Intelligent system for anomaly detection and decision-making support based on Semantic Web Technologies in manufacturing processes in Aerospace Industry

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Abstract

In the context of modern and complex manufacturing processes with the interactions between machines, materials and human operators, detecting anomalies is essential to guarantee maximum operational efficiency, product quality and general safety, thus identifying deviations from expected behaviour. Given the creation of semantic web technologies and the constant demand to formalise and structure all the knowledge involved in the process, there is an excellent opportunity to improve anomaly detection and apply this knowledge to decision support systems within this context. This article aims to use semantic web technologies to combat the difficulties with variability and the lack of well-defined standards in manufacturing data in the context of the aeronautical industry. In addition, the proposed system aims to identify anomalies or changes in 3D projects of Aerospace Sheet Metal (ASM) parts and, through an ontology model, infer the new processes and resources necessary to manufacture this model. Ontology serves as an organised and formal representation of knowledge. Within the context of anomaly detection and decision-making support, this knowledge influences the accuracy of this detection process and opens up an opportunity for the creation of future decision-making models. An application of this proposal was obtained as the final result of this work, as well as an analysis of the testing and validation procedures and the overall results. The model was applied to a simple example of ASM in which it was possible to identify changes in hole measurements and corner radius. The model can generate new drilling and machining processes for the part with this information. Therefore, it is possible to validate and implement the model in future projects in more complex parts and assembly lines.

Keywords

Anomaly Detection, 3D Feature Recognition, Ontology, Aerospace Industry.

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1. Introduction

The significant complexity of processes and the high technology involved are crucial characteristics of the aerospace industry, where the development and production of aircraft require the collaboration of engineers from diverse nationalities in various countries. This makes the sector a complex science with many factors to consider during the creation, design, and manufacturing processes of aircraft parts [1].

The need for sharing information and knowledge is inherent in all phases of the aircraft's planning, modelling, and production process, which involves numerous components and processes [2]. Furthermore, the manufacturing industry faces challenges in optimising methods for launching new products into the market quickly and competitively while maintaining high standards of quality and customisation [3].

The process of developing, designing, and manufacturing an aircraft necessitates the collaboration of specialists from various fields. This heightens the probability of errors occurring in any of the stages, subsequently resulting in financial implications for the aircraft manufacturing company [4].

Therefore, this paper explores the conception and development of an intelligent system for anomaly detection and decision-making support in aerospace sheet metal (ASM) part projects based on the characteristics of the part's geometry to predict potential production failures.

The solution relies on integrating an ontology implemented in the Ontology Web Language (OWL) and the semantic rules modelled in Semantic Web Rule Language (SWRL) and provide meaningful recommendations to address the identified problem with functions and libraries of the Python programming language, along with 3D feature recognition technologies to automate the extraction of information from the part model in order to classify them based on their features.

Section 2 of this article presents the steps of development of the intelligent system, followed by the simple case application in Section 3 and Section 4 presents the conclusions and ideas for future work.

2. Intelligent System for Anomaly Detection and Decision-making Support Development

This section provides an explanation of the project, and its main components will be listed, along with a definition of their respective functions. From a 3D model of a real aircraft part, (i) extract the features of this model, (ii) define an anomaly detection model, (iii) formalise and classify the data based on its geometric characteristics using previously defined patterns utilising an ontological structure, (iv) analyse and correctly detect anomalies in the geometric data of the models generated and propose a cloud of solutions through ontological inference to solve the involved problem.

2.1. Data Extraction from 3D Model

The Automated Feature Recognition (AFR) methodology emerges as an essential tool with various applications in the domain of product lifecycle management. Its function is of great importance in critical tasks such as computer-aided process planning, data retrieval, and identification of disparities in models [5].

This tool has played a central role in identifying key features in parts based on an analysis of 3D models, especially those related to ASM components [6]. The relevance of AFR lies in its versatility and the potential to revolutionize several aspects of engineering and design.

