EDITOR: Amit Sheth, amit@knoesis.org

A Semantic Web Approach to Fault Tolerant Autonomous Manufacturing

Fadi El Kalach, Ruwan Wickramarachchi, Ramy Harik, and Amit Sheth, *University of South Carolina, Columbia, SC, 29208, USA*

The next phase of manufacturing is centered on making the switch from traditional automated to autonomous systems. Future factories are required to be agile, allowing for more customized production and resistance to disturbances. Such production lines would be able to reallocate resources as needed and minimize downtime while keeping up with market demands. These systems must be capable of complex decision-making based on parameters, such as machine status, sensory/IoT data, and inspection results. Current manufacturing lines lack this complex capability and instead focus on low-level decision-making on the machine level without utilizing the generated data to its full extent. This article presents progress toward this autonomy by introducing Semantic Web capabilities applied to managing the production line. Finally, a full autonomous manufacturing use case is also developed to showcase the value of Semantic Web in a manufacturing context. This use case utilizes diverse data sources and domain knowledge to complete a manufacturing process despite malfunctioning equipment. It highlights the benefit of Semantic Web in manufacturing by integrating the heterogeneous information required for the process to be completed. This provides an approach to autonomous manufacturing not yet fully realized at the intersection of Semantic Web and manufacturing.

Smart manufacturing (SM) has taken a front seat in the advancement of manufacturing production lines. This vision of SM will be powered by industrial Internet of Things, big data analytics, and artificial intelligence. These capabilities can have a substantial effect on the profitability of the industry as a whole since manufacturers must respond to fast-changing requirements through productivity advancements and agility while maintaining high standards.

One aspect of manufacturing that SM seeks to tackle is the ability to minimize machine downtime. Downtime refers to the period that production is halted for a variety of reasons, such as to perform maintenance on equipment. According to Forbes (shorturl.at/gtWX6), unplanned downtime can cost up to $50 billion a year to manufacturers. This presents a challenge to manufacturers in finding solutions to such problems. Correspondingly, industries are embracing digital transformation and SM to develop next-generation manufacturing systems capable of overcoming faults while maintaining a continuous production line toward increased efficiency and throughput.

We describe a novel approach to fault tolerant autonomous manufacturing that can minimize the downtime of a production line through local data and domain knowledge utilization. It uses Semantic Web technologies that involve using knowledge graphs (KGs)[1] to incorporate sensor data with domain knowledge and thus integrating heterogeneous data. KGs also allow for further abstraction of data and deduction of implicit knowledge about the manufacturing line not traditionally available. This can help the system react to machine failures appropriately while maintaining production.

Semantic Web ontologies have been explored for manufacturing applications[2,3,4] alongside applications that use Internet of Things (IoT) data.[5,6,7] In this article,

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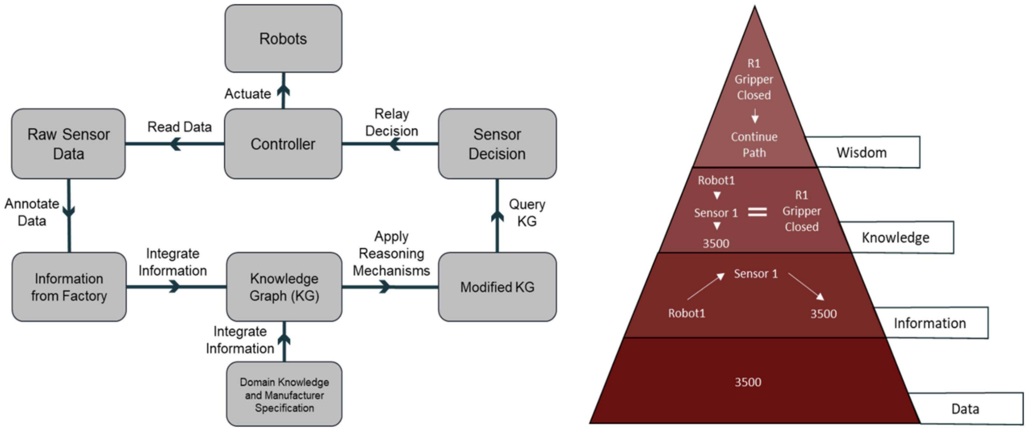

