning capabilities, and decidability. Unlike RDFS, which lacks inferencing power, and OWL Full, which presents decidability issues, OWL DL provides an optimal balance for rule-based reasoning and structured assessments.
Protégé is selected due to its Native support for OWL DL and SWRL, Modular and extensible architecture, Integration capabilities with industrial systems, Strong community and industry adoption, reasoning support and seamless integration with Pellet
Pellet is chosen as the primary reasoner for its:

- Full OWL DL compliance

- Efficient handling of SWRL rules and classification tasks
- Ability to handle complex axioms in Industry 4.0 readiness assessment

Compared to HermiT and FaCT++, Pellet offers superior SWRL rule reasoning, ensuring reliable inference for maturity classification.

4.2. The proposed Industry 4.0 Assessment Ontology

The Industry 4.0 Maturity Assessment Ontology is structured as a hierarchical framework, composed of core classes, as shown in figure 4:

- **Industry4.0MaturityAssessment** – Represents the overall evaluation process.
- **Company** : Represents the industrial entity undergoing assessment.
- **Dimension** : Categorizes maturity dimensions into **Strategic, Technological, Operational, and Cultural**.
- **SubDimension** : Further specifies thematic assessment areas.
- **Criteria** : Defines individual Industry 4.0 capabilities being measured.
- **Indicator** : Quantifies assessment criteria using measurable KPIs.
- **AssessmentResult** : Represents the inferred **maturity level** based on evaluation.

Each criterion is classified into a five-level maturity scale:

1. **Pre-adoption:** No Industry 4.0 initiatives implemented.
2. **Experimental:** Limited pilot testing and exploratory projects.
3. **Transitional:** Partial deployment, with scalability potential.
4. **Integrated:** Industry 4.0 technologies embedded in operations.
5. **Transformational:** Full connectivity, intelligence, and automation.

The root Object and Data Properties of the ontology are, as presented in figure 5 :

- **aggregates** : Defines hierarchical relationships.
- **hasCriteria** : Links sub-dimensions with assessment criteria.
- **isEvaluatedUsing** : Associates organizations with their evaluation parameters.
- **generates** : Establishes assessment outcomes.
- **isAssociatedWith** : Maps KPIs to specific technological enablers.

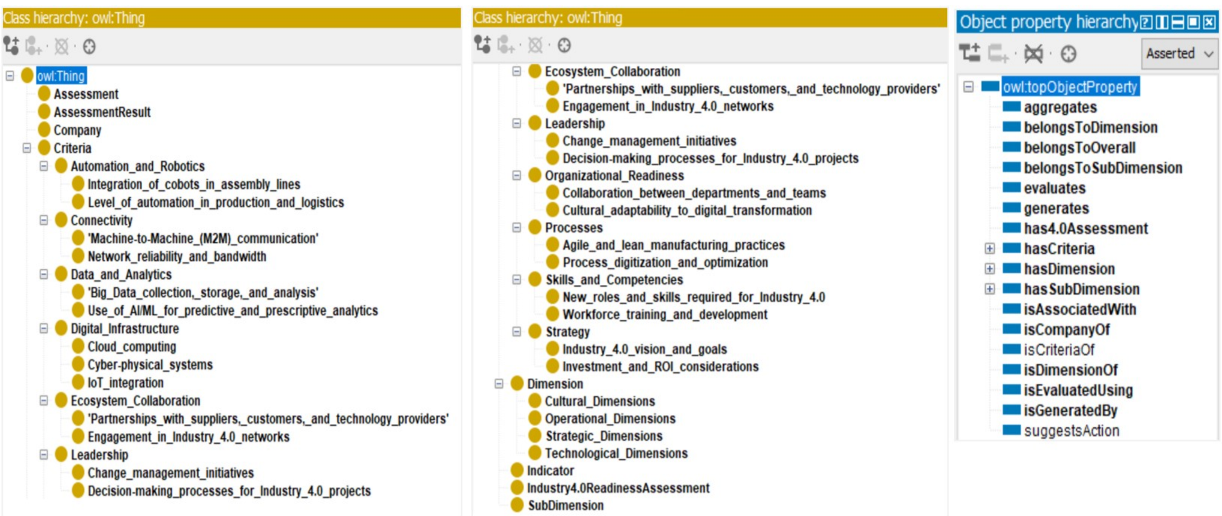

Figure 4. Main classes and object properties of the proposed Industry 4.0 Maturity Assessment Ontology.

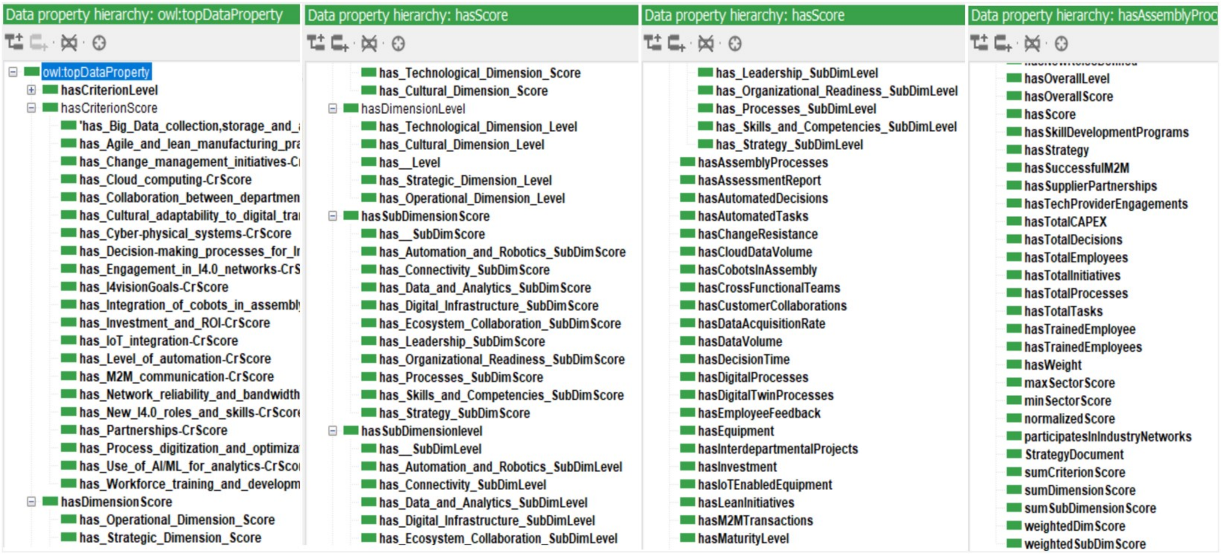

Figure 5. Main data properties of the proposed Industry 4.0 Maturity Assessment Ontology.

