

Design and Development of Semantic Ontology for Large Scale Manufacturing Industry with Help of Expert Miner

Soumitra Singh¹, Partha Sarathi Chakraborty², S. Nallusamy³, K. Balakannan⁴

¹ Research Scholar, Department of Adult, Continuing Education & Extension, Jadavpur University, Kolkata-700032, West Bengal, India

² Professor, Department of Adult, Continuing Education & Extension, Jadavpur University, Kolkata-700032, West Bengal, India

³ Professor, Department of Mechanical Engineering, Dr. M.G.R. Educational and Research Institute, Chennai-600095, Tamilnadu, India

⁴ Principal, Adhiparasakthi College of Engineering, Vellore-632506, Tamilnadu, India

¹soumitra.singha@gmail.com, ²p_s_c2001@yahoo.com, ³ksnallu@gmail.com, ⁴kbalakannan@gmail.com

Abstract - Process mining in industry encourages the professional and invention in industry raw data by machine learning and semantic technologies. Key problematic in trade businesses is drifting between professional and difficult to automate. In this situation, ontologies develop as a substantial technique for characterize manufacturing facts in an engine-understandable method. This information can then be applied by computerized problem resolving techniques to configure the regulator package that synchronizes and controls manufacturing schemes. Also, ontology shows a vital role in development of generating and handling the knowledge. This research illustrates the design and development of semantic knowledge in manufacturing industry using protege tool. This resource description framework is plug-in with java and python software. Integration of the manufacturing ontology produce more effective performance in car manufacturing company to find the car buyer patters effectively using data mining techniques.

Keywords: Semantic Mining, Ontology, Manufacturing Industry, Knowledge Base, Buyer Patterns, Clustering

I. INTRODUCTION

Ontology defines the shared terms, notions and an association between ideas used to define and shows an extent of knowledge. A well-formed ontology is one that is stated in a well-defined arrangement that has a well-defined machine understanding. Ontology is being comparable to an explanation logic facts base. Ontology delivers the shared language for the requests that is at one level of concept developed data models. Automated reasoning model figuring that automate the facility to variety implications by developing a prescribed language in which a difficulty's hypothesis and inference can be written and providing proper learning algorithms to solve the problem with a computer in an effective method.

II. RELATED WORK

A group of hub manufacturing models are branded and their semantics could be confined in prescribed logic based on developing and lengthening on hand standards' descriptions, where potentially together with a manufacturing examination of the ideas required. A winning tentative exploration is carrying to prove the function of the ontology found on the interaction between plan ideas and modern fields products in aerospace. A hub group of concepts has been informally distinct in Manufacturing Core Concepts Ontology (MCCO) and these concepts are utilized as manufacturing production knowledge [1]. The various points of generic relationship, domain specific concepts are described for MCCO. Usman investigated the semantic concepts called Manufacturing Foundation Ontology (MFO) for a company facilitates the company to build their own domain specific activities with help of rules and axioms [2].

The authors presented a foundational ontology for the modeling of production systems. They described the ontological knowledge as entities and temporal component and created meta modeling for manufacturing system domain [3-5]. Semantic expert system can developed with help of open-source ontology editing to tool called protege. The good product intends and production practice-based ontology for modern information reprocess [6-8]. Eventhough more associated attempts occur, lacking there rough, propose of product consistent and production process based ontology which leads to superior manufacturing embracing and knowledge reuse. Its future ontology influences a reputable manufacturing normal to standard for product design and manufacturing process. It can achieve by employing ontology knowledge [9-12].

Ontology can be applied information retrieval system. The automatic fuzzy ontology using distributed document clustering was investigated. It enhances the information retrieval system and applied for digital library management [13, 14]. The authors developed the ontology for tourism using social media point of interest. An ontology using machine learning technique of self organizing map for



manufacturing data for manufacturing production [15-17]. The authors proposed the data mining model using Linear classification, Decision Tree and Neural network [18]. Manufacturing domain specific ontology is developed in. The authors proposed an ontology which express the manufacturing resources as semantic manner [19-21].