FIGURE 1. Overall process of using KGs to represent manufacturing data and domain knowledge for a simple robot pick and place operation use case.

we discuss the use of knowledge and Semantic Web in manufacturing systems that include raw data generation, semantic annotation, knowledge deduction, and decision-making (see Figure 1).

This in turn can lead to a broader impact on the manufacturing industry as it is a step toward adopting innovative technologies and standards for SM that reduce costs. Fault tolerance is also required in a broad range of manufacturing industries, such as pharmaceutical, automotive, and aerospace.

METHODOLOGY AND IMPLEMENTATION

We present the overall methodology of leveraging KGs from the representation of data for inference within a manufacturing use case. To support fault tolerance, manufacturing assets must react appropriately to failures (e.g., malfunction of a certain sensor) allowing the process to continue without any downtime for maintenance or replacement. For this to happen, assets must be aware of the different data sources available that can be used. The use case of a simple robotic pick-and-place operation illustrates the concepts. The setup consists of one industrial robotic arm and two stations for the part to be placed on. This robot interfaces with a programmable logic controller (PLC), which provides the logic for the process to move forward. When the robot picks the item up, a sensor on the robot gripper (a potentiometer) changes values indicating that the gripper has closed, and the operation can continue. The potentiometer value is read by the PLC and a signal is sent to the robot to continue with the operation. However, when the potentiometer malfunctions, the operation can continue by relying on a timer, essentially waiting a few seconds to ensure the gripper is closed before continuing with the operation.

The process begins by reading the raw sensor data from the equipment. These data are semantically annotated using a user-defined mapping derived from the semantic sensor network (SSN) ontology.[3] This information is then integrated with other information, including the domain knowledge of the facility and manufacturer specifications. Next, all this information is integrated into a central KG, on which the reasoning process is run to deduce whether the sensor is functioning properly. A corresponding triple based on the reasoning output may then be added to the KG to denote the sensors' functionality status. This additional triple links the sensor entity with a boolean determining its functionality. An SPARQL query engine then parses through the KG to project the functionality entity that was modified through reasoning. The query would return "False" if the potentiometer is malfunctioning or "True" if functioning properly. Correspondingly, the query engine will then parse through the KG again for the replacement sensor should the initial return value be "False." This decision on which sensor to use can then be relayed to the controller.

Data Modeling

We begin by modeling the sensor data to improve expressivity (see Figure 2). The information presented is modeled using the resource description framework schema where the top half of Figure 2 represents the ontology adopted, the SSN ontology. Next, we discuss how the information collected from three sources is represented in support of the use case considered.

The first source of information modeled in our use case is the data generated by the physical sensor (e.g., potentiometer). To represent these data, three