The ontology evaluates Industry 4.0 maturity across four primary dimensions, each comprising multiple sub-dimensions and criteria :

a. Strategic Dimension

- **Strategy:** Assesses digital transformation roadmaps, alignment with business goals, and ROI-based investment strategies.
- **Leadership:** Evaluates executive decision-making, change management initiatives, and governance for digital transformation.

b. Technological Dimension

- **Digital Infrastructure:** Measures IoT integration, cloud adoption, and cyber-physical system (CPS) deployment.
- **Data & Analytics:** Assesses big data handling, real-time analytics, and AI-driven predictive capabilities.
- **Automation & Robotics:** Evaluates the level of robotic automation, cobot integration, and autonomous systems.
- **Connectivity:** Measures M2M communication, network reliability, and bandwidth.

c. Operational Dimension

- **Processes:** Assesses digitalization levels, MES implementation, and agile manufacturing adoption.
- **Skills & Competencies:** Evaluates workforce training, job role evolution, and Industry 4.0 skill maturity.

d. Cultural Dimension

- **Organizational Readiness:** Examines cultural adaptability, digital innovation mindset, and cross-departmental collaboration.
- **Ecosystem Collaboration:** Evaluates industrial partnerships, supplier-customer cooperation, and participation in Industry 4.0 networks.

Each criterion is assigned a **maturity level** based on SWRL rules, ensuring an automated and intelligent Industry 4.0 assessment. The Industry 4.0 Maturity Assessment Ontology serves as a structured, scalable, and automated framework for evaluating an organization's maturity in digital transformation. Through OWL DL, Protégé, and Pellet reasoning, the ontology enables automated inferencing, strategic benchmarking, and integration with industrial data systems. The structured approach supports both academic research and industrial applications, ensuring a comprehensive and data-driven Industry 4.0 transformation roadmap.

4.3. The Proposed Smart Decision-Making System for Industry 4.0 Maturity Assessment

The proposed decision-making smart system for Industry 4.0 maturity assessment integrates an ontology-based framework with SWRL inference rules and SQWRL queries to automate, optimize, and enhance the assessment process. By leveraging semantic reasoning, rule-based inference, and intelligent recommendations, the system ensures a structured, data-driven, and scalable evaluation of an organization's digital transformation maturity. This approach reduces subjectivity, accelerates decision-making, and provides actionable insights for strategic planning.

a. Inference SWRL rules for criteria evaluation and maturity level assignment
To ensure precise Industry 4.0 maturity evaluation, the system applies SWRL inference rules to assess individual criteria based on data extracted from the industrial information system (SCADA, ERP,MES, etc..) of the assessed plant. Each criterion undergoes a structured evaluation where relevant indicators are measured, and a corresponding maturity score is assigned as described before, using the inference rules of the first category presented in table 2. For example, when assessing IoT integration, the swrl rule R1 calculates the proportion of IoT-enabled equipment relative to total equipment. If this ratio surpasses the predefined threshold, the inference engine automatically assigns a maturity level such as "Transitional. This rule-based classification eliminates subjectivity, enhances consistency across assessments, and ensures a standardized evaluation process across different industrial contexts.

b. Inference rules and SQWRL queries for the Aggregation of Maturity Scores
A holistic Industry 4.0 assessment requires aggregating scores across multiple hierarchical levels to provide a comprehensive view of an organization's digital transformation status.

The ontology-based system follows a structured, stepwise aggregation process respecting the workflow of the proposed assessement model:

1. **Criteria-Level Assessment** : Each criterion receives an individual readiness score based on SWRL rules presented in table 2.
2. **Sub-Dimension Aggregation** : The system computes the average scores for related criteria to generate sub-dimension maturity scores, using rules S1, S2 and S3 in table 3.
3. **Dimension-Level Aggregation** : Sub-dimension scores roll up into broader Industry 4.0 dimensions (Strategic, Technological, Operational, and Cultural) using the rules S4 and S5.
4. **Overall Maturity Score Calculation** : A weighted algorithm integrates all dimension scores to determine the organization's overall Industry 4.0 maturity, using rules S6, S7 and S8.
5. **Normalization for Cross-Company Benchmarking** : To ensure fair comparisons across different industrial sectors, the system applies normalization techniques that enable benchmarking, using the rule S9.

This structured aggregation process helps organizations pinpoint their strengths and weaknesses, prioritize improvement efforts, and compare their Industry 4.0 maturity against industry benchmarks.

c. Inference rules to support Intelligent Insights Generation and Recommendations
One of the proposed ontology-based system key advantages is its ability to generate intelligent, actionable recommendations based on inferred maturity levels, using swrl inference rules of category 3 presented in table 4. The ontology-driven reasoning mechanism not only assesses the current state but also suggests strategic next steps to accelerate digital transformation. For instance, if a company's cybersecurity preparedness is at the "Pre-Adoption" level, the system may recommend implementing a risk assessment framework, adopting best practices for industrial cybersecurity, and investing in employee training programs. Similarly, for companies lagging in AI adoption, the system could suggest launching pilot projects, integrating predictive analytics into

Table 2. Sample of the proposed SWRL inference rules for criteria evaluation and maturity level assignment.