III. PROPOSED CONCEPT ONTOLOGY FOR CAR MANUFACTURING INDUSTRIES (COCMI)

Figure 1 shows the ontology creation for the manufacturing industries. Thing is main class. That means root class. The components of the car contain CarHeight, CarLength, Drive, ID, Make, Engine Type, Fueltype, Transmission and Classification. These fields are treated as main classes under the Thing. Ontology provides relationships between the classes. Protégé is the one of the auto editing tool.

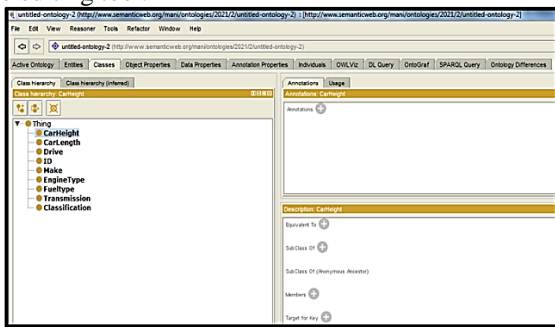


Fig. 1. Ontology Class Creation

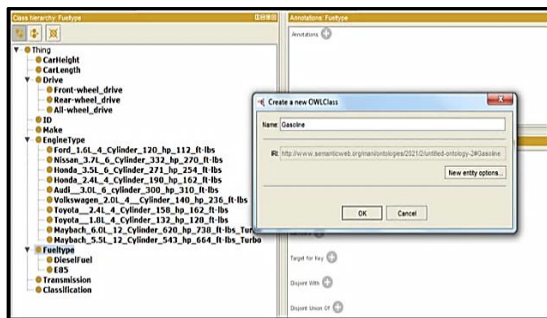


Fig. 2. Ontology Subclass Creation

Figure 2 shows the creation of subclasses for drive, engine type, fuel type etc. Fuel type contain gasoline, diesel fuel and E85. When highlighting any, protege illustrates whether subclass and superclass and other detailed description. Figure 3 indicates that the subclass of fuel type when selection of Gasoline. Hence ontology gives automatic reasoning.

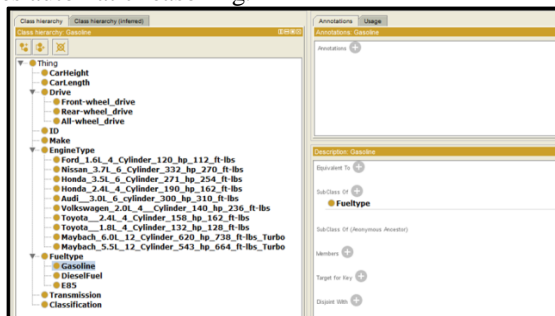


Fig. 3. Reasoning Superclass and Subclass in Manufacturing Ontology

Two positions are supposed to be disjoint sets if they have refusal element in general. consistently, two disjoint sets are positioning whose joints is the unfilled positions. For instance, {7, 8, 9} and {10, 11, 12} are disjoint sets, while {7, 8, 9} and {9, 10, 11} are not disjoint. In Figure 4 subclass of All_wheel_drive is disjoint with engine type.

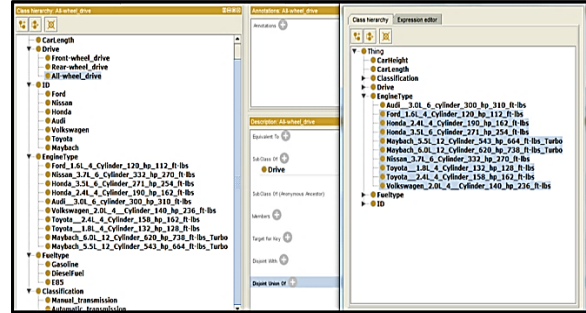


Fig. 4. Disjoint Set

Hierarchy of the data property shows the inferred and asserted hierarchies of data properties. It is perceptible as default. The asserted data property hierarchy view is one of the key routing tools in protege editing. It is presented as a tree where tree nodes correspond to data properties. A child node stand for a data property and parent node shows the sub property in the hierarchy. Figure 5 shows the creation of data properties. The top data property is the root data properties and it comes by default. Next _Speed_Manual, _Speed_Automatic_Selet_Shift, _Speed_Automatic and _Speed_Manual are sub data properties.