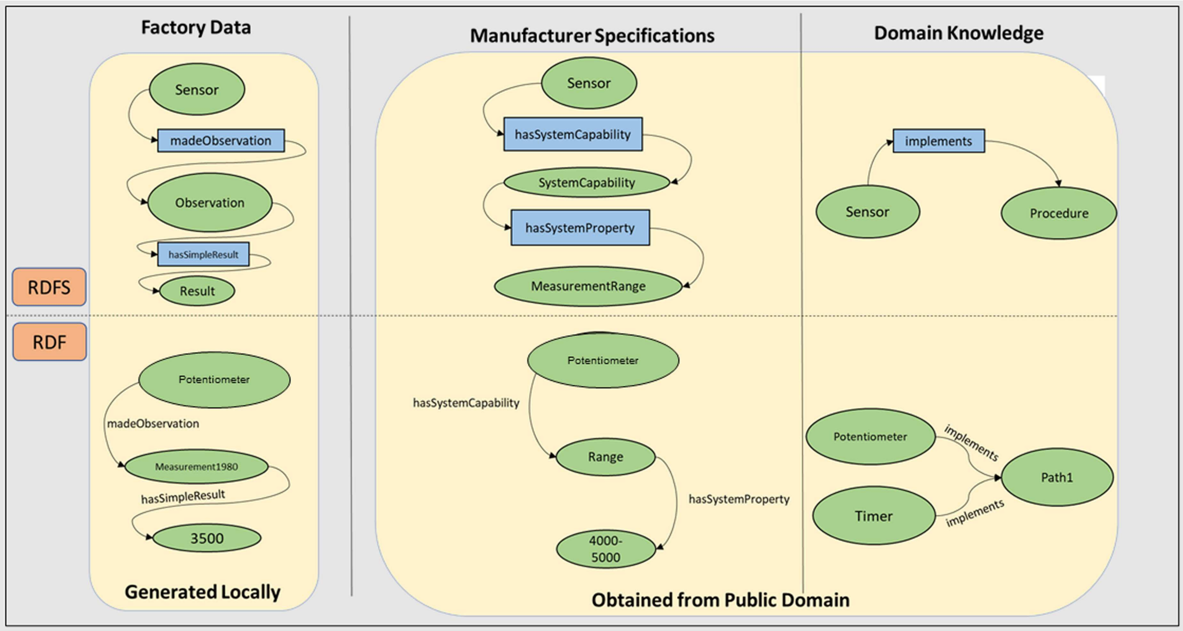

FIGURE 2. Modeling of sensor data along with domain knowledge for the use case.

entity classes, sensor, observation, and result, are defined within the schema.

1. *sosa:Sensor*: This entity represents a device that responds to a stimulus and generates a result, which relates to the potentiometer, a sensor that generates different results depending on the change in linear motion of its extrusion.
2. *sosa:Observation:* This entity represents the value of a property, which in our case is the measurement of the potentiometer. These two entities are linked together using the *sosa:madeObservation* property.
3. *sosa:Result:* This entity represents the actual value of the observation made, which is the value given by the potentiometer. This is linked to the observation using the *sosa:hasSimpleResult* property. The lower half of the figure illustrates the instances created from the described ontology for this use case.

The second source of information is the data obtained from the manufacturer. This source supplies information about the normal output range that the sensor should be yielding. This is needed as it provides the information set used to deduce the functionality of the potentiometer. The information is mapped as follows.

1. *sosa:Sensor*: Similar to the first set, this entity represents the potentiometer again and will be unified into one entity instance in the subsequent KG.
2. *ssn-system:SystemCapability:* This entity represents a property of the *sensor* entity. In this use case, this represents the range attribute of the potentiometer. This entity is mapped to the *sensor* entity through the *ssn-system:hasSystemCapability* property.
3. *ssn-system:MeasurementRange:* This entity is the set of values that a sensor can return, which is the normal output range that the manufacturer specified for the potentiometer. This entity is mapped to the abovementioned entity using the *ssn-system:hasSystemProperty* property.

Finally, the third data source is the domain knowledge about the operation. As described previously, a robot arm can use two sensors' data to continue with the operation. Either the potentiometer or a timer can provide the needed data to deduce whether the gripper is in the required state or not. This set of information is integral as it will be the basis of which the system will decide which sensor to rely on for the process to move forward. This information is mapped as follows.