Rule ID	SWRL Rule	Assessment Criteria
R1	Company(?f)^hasEquipment(?f,?e)^hasIoTEnabledEquipment(?f,?i) ^swrlb:divide(?p,?i,?e)^swrlb:multiply(?rate,?p,100) ^swrlb:greaterThan(?rate,80)->has_IoT_integration-CrScore(?f,?rate) ^has_IoT_integration_CrLevel(?f,"Transitional")	IoT integration
R2	Company(?c)^hasDataVolume(?c,?d) ^hasCloudDataVolume(?c,?cd) ^swrlb:divide(?p,?cd,?d) ^swrlb:multiply(?rate,?p,100)^swrlb:greaterThan(?rate, 60)->has_Cloud_computing-CrScore(?c, ?rate)^has_Cloud_computing_CrLevel(?c, "Transitional")	Cloud computing
R3	Company(?f)^hasTotalProcesses(?f, ?p)^hasDigitalTwinProcesses(?f, ?d)^swrlb:divide(?r, ?d, ?p)^swrlb:multiply(?rate, ?r, 100)^swrlb:greaterThan(?rate, 50) ->has_Cyber-physical_systems-CrScore(?f, ?rate)^has_Cyber-physical_systems_CrLevel(?f, "Experimental")	Cyber-physical systems
R4	Company(?f)^hasDataAcquisitionRate(?f, ?rate)^swrlb:greaterThan(?rate, 10) ->has_Big_Data_analysis-CrScore(?f, ?rate)^has_Big_Data_analysis_CrLevel(?f, "Integrated")	Big Data analysis
R5	Company(?c)^hasAutomatedDecisions(?c,?y)^hasTotalDecisions(?c,?t) ^swrlb:divide(?p,?y,?t) ^swrlb:multiply(?rate,?p,100)^swrlb:greaterThan(?rate, 40)->has_Use_of_AI/ML_for_analytics-CrScore(?c, ?rate)^has_Use_of_AI/ML_for_predictive_and_prescriptive_analytics_CrLevel(?c, "Transitional")	Use of AI/ML for prediction
R6	Company(?f)^hasM2MTransactions(?f, ?t)^hasSuccessfulM2M(?f, ?s)^swrlb:divide(?p, ?s, ?t)^swrlb:multiply(?rate, ?p, 100)^swrlb:greaterThan(?rate, 95) ->has_M2M_communication-CrScore(?f, ?rate)^has_Machine-to-Machine_communication_CrLevel(?f, "Integrated")	Machine-to-Machine (M2M) communication
R7	Company(?c)^hasI4_0Capex(?c, ?capex)^hasTotalCapex(?c, ?total_capex)^swrlb:divide(?p, ?capex, ?total_capex)^swrlb:multiply(?rate, ?p, 100)^swrlb:greaterThanOrEqual(?rate, 21)^swrlb:lessThanOrEqual(?rate, 40) ->has_InvestmentROI_CrLevel(?c, "Experimental")	Investment and ROI considerations
R8	etc..	etc..

operations, and upskilling employees in machine learning technologies.

These intelligent recommendations ensure that organizations receive tailored guidance, helping them align their Industry 4.0 transformation roadmap with strategic business objectives.
The integration of SWRL inference rules and SQWRL queries significantly enhances the decision-making process by integrating:

- **Automated and Scalable Assessment** – Eliminates manual evaluations, ensuring faster and more efficient Industry 4.0 maturity assessment.
- **Data-Driven Insights** – Reduces subjectivity by leveraging real-time industrial data for accurate and objective evaluations.
- **Improved Decision-Making** – Provides targeted recommendations, helping manufacturers prioritize investment in digital transformation initiatives.
- **Benchmarking and Competitiveness –** Enables cross-company comparisons to identify best practices and areas for improvement.

Table 3. The proposed SWRL Inference Rules for Industry 4.0 Maturity Scores Aggregation.

Rule ID	SWRL Rule	Rule Description
S1	Criteria(?c) ˆhasScore(?c, ?s) ˆbelongsToSubDimension(?c, ?sd) → sumCriterionScore(?sd, swrl:add(?s))	Aggregates scores of all criteria within a sub-dimension.
S2	SubDimension(?sd) ˆsumCriterionScore(?sd, ?sum) ˆcountCriteria(?sd, ?n) → hasScore(?sd, swrl:divide(?sum, ?n))	Computes sub-dimension score as the average of its associated criteria scores.
S3	SubDimension(?sd) ˆhasScore(?sd, ?s) ˆbelongsToDimension(?sd, ?d) ˆhasWeight(?sd, ?w) → weightedSubDimScore(?d, swrl:multiply(?s, ?w))	Computes weighted scores for sub-dimensions before dimension-level aggregation.
S4	Dimension(?d) ˆweightedSubDimScore(?d, ?ws) → sumSubDimensionScore(?d, swrl:add(?ws))	Aggregates all weighted sub-dimension scores within a given dimension.
S5	Dimension(?d) ˆsumSubDimensionScore(?d, ?sum) → hasScore(?d, ?sum)	Assigns the aggregated sub-dimension score as the dimension's maturity score.
S6	Dimension(?d) ˆhasScore(?d, ?s) ˆbelongsToOverall(?d, ?a) ˆhasWeight(?d, ?w) → weightedDimScore(?a, swrl:multiply(?s, ?w))	Computes weighted score of each dimension before final aggregation.
S7	Assessment(?a) ˆhasDimension(?a, ?d)ˆweightedDimScore(?d, ?ws) → sumDimensionScore(?a, swrl:add(?ws))	Aggregates all weighted dimension scores to compute the final Industry 4.0 maturity score.
S8	Assessment(?a) ˆsumDimensionScore(?a, ?sum) → hasOverallMaturityAssessment_Score(?a, swrl:divide(?sum, ?4))	Assigns the aggregated dimension score as the overall Industry 4.0 maturity score.
S9	Assessment(?a) ˆhasScore(?a, ?s) ˆminSectorScore(?a, ?min) ˆmaxSectorScore(?a, ?max) → normalizedScore(?a, swrl:divide(swrl:subtract(?s, ?min), swrl:subtract(?max, ?min)))	Normalizes the maturity score within the industry sector to allow cross-company benchmarking.