Figure 1 shows the feature recognition of a 3D part. With this, it is possible to put information in the ontology model. The suggested automated feature recognition approach involves two primary steps: categorising and grouping elements in a 3D B-rep model and identifying aerospace sheet metal features.

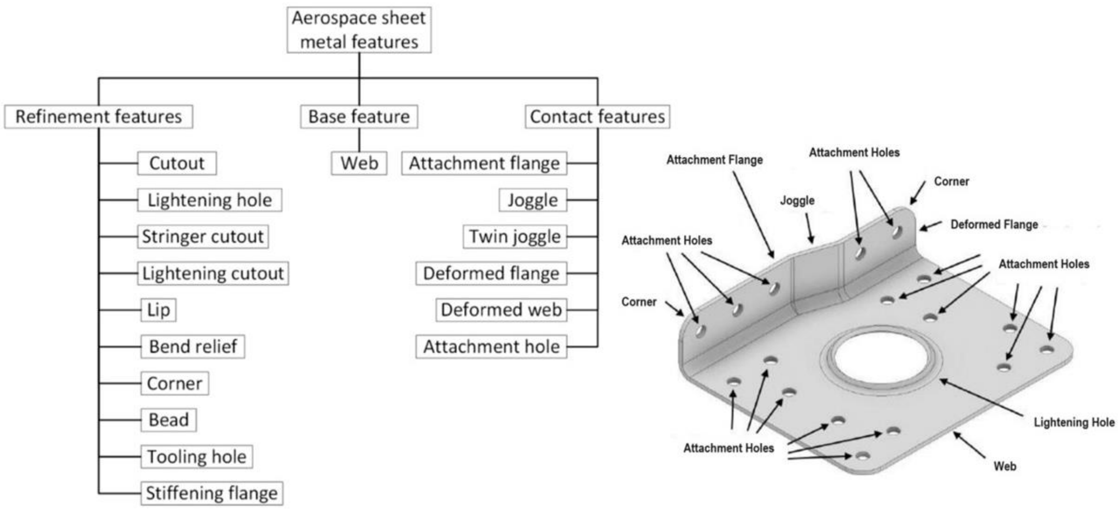

Figure 1: Feature Recognition of 3D airplane part.

The tool was applied to identify the features of the parts, based on 3D models, specifically on sheet metal parts used in aviation, allowing the developed programming algorithm to apply this information in its processes.

Figure 2 presents a representation of the AFR software. It starts from a Computer-Aided Design (CAD) 3D model, extracting all its information directly from the modelling software to a file in Standard for the Exchange of Product (STEP) format and processes the data. With this, it is possible to formalize the geometric data of the model and establish a hierarchy in the information based on the relationships proposed by the taxonomy.

The result is a text file (.txt) containing the taxonomy of each of the characteristics, along with their identifiers and geometric information related to these characteristics.

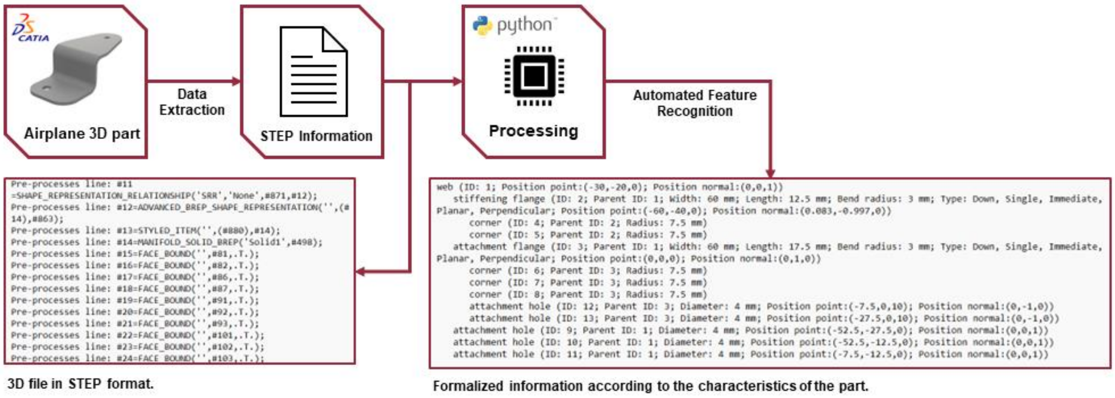

Figure 2: AFR Representation Diagram.