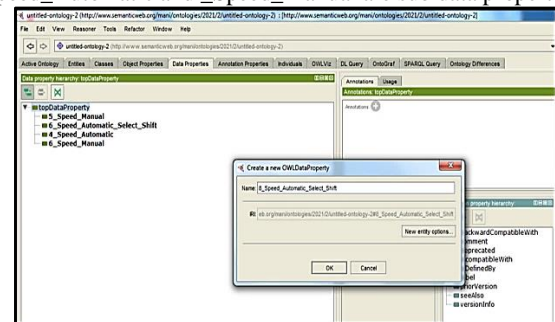


Fig. 5. Adding Data Properties

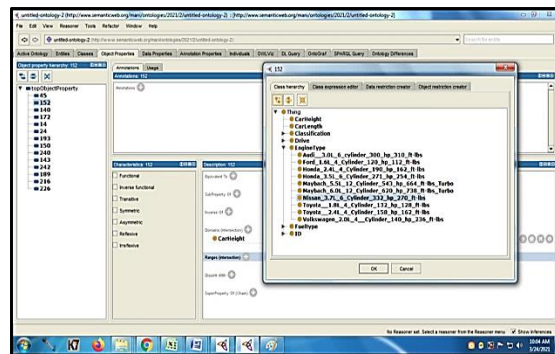


Fig. 6. Adding Range and Domain for Object Properties

Adding range and domain for data properties and object properties are shown in Figure 6. Process and production components like drilling components, machining components, molding and welding components are acts as individual as shown in Figure 7. The Figure 8,

Figure 9 and Figure 10 shows the created ontograf for manufacturing process. This design of ontology produces very good effect in manufacturing side. It gives the car good buyer pattern and increase the sales by integrated with data mining plug in with machine. This manufacturing ontology provides automatic reasoning to user for decision making with help of semantic knowledge.

IV. RESULTS AND DISCUSSION

The Figure 11, Figure 12 and Figure 13 shows the buyer patterns using machine learning techniques as K-means clustering with integration of manufacturing semantic ontology.

```
#import libraries
import pandas as pd
import numpy as np
import random as rd
import matplotlib.pyplot as plt
```