- **Continuous Monitoring** – Facilitates ongoing Industry 4.0 maturity tracking, allowing enterprises to measure progress and adapt strategies dynamically.

5. USE CASE ON INDUSTRY 4.0 MATURITY ASSESSEMENT IN AUTOMOTIVE MANUFACTURING INDUSTRY

To validate the proposed ontology-based Industry 4.0 maturity assessment approach and its potentialities, a real-world case study was conducted in an automotive manufacturing plant specializing in the production of engine components and chassis assemblies.

5.1. Use case specification

The plant operates under a high-mix, mid-volume production system, requiring flexible and adaptive manufacturing processes. Given the increasing demand for customized automotive parts and just-in-time (JIT) delivery models, the company has initiated an Industry 4.0 transformation to enhance efficiency, reduce downtime, and optimize resource utilization.
The plant integrates multiple **discrete and process manufacturing operations**, including:

- **CNC machining** for high-precision engine components.

Table 4. The Proposed Inference Rules to Support Industry 4.0 Insights and Recommendations.

Rule ID	SWRL Rule	Rule description
I1	Criterion(?c) ˆhasMaturityLevel(?c, PreAdoption) → suggestsAction(?c, "Promote Industry 4.0 literacy through training workshops.")	Develop structured Industry 4.0 training programs, ensuring employees adapt to digital transformation.
I2	Criterion(?c) ˆhasMaturityLevel(?c, Experimental) → suggestsAction(?c, "Allocate test budgets and pilot key Industry 4.0 technologies.")	Pilot IoT, AI, and automation projects in controlled environments, measure feasibility, and define expected ROI to justify scaling.
I3	Criterion(?c) ˆhasMaturityLevel(?c, Transformational) → suggestsAction(?c, "Enable autonomous decision-making using AI-driven insights.")	Move towards real-time AI-based decision-making with automated feedback loops for continuous optimization.
I4	Criterion(?c) ˆhasMaturityLevel(?c, PreAdoption) → suggestsAction(?c, "Deploy IoT sensors for real-time data collection.")	Start with critical asset monitoring, set up IoT connectivity, and test predictive maintenance capabilities.
I5	Criterion(?c) ˆhasMaturityLevel(?c, Experimental) → suggestsAction(?c, "Integrate cloud-based platforms for scalable data storage.")	Implement hybrid cloud models, assess latency concerns, and ensure data security compliance.
I6	Criterion(?c) ˆhasMaturityLevel(?c, Transitional) → suggestsAction(?c, "Optimize cyber-physical system connectivity for automation.")	Implement PLC-to-cloud connectivity, integrate edge computing, and ensure cybersecurity protocols.
I7	Criterion(?c) ˆhasMaturityLevel(?c, Integrated) → suggestsAction(?c, "Deploy AI-driven predictive maintenance.")	Leverage AI for predictive analytics, integrate data lakes, and establish real-time monitoring dashboards.
I8	Criterion(?c) ˆhasMaturityLevel(?c, Transformational) → suggestsAction(?c, "Implement self-learning AI for automated prescriptive analytics.")	Deploy machine learning algorithms to self-optimize production and enable AI-assisted decision-making.
I9	Criterion(?c) ˆhasMaturityLevel(?c, Transformational) → suggestsAction(?c, "Implement end-to-end smart manufacturing integration.")	Deploy digital twins, real-time MES integration, and ensure self-optimizing supply chains.
I10	Criterion(?c) ˆhasMaturityLevel(?c, Integrated) → suggestsAction(?c, "Enhance supply chain collaboration with blockchain and AI.")	Implement blockchain-based supply chain visibility, automated contract execution, and AI-powered supply chain risk management.
I11	Etc..	Etc..

- **Automated robotic welding and assembly** of chassis and structural parts.
- **Surface treatment and quality control** using vision-based inspection systems.
- **Flexible production lines** capable of adapting to different vehicle models.

To manage these operations, the plant relies on a combination of industrial information systems that provide real-time data for monitoring and decision-making. The primary systems feeding data into the ontology-based assessment include:

- **Supervisory Control and Data Acquisition (SCADA)** : that monitors real-time machine performance, energy consumption, process stability and collects sensor data for predictive maintenance.
- **Enterprise Resource Planning (ERP) System**: that manages production planning, procurement, inventory, supply chain logistics and provides data on material flow and resource allocation.

- **Manufacturing Execution System (MES)** : that tracks production progress and operational efficiency and records deviations, downtime, and work orders.
- **IoT and Edge Computing Infrastructure** : that connects industrial sensors, actuators, machines for real-time condition monitoring and enables cyber-physical systems for adaptive control strategies.

Data from these systems were integrated into the proposed Industry 4.0 maturity ontology, where SWRL rules and SQWRL queries were executed to infer maturity levels, detect bottlenecks and recommend improvement actions.

5.2. Industry 4.0 Maturity Assessment using the proposed Ontology-based system

The assessment was conducted based on 21 key Industry 4.0 criteria. Figures 6 and 7 present a sample of the results of the Industry 4.0 criteria assessment obtained by the proposed ontology and swrl rules.