2.2. Anomaly Detection

Anomaly detection compares data in real-time with the characteristics of normal products or those associated with faults, constantly monitoring specific product characteristics in order to indicate abnormal operating conditions that could result in a significant degradation in performance [7], such as a rotation fault in an aircraft engine. The anomaly detection process is highly critical in many safety environments, as it aims to identify rare and sensitive data whose behaviour is out of the ordinary compared to other data with the same characteristics [8]. To contextualise and explain in an understandable way, an anomaly can be defined as an observation that deviates so much from other observations as to arouse suspicion that it was generated by a different mechanism [9]. Given the complexity of manufacturing processes in the aeronautics sector, the integration of knowledge and the constant verification of information makes the process of identifying an anomaly a relevant tool in terms of the feasibility of a solution.

Within the context of this work, the anomaly detection process was made possible by applying models such as K Nearest Neighbour (KNN), which uses Euclidian distance metrics to calculate the distance between the test point and the K-chosen neighbours. KNN is applied to calculate the distance between the test part points and the points of the parts in the adjusted model, generating similarity scores. Anomaly detection occurs by comparing the test part with the adjusted models, using the median of the distances to determine significant deviations from the expected patterns. If the median of the distances exceeds the established tolerances, the part is considered an anomaly. This non-parametric approach is suitable for handling complex and non-linear datasets, which are common in geometric model analysis.

The proceedings for the anomaly detection are based on using the output file of each part extracted from the AFR software, applying a clustering process based on the header of each line to formalise the datasets, resulting in a more fitted model for each class and each property of the part, as shown in Figure 3. The anomaly detection itself compares the test part with the models adjusted for each class and property, using the distance between the points to generate scores between the model and the part in question. Based on this, it is possible to determine how similar the test part is to the models. If the test part exceeds the established tolerances in one or more characteristics, this indicates the presence of an anomaly, as well as its relation to other classes and properties, enabling the traceability of faults in the production process.