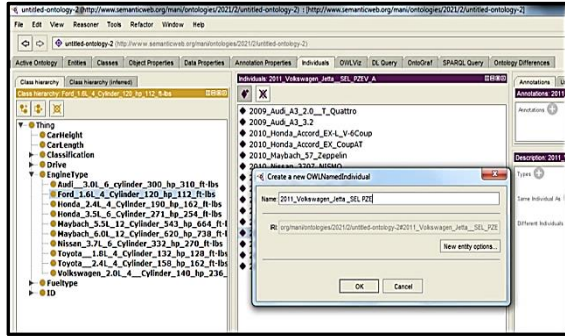


Fig. 7. Adding Individuals

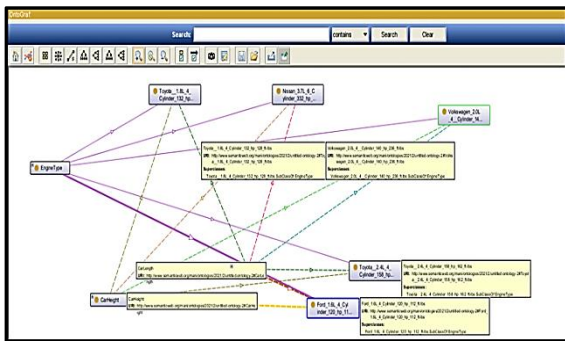


Fig. 8. Ontograf Part 1

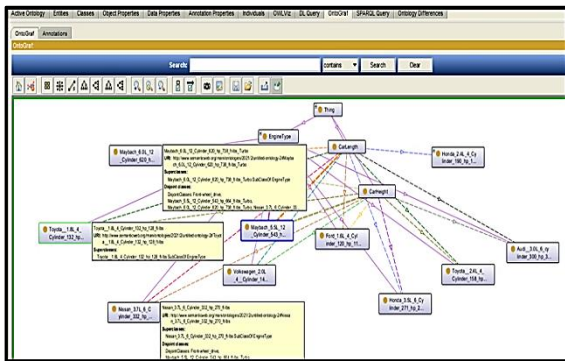


Fig. 9. Ontograf Part 2

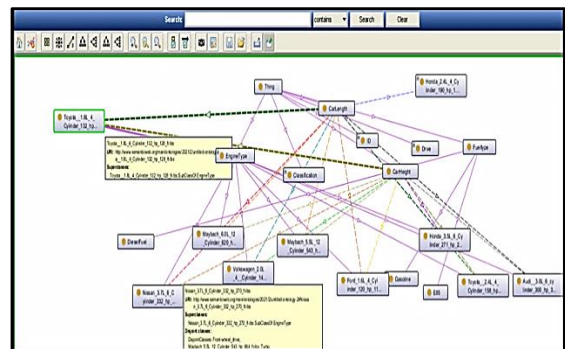


Fig. 10. Ontograf Part 3

```
dataset = pd.read_csv('/content/drive/MyDrive/cars.csv')
dataset
```

	age	gender	miles	debt	income	sales
0	28	0	23	0	4099	620
1	26	0	27	0	2677	1792
2	30	1	58	41576	6215	27754
3	26	1	25	43172	7626	28256

Fig. 11. Car Buyer Dataset

```
data=pd.read_csv('/content/drive/MyDrive/ml
lab/carsdataclustering.csv')
data.head()
```

```
from sklearn.preprocessing import StandardScaler
sc_x = StandardScaler()
x = sc_x.fit_transform(x)
x
```

```
array([[ -0.81175459, -1.02630644, -0.35180374, -0.77249454, -0.63733127],
 [ -0.97456197, -1.02630644, -0.05265407, -0.77249454, -1.07366455],
 [ -0.6489472 ,  0.97436785,  2.26575586,  1.50386974,  0.01195229],
 ...,
 [ -0.81175459,  0.97436785,  0.02213335, -0.26264501, -1.06047022],
 [  0.97912667, -1.02630644,  0.09692076,  2.03863137,  0.77845855],
 [  0.73491559,  0.97436785, -0.95010307, -0.56799626,  0.07055964]])
```

Fig. 12. Result of Preprocessing

```
sc_y = StandardScaler()
y = sc_y.fit_transform(y.reshape(y.size, 1))
y
```

```
[ 2.64203795e-01]
 [ 4.60815262e-04]
 [ 2.26239947e-01]
 [ -3.98215254e-01]
 [ -8.25837367e-01]
 [ -2.02718137e-01]
 [ 7.23889215e-01]
 [ -3.57468133e-01]
 [ -7.97893303e-01]
 [ 8.13510616e-01]
 [ 1.23924010e+00]
 [ -8.59570639e-01]
 [ -7.01229960e-02]
 [ 1.83597390e+00]
 [ 6.53639397e-01]
```

Fig. 13. Apllying Transformation and Applying K-Means Clustering

Table 1. Results of LR-COCMI

Sl. No	Techniques	Accuracy (%)
Current Structures		
1	Linear Regression	91.78
2	Decision Tree	85.46
3	Neural Network	85.88
Proposed Classifier		
4	LR-COCMI	98.68

Table 1 shows the performance of Linear Regression with Concept Ontology for Car Manufacturing Industries (LR-COCMI). Concept ontology was applied with linear regression classifier. It outperforms the other existing classifier of linear regression, decision tree and neural network. User can create the automatic ontology's for specific domain. It gives reasoning and relationships association between concept, fields and knowledge. Classification result of LR-COCMI is 98.68% was obtained with help of ontological knowledge.

V. CONCLUSION

To conclude knowledge about roles and supportable solutions, it is in circumstance required a Hugh stage of aspect for function outcomes description and in invention, developments and resources descriptions. In this research, ontology was developed to improve the process and production in worldwide industries. Process and production product protocols and design are presented. In car manufacturing company buyers' patters are analysed using K-means clustering. Based on the execution of ontological knowledge about 99% of classification performance was achieved.