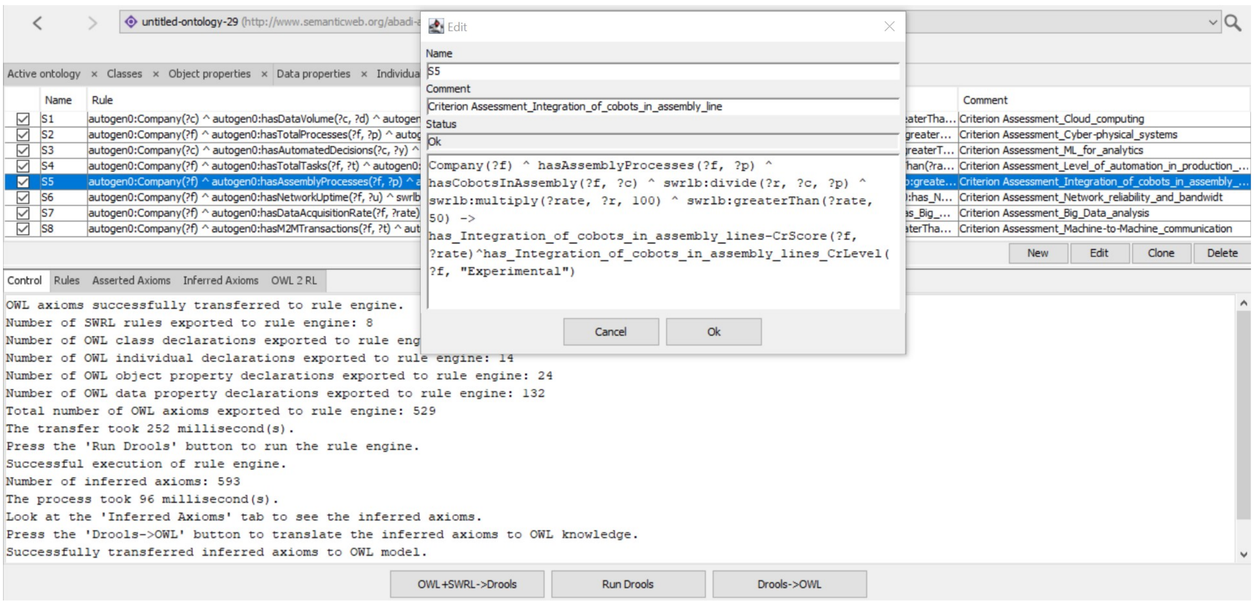

Figure 6. Illustration of the SWRL inference rules implemented in Protégé 5 to assess the Industry 4.0 Maturity Criteria.

In fact, for the assessment criteria related to the Strategic Dimension :

- The plant has a clear Industry 4.0 vision and goals (75%, Integrated) but limited investment in digital transformation (15%, Experimental).
- Decision-making processes for Industry 4.0 initiatives remain underdeveloped (30%, Experimental) due to a lack of structured change management frameworks.

For the Technological Maturity :

- IoT integration is at 69% (Transitional), with ongoing sensor deployment for real-time monitoring.
- Cloud computing and cyber-physical systems are still in early-stage adoption (50% and 30%, respectively).
- AI/ML for predictive analytics has reached 55% maturity, with applications in predictive maintenance but not yet in full-scale production optimization.
- Automation levels are high (75%, Integrated), but cobot integration remains limited (30%, Experimental).
- Connectivity is one of the strongest areas, with M2M communication at 85% (Integrated) and network reliability at 99.2% (Transformational).

For the assessment criteria related to the Operational Dimension :

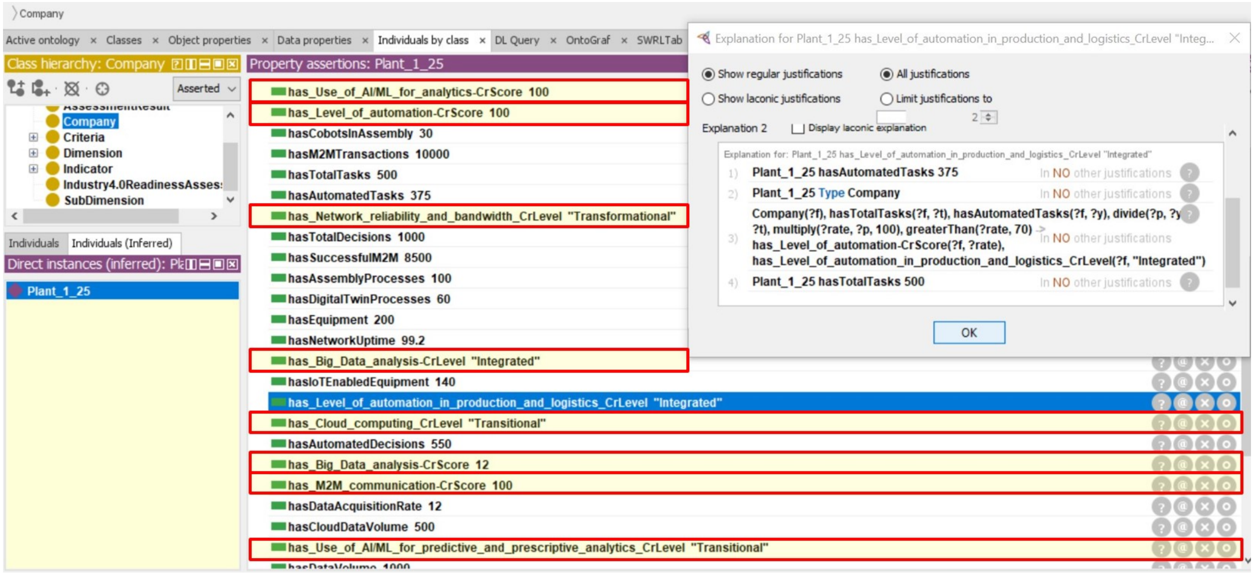

Figure 7. The results of Industry 4.0 Criteria Maturity Assessment.