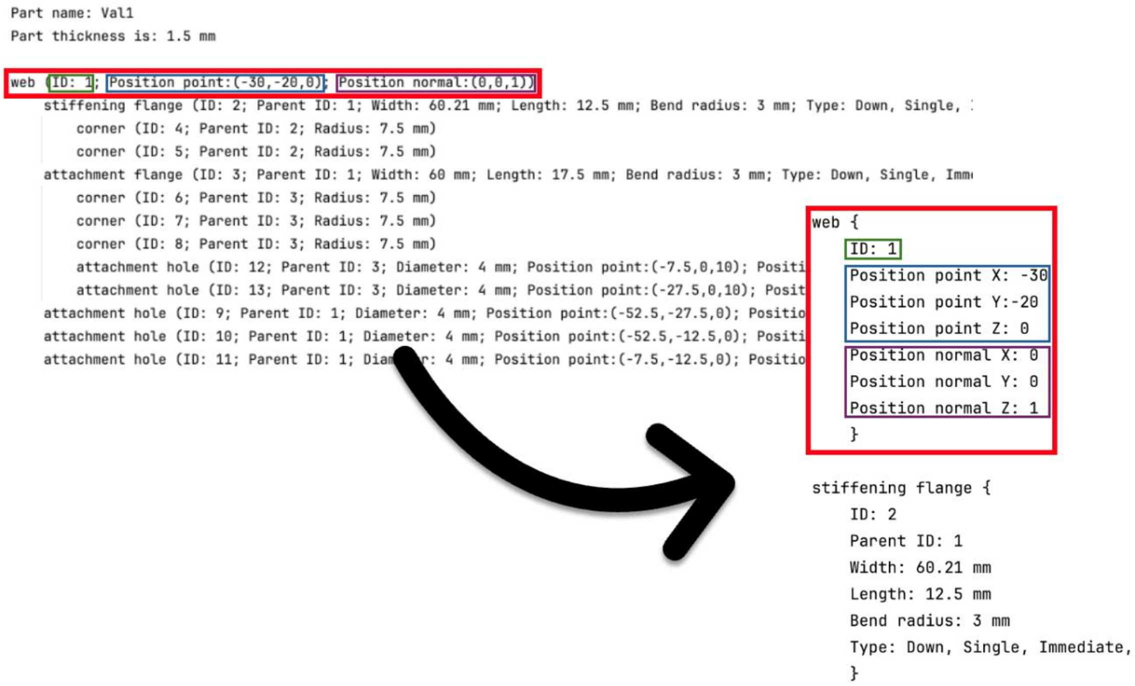

Figure 3: Dataset Formalization

2.3. Ontology Formalisation

This section highlights the main tool in the context of Web semantics for formalising and structuring knowledge: the ontology, a tool that defines hierarchical knowledge classes by means of semantic relationships, providing a way of structurally illustrating domain knowledge and enabling its reuse [10]. Faced with this growing perspective of industries seeking to solve problems with low efficiency and high cost, the use of the conversion of information and knowledge into an ontology makes it possible to establish a relevant knowledge model, thus allowing the reuse and sharing of knowledge, as well as its integration with various other systems [11]. The ontology design follows the principles of Domain Ontologies in that they describe concepts specific to a particular domain, detailing the entities and relationships within that context.

Given the context of this work, the ontology was chosen with the main objective of formalising and classifying all the information coming from the stage of extracting features from the 3D model of the part, as well as joining this information with other information related to the context of manufacturing parts such as machines and tools and their respective information and necessary data. Figure 4 shows the formalisation of knowledge of the manufacturing processes and characteristics of STEP models in an OntoGraph generated by Protegé and the main classes and relations of both object properties and data properties.

The ontology includes concepts to represent machines that perform the process in parts, using concepts of relationship with the characteristic of the part [12] and, according to the characteristic represented in the 3D model, it can infer the most appropriate manufacturing process and with that, the available machine to be used.

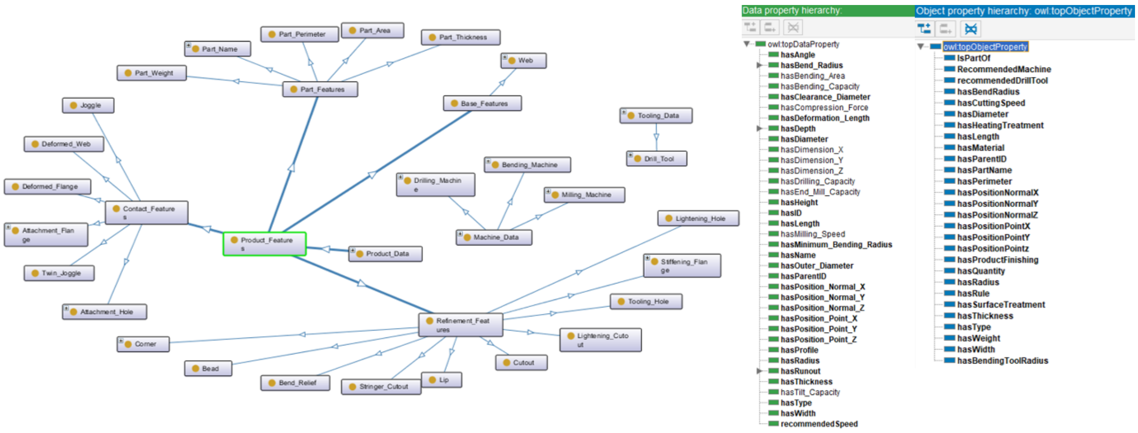

Figure 4: Formalized knowledge in the ontology.