1. *sosa:Sensor*: Once again this entity describes the sensors used and will be instanced twice for this source, once for the potentiometer and once for the timer.
2. *sosa:Procedure*: This entity describes a workflow, plan, or algorithm that makes a change to the state of the world. In our use case, this will be instanced

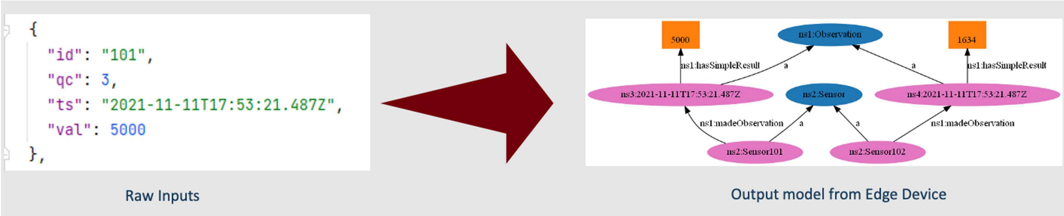

FIGURE 3. Semantic annotation of data.

as Path1, which is the path programmed on the robot to pick up the object. Path1 moves the robot from its home location to the location of the part needed to be picked up. Once the part, which is shown by the potentiometer value, is picked up, this path finishes by moving that part to a second predetermined location. This entity is linked to the sensor entity using the *ssn:implements* property.

Semantic Annotation

The translation from raw sensor data to contextualized information requires mapping the sensor data values to existing entities in the KG. To do so, we utilized SDM-RDFizer,[8] an interpreter that transforms unstructured data into RDF format. SDM-RDFizer requires the user to define the mapping that the interpreter adopts using RDF mapping language.

Figure 3 displays a snippet of the JSON object that the raw data are sent within. This object has four separate key-value pairs. The first is the unique ID of the sensor, which allows us to identify which sensor this value corresponds to. The "qc" key refers to the quality code or quality of service that determines the status of the message delivery. The "ts" key is the timestamp of the generated value and finally "val" is the actual value that the sensor is generating. The figure also shows an example of the instantiation of four triples to be included in the KG. This semantic annotation was achieved at the edge level by deploying the custom-made application onto the Siemens IPC227E Edge Device. The application reads data from the controller of the manufacturing equipment and annotates them in real time before outputting the corresponding triples to be integrated into the manufacturing KG.

Knowledge Deduction and Decision Making

With the RDF triples being generated on the edge level, the next step is to consolidate them into a central KG and perform reasoning on it. This is done on a separate machine to simulate cloud-level processing. At this level, the Jena reasoning mechanism[9] is utilized to integrate all the different information into one KG.

Reasoning was then introduced in the form of rules that allow the creation of new entities, which will be used in the decision-making process. Should the generated KG have a potentiometer value of less than that given in the manufacturer specifications, then the sensor needs changing. The visualized output KGs can be seen in Figure 4.

With the KG manipulation accomplished, the next step is to arrive at the final decision regarding completion of the required path. To iterate through the KG, SPARQL (shorturl.at/QWZ35), a query language for RDF, was used. In the query response, the status of the sensor is extracted. If the status returned was that the sensor needs changing (i.e., the "NeedChange" attribute yields "True") then the different sensors that can be used are discovered, as seen in Figure 5. The final projected result of the query statement can also be seen which reflects the decision made over which sensor to use for the operation.

DISCUSSION

In this article, the incorporation of Semantic Web technologies in a manufacturing environment was described. The presented use case showcases fault tolerance capabilities that were adopted that follow the full process of semantic annotation, KG generation, deduction of knowledge, and decision-making. On top of that, this article also provides a detailed process for semantic integration of sensor data, increasing interoperability and domain knowledge utilization in manufacturing.