- Process digitization and optimization has reached 60% maturity (Transitional), demonstrating progress in automation but gaps in real-time analytics and process simulation.
- Workforce training and development is at 40% (Transitional), indicating a need for stronger upskilling initiatives.

And for the criteria of the Cultural Dimension :

- Organizational adaptability to digital transformation scored 65% (Transitional), showing a moderate level of cultural readiness.
- Collaboration with suppliers and external partners remains weak (37%, Experimental).

5.3. Overall Maturity Assessment and decision making support for insights generation

Using SWRL inference rules and SQWRL queries, the proposed ontology automatically inferred the plant's Industry 4.0 maturity across different dimensions. The Technological Maturity was assessed at a Transitional level (68%), as presented in figure 8, reflecting progress in automation, IoT integration, and data analytics, but highlighting gaps in AI adoption and cobot deployment.
The Operational Maturity also remained Transitional (48%), indicating moderate advancements in process digitization and lean manufacturing, yet revealing a need for further workforce training and skill development. Similarly, the Cultural Maturity was classified as Transitional (51%), emphasizing the organization's adaptability to digital transformation while pointing out weaknesses in ecosystem collaboration and engagement in Industry 4.0 networks. Based on these assessments, the Overall Industry 4.0 Maturity Score was determined to be 50% (Transitional), as presented in figure 9, suggesting that while the plant has initiated its digital transformation journey, additional efforts are required to reach higher maturity levels.
The last step was then to implement the third SWRL rules category to propose actionable recommendations to accelerate the plant's Industry 4.0 transformation. Figure 9 illustrates the obtained results. The recommendations focus mainly on:

1. **Increase AI Adoption:** The plant should expand AI-based analytics for supply chain forecasting and production optimization. A target of AI adoption in critical decision-making processes is recommended to improve operational efficiency and predictive capabilities.

2. **Enhance Cobot Deployment:** The integration of collaborative robots (cobots) in assembly lines should be increased. Additionally, improving human-robot collaboration will enhance production flexibility and adaptability in dynamic manufacturing environments.
3. **Expand IoT Coverage:** To strengthen connectivity, legacy machines should be retrofitted with IoT sensors, raising IoT coverage. This will enable enhanced real-time data collection, improving process optimization and predictive maintenance capabilities.
4. **Deploy Private 5G and Edge Computing:** Strengthening network reliability through a private 5G infrastructure will support high-speed, low-latency communication. Additionally, deploying edge computing will reduce latency in data transmission, enabling real-time adaptive manufacturing and improving system responsiveness.

By implementing these recommendations, the plant can systematically enhance its technological infrastructure, workforce capabilities, and digital transformation strategy, ultimately advancing toward higher Industry 4.0 maturity levels.

5.4. The proposed system evaluation

To validate the effectiveness of the developed ontology-driven system for Industry 4.0 maturity assessment,a quantitative evaluation was conducted using real-world industrial data. While the case study demonstrates the system's reasoning capabilities, a structured validation approach provides deeper insights into its optimization potential. The evaluation compares the assessment outcomes before and after ontology integration in the studied automotive manufacturing plant. The pre-ontology assessment relied on conventional maturity assessment methods, while the post-ontology assessment employed the proposed ontlogy-based system. The evaluation focuses on various key performance categories: Data Processing Efficiency, Maturity Level Accuracy and System Usability.

- **a. Data Processing Efficiency Analysis**

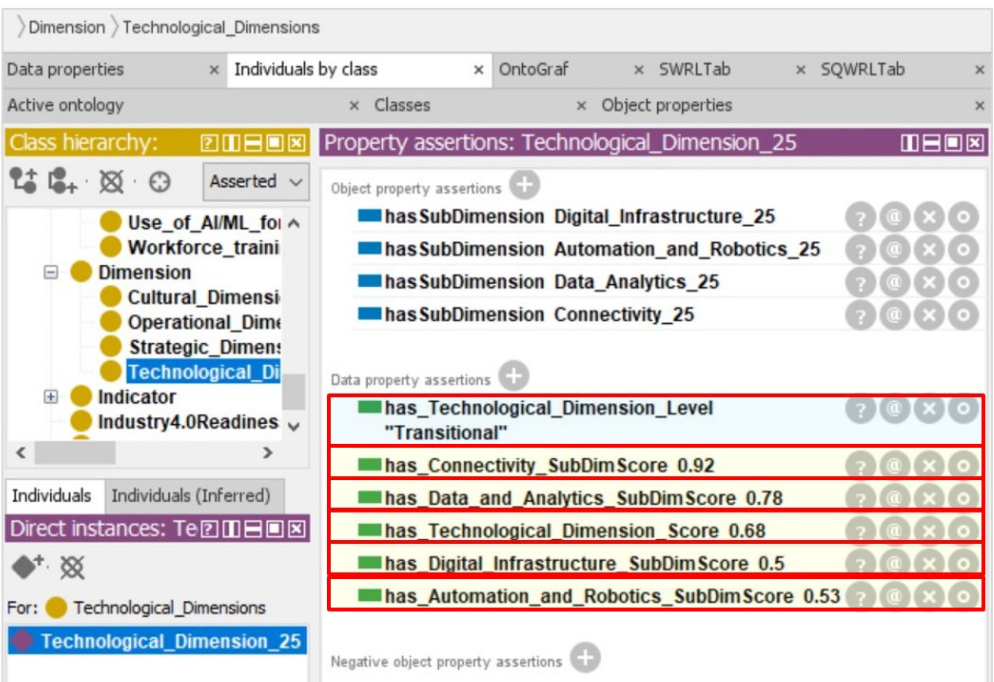

Figure 8. The results of the aggregation of sub-dimensions and dimension maturity scoresof the Technological Assessment.