2.4. Rules and Inference Engine

In this section, we explore the rules and the inference engine, which processes the data derived from anomaly detection to provide decision-making support. These components serve as the backbone of the intelligent system, as they, upon obtaining data from the anomalous piece, insert it into the ontology within their respective classes. Utilising the Pellet inference engine, the system can process the semantic rules modelled in Semantic Web Rule Language (SWRL) and provide meaningful recommendations to address the identified problem.

Through the analysis of the features of the anomalous piece and the rules established in the ontology, the system can suggest changes in equipment or manufacturing processes that may correct the problem. For example, based on the piece's class and its specific characteristics, the system may recommend adjustments to the machining parameters of a specific machine or suggest the use of alternative tools to improve production quality. Presented below are examples of rules and their respective descriptions.

1. **Recommendation Rule for Bending Machine:** This rule checks whether a specific bending machine has the adequate capacity to bend a piece based on its width, length, and bend radius. If it meets the criteria, the machine is recommended as the most suitable choice to perform the bending operation.
   ```hasWidth(?attachmentFlange, ?width) ^ hasLength(?attachmentFlange, ?length) ^ swrlb:multiply(?area, ?length, ?width) ^ hasBend_Radius(?attachmentFlange, ?bendRadius) ^ Bending_Machine(?bendingMachine) ^ hasBending_Capacity(?bendingMachine, ?bendingCapacity) ^ hasBending_Area(?bendingMachine, ?bending_Area) ^ hasMinimum_Bending_Radius(?bendingMachine, ?minimumBendingRadius) ^

swrlb:greaterThanOrEqual(?bendRadius, ?minimumBendingRadius) ^ swrlb:lessThanOrEqual(?bendRadius, ?bendingCapacity) ^ swrlb:lessThanOrEqual(?area, ?bending_Area) -> recommendedMachine(?attachmentFlange, ?bendingMachine) ```

2. **Recommendation Rule for Milling Machine**: This rule checks whether a milling machine has the adequate capacity to mill and tilt a piece based on its outer diameter and angle. If it meets the criteria, the milling machine is recommended as the most suitable choice for performing the machining operation.
   ```*Milling_Machine(?machine) ^ hasOuter_Diameter(?piece, ?outerDiameter) ^ hasMilling_Capacity(?machine, ?millingCapacity) ^ swrlb:greaterThanOrEqual(?millingCapacity, ?outerDiameter) ^ hasAngle(?piece, ?angle) ^ hasTilt_Capacity(?machine, ?tiltCapacity) ^ swrlb:greaterThanOrEqual(?tiltCapacity, ?angle) -> recommendedMachine(?piece, ?machine)* ```
3. **Recommendation Rule for End Mill (Milling Machine):** This rule checks whether a milling machine has the adequate capacity to mill a piece based on its edge radius. If it meets the criteria, the milling machine is recommended as the most suitable choice to perform the milling operation.
   ```*Corner(?x) ^ hasRadius(?x, ?radius) ^ Milling_Machine(?machine) ^ hasEnd_Mill_Capacity(?machine, ?mill) ^ swrlb:lessThanOrEqual(?radius, ?mill) -> recommendedMachine(?x, ?machine)* ```
4. **Recommendation Rule for Drilling Machine:** This rule checks whether a drilling machine has adequate capacity to drill a hole based on the hole's diameter and whether a suitable drill tool is available for subsequent manufacturing. If it meets the criteria, the drilling machine is recommended as the most suitable choice to perform the drilling operation, and suitable drill tools are also recommended for subsequent manufacturing.
   ```*hasDiameter(?hole, ?diameter) ^ Drilling_Machine(?machine) ^ hasDrilling_Capacity(?machine, ?drilling_diameter) ^ swrlb:greaterThanOrEqual(?diameter, ?drilling_diameter) ^ Drill_Tool(?drill_tool) ^ hasDiameter(?drill_tool, ?sdiameter) ^ swrlb:lessThanOrEqual(?sdiameter, ?drilling_diameter) -> recommendedMachine(?hole, ?machine) ^ recommendedDrill_Tool(?hole, ? drill_tool)*```