Standardized Data Integration Process

The steps taken within this article to integrate the different information sources can be applied within many different domains and use cases. Even though this use case focuses mainly on one certain instance of a malfunctioning sensor, this process can be generalized to encapsulate whichever capability required. This article also showcases the applicability of undergoing real-time semantic annotation of the raw data and presents a path for

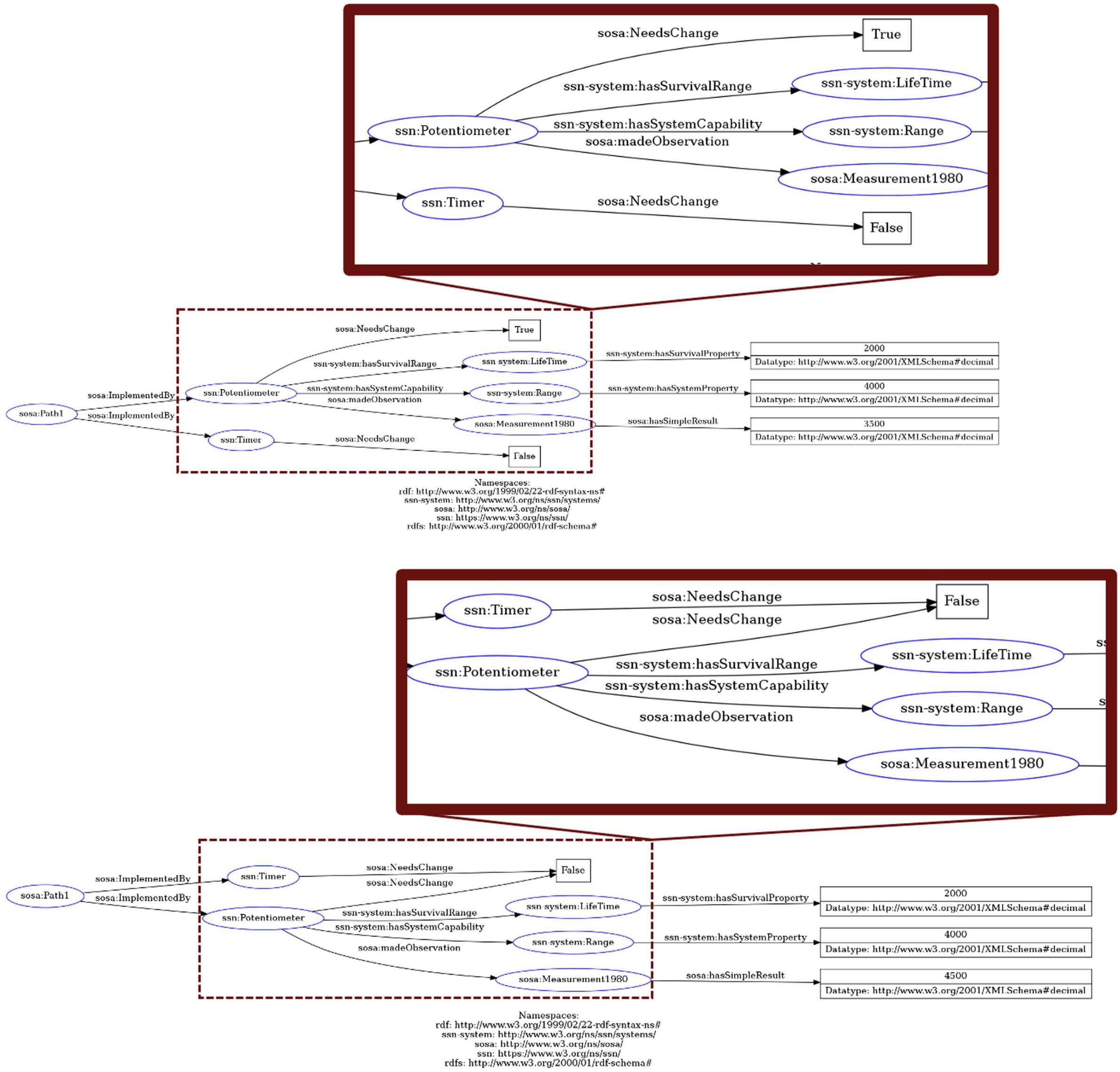

FIGURE 4. Final generated KG with functioning or malfunctioning potentiometer.