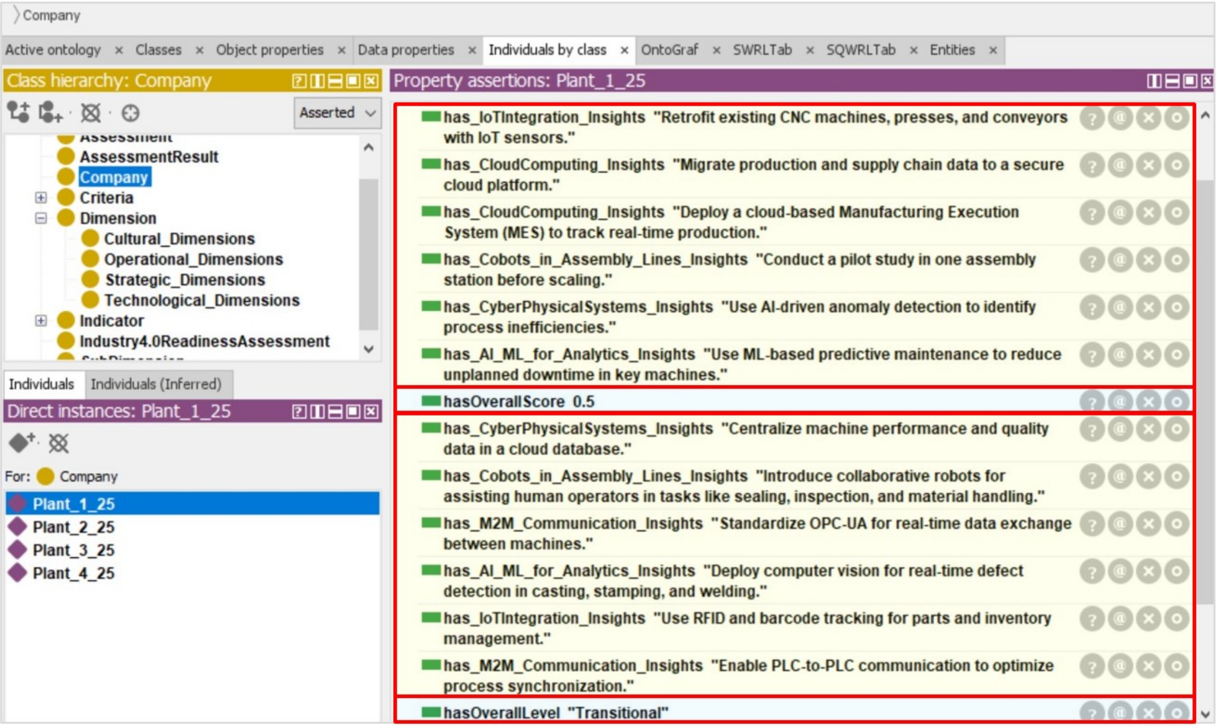

Figure 9. Results on Industry 4.0 Overall Assessment and Generated Insights.

The ontology formalizes Industry 4.0 maturity assessment by embedding domain knowledge through structured concepts and logical relationships. The system's efficiency was evaluated based on inference execution time, integration latency and processing throughput by measuring the time taken for SWRL rule execution and ontology reasoning over diverse industrial datasets. Results demonstrated a 49% improvement in processing efficiency, as the ontology significantly reduced latency in handling data from heterogeneous industrial sources such as SCADA, ERP, and IoT systems. The automated reasoning process minimized manual effort, ensuring real-time assessment capabilities. Beyond predefined assessment models, the ontology's dynamic reasoning capabilities facilitate sector-specific refinements. As Industry 4.0 adoption varies across industries, the system offers modular extension capabilities, allowing seamless adaptation to automotive, pharmaceutical, logistics, and energy sectors without requiring fundamental reconfiguration.

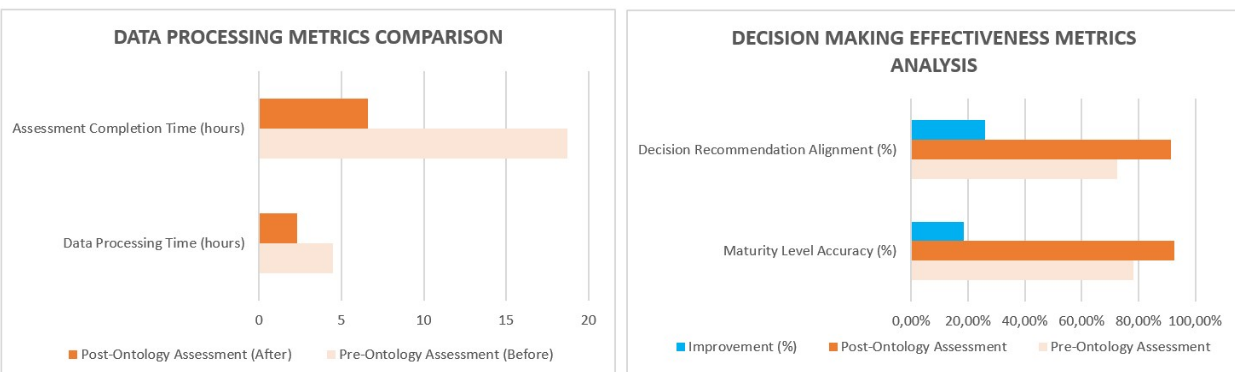

Figure 10. Data processing and Decision-making metrics analysis in pre and post use of the 4.0 Assessement ontology.

- **b. Maturity Level Accuracy Assessment and interoperability**

By leveraging ontology-based reasoning, the system dynamically processes industrial data streams from SCADA, ERP, and IoT devices, ensuring real-time assessment without manual intervention. To validate the accuracy of maturity level classifications, the ontology's inference results were compared with expert evaluations and benchmarked against established model The assessment leveraged precision-recall analysis to measure correctness and inter-rater agreement scores to evaluate consistency. Findings indicated an 18.5% increase in maturity level accuracy, demonstrating the system's ability to provide reliable and objective maturity assessments with minimal variance from expert evaluations. Furthermore, data inconsistencies decreased by 22%, as SWRL rules enforce structured and standardized interpretations across heterogeneous data sources. This adaptability underscores the ontology's role as a universal Industry 4.0 assessment framework, capable of integrating seamlessly with diverse legacy systems, edge computing platforms, and cloud-based architectures.