REFERENCES

- [1] Zahid Usman, Robert Ian Marr Young, Nitishal Chungoora, Claire Palmer, Keith Case and Jenny Harding, A manufacturing core concepts ontology for product lifecycle interoperability, International IFIP Working Conference on Enterprise Interoperability. 76 (2011) 5-18.
- [2] Usman, Z., A manufacturing foundation ontology for product life cycle interoperability, Enterprise Interoperability IV. (2010) 147-155.
- [3] Viktor Zaletelj, Rok Vrabic, Elvis Hozdic, Peter Butala, A foundational ontology for the modelling of manufacturing systems, Advanced Engineering Informatics. 38 (2018) 129-141.
- [4] Gunji Venkata Punna Rao, Nallusamy, S. and Rajaram Narayanan, M., Augmentation of production level using different lean approaches in medium scale manufacturing industries, International Journal of Mechanical Engineering and Technology. 8(12) (2017) 360-372.
- [5] Wan, J., Chen, B., Imran, M., Tao, F., Li, D., Liu, C. and Ahmad, S., Towards dynamic resources management for IoT based manufacturing, IEEE Communications Magazine. 56(2) (2018) 52-59.
- [6] Nilsson, J. and Sandin, F. Semantic interoperability in industry 4.0: Survey of recent developments and outlook, IEEE International Conference on Industrial Informatics. (2018) 127-132.
- [7] Sanya, O.I. and Shehab, M.E., A framework for developing engineering design ontologies within the aerospace industry, International Journal of Production Research. 53(8) (2015) 2383-2409.
- [8] Allen, R.H. and Sriram, R.D. The role of standards in innovation, Technological Forecasting and Social Change. 64(2-3) (2000) 171-181
- [9] Inden, U., Mehandjiev, N., Monch, L. and Vrba, P., Towards an ontology for small series production, Proceedings of the 6th International Conference on HoloMAS. (2013) 128-139.
- [10] Zhang, T., Gu, X. and He, E. Heterogeneous problems and elimination methods for modular ontology of product knowledge engineering, Proceedings of the 9th International Symposium on Linear Drives for Industry Applications. (2014).
- [11] Peter Chhim, Ratna Babu Chinnam and Nouredin Sadawi, Product design and manufacturing process based ontology for manufacturing knowledge reuse, Journal of Intelligent Manufacturing. 30 (2019) 905-916.
- [12] Soumitra Singh, Chakraborty, P.S., Nallusamy, S. and Balakannan, K. Process analysis on large scale manufacturing industry for performance and sustainable development, Journal of Green Engineering. 10(12) (2020) 12737-12752.
- [13] Thangamani. M. and Thangaraj, P. Fuzzy ontology for distributed document clustering based on genetic algorithm, Applied Mathematics and Information Sciences. 7(4) (2013) 1563-1574.
- [14] He, Y.H., Wang, L.B., He, Z.Z. and Xie, M., A fuzzy TOPSIS and rough set based approach for mechanism analysis of product infant failure, Engineering Applications of Artificial Intelligence. 47 (2016) 25-37.
- [15] Suresh Kumar, N. and Thangamani, M., Multi-ontology based points of interests (MO-POIS) and parallel fuzzy clustering (PFC) algorithm for travel sequence recommendation with mobile communication on big social media, Wireless Personal Communications. 103(1) (2018) 1-8.
- [16] Mohammed Alkahtani, Arijit De, Alok Choudhary and Jenny Harding, A decision support system based on ontology and data mining to improve design using warranty data, Computers and Industrial Engineering. 128 (2019) 1027-1039.
- [17] Chang, W. L., Pang, L.M. and Tay, K.M., Application of self-organizing map to failure modes and effects analysis methodology, Neuro Computing. 249 (2017) 314-320.
- [18] Yap Bee Wah, Nor Huwaina Ismail and Simon Fong, Predicting car purchase intent using data mining approach, 2011 Eighth International Conference on Fuzzy Systems and Knowledge Discovery, (2011) 1994-1998.
- [19] Wollschlaeger, M., Sauter, T. and Jasperneite, J., The future of industrial communication: Automation networks in the era of the internet of things and industry 4.0, IEEE Industrial Electronics Magazine. 11(1) (2017) 17-27.
- [20] Wan, J., Tang, S., Li, D., Imran, M., Zhang, C., Liu, C. and Pang, Z., Reconfigurable smart factory for drug packing in healthcare industry 4.0, IEEE Transactions on Industrial Informatics. 15(1) (2019) 507-516.
- [21] Eeva Jarvenpaa, Niko Siltala, Otto Hylli and Minna Lanz, The development of an ontology for describing the capabilities of manufacturing resources, Journal of Intelligent Manufacturing. 30 (2019) 959-978.