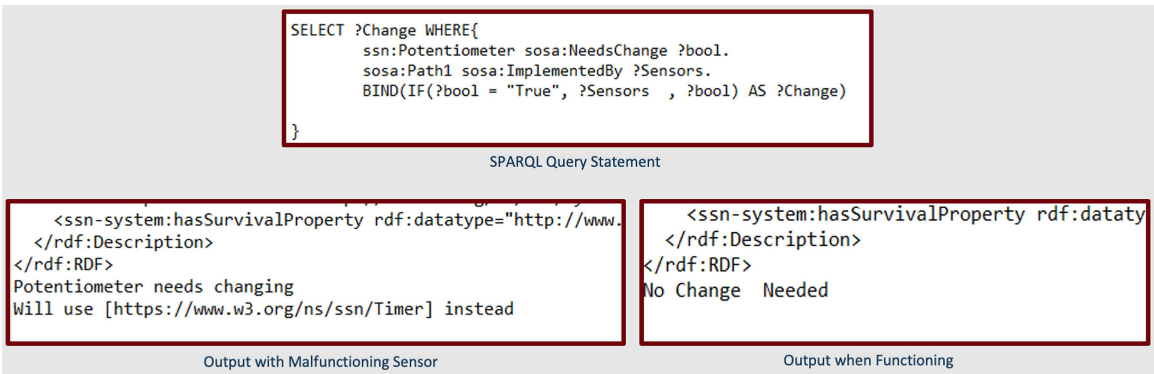

FIGURE 5. Query statement deployed on the KG with corresponding output messages.

incorporating heterogeneous data sources. With this procedure outlined alongside the technologies, further work can be undergone to integrate more information and address other issues that may occur in manufacturing.

Interoperability

With more data being generated on manufacturing shop floors using diverse devices, interoperability and integration of that data becomes a significant challenge. Semantic Web provides a step toward addressing this challenge. The use of ontologies, such as the SSN ontology and KGs, provide the critical capability for this purpose.

Domain Knowledge

KGs present a great opportunity for integrating domain knowledge for manufacturing processes. As such, datasheets and manuals can be integrated to include much of the information within the KG. This use case focused only on output range but there are endless possibilities of information that can be extracted whether it is operating or set up instruction. Having all this integrated into KGs can lead to different data accessibility and autonomous manufacturing capabilities.

CONCLUSION

SM has brought focus to the need for autonomous manufacturing. With an ever-changing market and added focus on customized production, factory floors must be agile and dynamic to adapt to diverse needs while also maintaining a consistent production schedule. In that regard, the added capability of fault tolerance can enable SM at a greater scale. This article describes how Semantic Web techniques can help in this objective.

We show that reducing downtime through fault tolerance is made possible by adopting Semantic Web for manufacturing primarily to deal with the heterogeneous data found in smart manufacturing. This article uses the simple use case of fault tolerance to illustrate the core ideas. The simplified example can be extended to support the integration of further diverse data and hence increase the knowledge acquired about the manufacturing process. The availability of these data in one KG can also allow knowledge-infused learning[10] algorithms to be deployed. Similar to recent neurosymbolic advancements for scene understanding in the autonomous driving domain,[11] this can lead to more complex event understanding in manufacturing that utilizes massive-scale heterogeneous sensor data through Semantic Web technologies.