- **c. Decision-Support Effectiveness and Strategic Alignment**

By embedding domain expertise into the ontology, the system not only classifies Industry 4.0 maturity levels but also provides automated strategic recommendations. These insights align with industry-specific digital transformation roadmaps, ensuring informed decision-making. Experts who interacted with the system reported a 26% increase in decision-making efficiency, as visual analytics and rule-based recommendations reduced subjectivity in planning digital transformation strategies.

5.5. Discussion of system scalability and performance implications

The proposed ontology establishes a scalable, automated, and intelligent foundation for Industry 4.0 maturity assessment. Its high expressiveness, real-time inference, and cross-sector applicability position it as a robust decision-support tool for industrial transformation.

- **System scalability and interoperability**

The proposed ontology-based system is designed with a core conceptual model that ensures its applicability across various industries. The dimensions and industry 4.0 technologies embedded within the model are independent of any particular sector, allowing for versatility and scalability. While each industry may require tailored applications, the underlying technologies, such as the use of OWL DL (Web Ontology Language Description Logic) and the assessment steps remain consistent. This ensures that the system can seamlessly integrate into different industrial ecosystems, providing standardized, reliable assessments that are adaptable to specific sector needs. The core technologies and methodologies utilized in the ontology-based system are the same, whether applied to the automotive, pharmaceutical, logistics, or energy sectors, reinforcing the system's cross-industry relevance. To enhance the integration of diverse industrial data formats, the proposed system leverages OWL DL, which offers a balance between expressivity and computational efficiency. This framework enables precise modeling of complex relationships and dependencies within Industry 4.0 assessments while maintaining compatibility with widely adopted XML-based standards. By ensuring interoperability with systems like SCADA, PLM, ERP, and MES, the ontology-based system facilitates real-time data exchange and decision-making. This capability is key to automating the mapping of various data formats, including legacy systems and IoT devices, into the ontology, thereby minimizing the need for manual configuration efforts and enhancing scalability in diverse project ecosystems. The ontology-based system is inherently designed to be extendible, allowing it to handle high-volume data streams without compromising performance. The scalability of the system can be optimized through the use of advanced techniques, such as parallel reasoning engines, which are particularly effective for processing large datasets. The flexibility of the ontology enables it to be tailored to support distributed reasoning frameworks, like Apache Jena, for large-scale applications. This adaptability ensures that the system remains responsive and effective as data volumes increase, making it suitable for a wide range of industrial applications.

- **System performance implications**

The extendibility of the ontology also plays a critical role in ensuring its dynamic evolution in line with emerging Industry 4.0 trends. By incorporating, in further works, machine learning techniques such as active learning and natural language processing (NLP), the ontology can automatically detect and integrate new developments in the industrial landscape. This functionality ensures that the ontology remains current and capable of addressing new challenges and opportunities within Industry 4.0 without requiring manual updates, thus facilitating continuous improvement and adaptability. The system's security measures, including encryption, role-based access control, and anomaly detection mechanisms are to be investigated even if th use of Protogé as a development framework is secured. These protocols are aligned with established cybersecurity standards such as IEC 62443, ensuring that the system adheres to best practices in industrial security. The implementation of these security measures is essential to maintain the integrity and confidentiality of the data, particularly in highly regulated sectors where data protection is critical. In handling complex ontologies, managing rule conflicts and ambiguities is crucial for maintaining system robustness. To address this challenge, Pellet, a reasoning engine, was selected over other alternatives like Fact++ and HermiT. Pellet's comprehensive support for OWL DL reasoning tasks, including classification, consistency checking, and SWRL query answering, makes it well-suited for dynamic environments where data and dependencies evolve rapidly. Unlike Fact++, which excels in speed but struggles with complex ontology structures, or HermiT, which is optimized for expressive ontologies but can face performance bottlenecks, Pellet offers a balanced solution. Its incremental reasoning strategies and modular task partitioning make it ideal for environments with frequent updates, providing a more flexible approach to rule conflict resolution.

6. CONCLUSION AND PERSPECTIVES

This paper presented a smart data-driven system for Industry 4.0 maturity assessment, integrating strategic, operational, technological, and cultural dimensions into a holistic decision-support system. By leveraging OWL for the development of the reference assessment ontology and SWRL rules for intelligent inference, the proposed system enables optimized assessment of industrial enterprises into five maturity levels, utilizing real-time KPIs from the plant information system and workforce. A case study in an automotive manufacturing plant validated its effectiveness criteria assessment, dimensions aggregations and instructive insights generation for next digital transformation implementation steps.

Beyond its core function of maturity assessment, the proposed ontology-based system ensures interoperability between existing assessment models, harmonizing Industry 4.0 assessment frameworks into a unified, standardized evaluation methodology. Additionally, it provides a comprehensive, multi-dimensional assessment, incorporating all key dimensions of Industry 4.0 transformation rather than focusing on isolated aspects. The expressiveness of OWL and the reasoning capabilities of SWRL inference rules further optimize the assessment process by enabling automated reasoning, knowledge consistency validation, and rule-based decision support. By extracting and analyzing real-time industrial data, the ontology facilitates automated, objective maturity assessment, reducing manual effort and enhancing strategic decision-making for digital transformation roadmaps.

Future research will explore the integration of real-time sensor data streams and reinforcement learning algorithms to enable adaptive reasoning. Furthermore, linking the ontology with digital twins could provide real-time monitoring and scenario analysis, ensuring continuous adaptation to evolving industrial environments. These advancements position the ontology as a scalable and intelligent tool for accelerating Industry 4.0 adoption across diverse manufacturing sectors.

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