3. Simple Case Application and Results

The application was executed on a simple ASM part in order to validate the methodology for detecting design changes and thus infer new manufacturing processes and industrial resources. Figure 5 shows the execution steps of this system. First, (A) the system is able to identify the changes of the new part in relation to the initial design, identifying which characteristic of the part has been changed. In sequence (B), it is possible to observe which measures of each characteristic have been changed, and finally, in (C), the ontology model infers new processes, machines and tools necessary for the manufacture of the new model.
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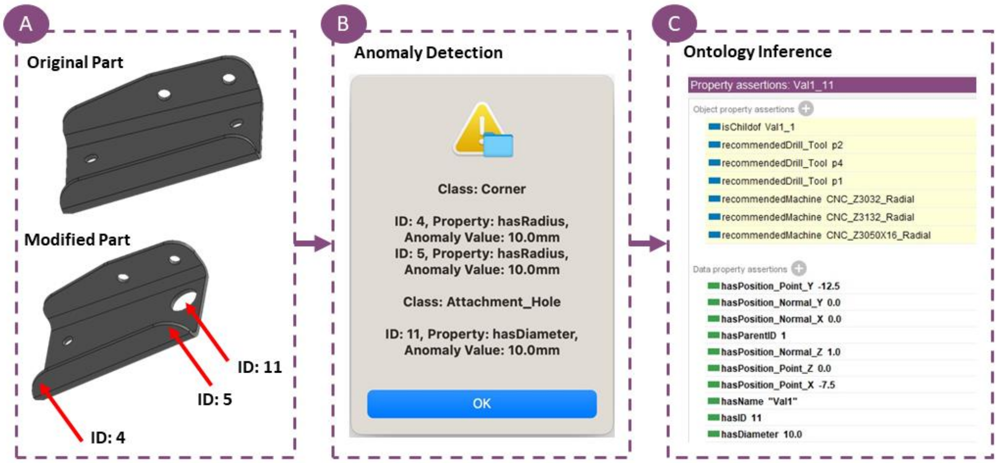

Figure 5: Intelligent system for anomaly detection and decision-making support

In this practical example, three features of the part have been changed: one attachment hole (ID 11) and two corners (ID 5, ID 6). The original piece consisted of a hole with a diameter of 4mm and corners with a radius of 7.5mm. The modified part of the hole was moved to a diameter of 10mm and the radius of the corners to 10mm.

With this information, the ontology can infer a new drilling process and a new tool for the fabrication of the 10mm diameter hole, *recommendedDrill_Tool p2.* It also indicated a new machining process to change the corner radius to 10mm *recommendedMachine CN_Z3050X16_Radial.*

4. Conclusion and Future Works

The failures resulting from anomalies present in product design projects related to the geometry of the models are the target of this work, in which the application of ontologies aims to enable early identification of patterns and anomalies in the data, allowing for an integrated view of the problem, validation of data integrity, and quick response to issues.

Therefore, this project aims to identify changes in designs and generate a potential space for solutions through an ontology that can infer new production processes according to the modification of the original part with the objective of showcasing the industrial impact. In this work, a simple application example is proposed to demonstrate the capacity and feasibility of implementation. In continuation of the research, this system will also be implemented in assembly lines to cover more sectors of the industry, generating a more comprehensive model in a graphical interface that can interact with production engineers in order to integrate rules with knowledge.

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