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REFERENCES

1. A. Sheth, S. Padhee, and A. Gyrard, “Knowledge graphs and knowledge networks: The story in brief,” *IEEE Internet Comput.*, vol. 23, no. 4, pp. 67–75, Jul./Aug. 2019, doi: 10.1109/MIC.2019.2928449.
2. Y. Lu, H. Wang, and X. Xu, “ManuService ontology: A product data model for service-oriented business interactions in a cloud manufacturing environment,” *J. Intell. Manuf.*, vol. 30, no. 1, pp. 317–334, Jan. 2019, doi: 10.1007/S10845-016-1250-X/FIGURES/15.
3. M. Compton et al., “The SSN ontology of the W3C semantic sensor network incubator group,” *J. Web Semantics*, vol. 17, pp. 25–32, Dec. 2012, doi: 10.1016/J.WEBSEM.2012.05.003.
4. M. Dinar and D. W. Rosen, “A design for additive manufacturing ontology,” *J. Comput. Inf. Sci. Eng.*, vol. 17, no. 2, Jun. 2017, Art. no. 021013, doi: 10.1115/1.4035787/446471.
5. C. Henson, A. Sheth, and K. Thirunarayan, “Semantic perception: Converting sensory observations to abstractions,” *IEEE Internet Comput.*, vol. 16, no. 2, pp. 26–34, Mar./Apr. 2012, doi: 10.1109/MIC.2012.20.
6. P. Desai, A. Sheth, and P. Anantharam, “Semantic gateway as a service architecture for IoT interoperability,” in *Proc. IEEE 3rd Int. Conf. Mobile Serv.*, 2015, pp. 313–319, doi: 10.1109/MOBSERV.2015.51.
7. P. Patel, A. Gyrard, D. Thakker, A. Sheth, and M. Serrano, “SWoTSuite: A development framework for prototyping cross-domain semantic web of things applications,” in *Proc. 15th Int. Semantic Web Conf.*, 2016, doi: 10.48550/arxiv.1609.09014.
8. E. Iglesias, S. Jozashoori, D. Chaves-Fraga, D. Collarana, and M.-E. Vidal, “SDM-RDFizer,” in *Proc. 29th ACM Int. Conf. Inf. Knowl. Manage.*, 2020, pp. 3039–3046, doi: 10.1145/3340531.3412881.

9. A. Ameen, K. U. R. Khan, and B. P. Rani, "Reasoning in semantic web using Jena," *Comput. Eng. Intell. Syst.*, vol. 5, no. 4, pp. 39–47, 2014. Accessed: Jul. 07, 2022. [Online]. Available: www.iiste.org
10. A. Sheth, M. Gaur, U. Kursuncu, and R. Wickramarachchi, "Shades of knowledge-infused learning for enhancing deep learning," *IEEE Internet Comput.*, vol. 23, no. 6, pp. 54–63, Nov./Dec. 2019, doi: 10.1109/MIC.2019.2960071.
11. R. Wickramarachchi, C. Henson, and A. Sheth, "Knowledge-based entity prediction for improved machine perception in autonomous systems," *IEEE Intell. Syst.*, vol. 37, no. 5, pp. 42–49, Sep./Oct. 2022, doi: 10.1109/MIS.2022.3181015.

FADI EL KALACH is a Ph.D. student at the University of South Carolina, Columbia, SC, 29208, USA. His research focuses on smart manufacturing and artificial intelligence. His master's thesis focused on integrating Semantic Web into manufacturing for increased fault tolerance capabilities. Contact him at elkalach@email.sc.edu.

RUWAN WICKRAMARACHCHI is a Ph.D. student at the AI Institute, University of South Carolina, Columbia, SC, 29208, USA. His dissertation research focuses on introducing novel neuro-symbolic AI techniques to improve machine perception and context understanding in autonomous systems (e.g., autonomous driving and smart manufacturing). Contact him at ruwan@email.sc.edu.

RAMY HARIK is a professor in the Department of Mechanical Engineering, University of South Carolina, Columbia, SC, 29208, USA. He is also the principal investigator of the neXt (new and emerging X technologies) Research Team. He is a Fulbright Scholar. Contact him at harik@mailbox.sc.edu.

AMIT SHETH is the founding director of the AI Institute, University of South Carolina, Columbia, SC, 29208, USA. His current core research is in knowledge-infused learning and explanation, and transnational research includes personalized and public health, social good, education, and future manufacturing. He is a fellow of IEEE, AAAI, AAAS, and ACM. Contact him at amit@sc.edu.