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Semantic Modelling of a Manufacturing Value Chain: Disruption Response Planning

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Abstract:
Supply chains have been profoundly impacted by recent global disruptions, resulting in widespread shortages of parts, goods, and raw materials, significantly affecting the manufacturing sector to the extent of halting production lines completely. This paper employs semantic ontology reasoning to model a disruption in the value chain for a manufacturer, to generate and plan potential responses. First, a clear understanding of the available resources, capabilities, and entities is essential to construct a digital representation of the relationships throughout the chain. Then, using ontological reasoning, the model identifies the affected processes and products specific to the disruption, subsequently suggesting a set of coordinated responses to maintain productivity.

Keywords: Semantic Ontology, Disruption Modelling, Supply Shortages, Reasoning Engines, Supply Network Resilience, Automated Responses to Disruptions.

1. INTRODUCTION

In a world where longer production times are both costly and unsustainable, manufacturing companies are expected to maintain quality and productivity amidst dynamic changes in demand and challenging supply chain disruptions. A major challenge in current global supply chains is the sourcing of raw materials due to their low or inconsistent availability, leading manufacturers to halt their production. Companies are addressing these challenges through the development of sets of strategies that work on building more resilient facilities, which include increasing the onsite inventory storage, outsourcing, and switching to more adaptive and re-configurable shop floors to work around running close to their limited capacities Elshafei et al. (2023). However, these strategies are usually contingency plans that need continuous improvements, providing temporary rather than consistent solutions to the dynamic problem. Subsequently, the strategies are inefficient when faced with new challenges. Contrarily, strengthening the external sourcing capability by diversifying the supply chain networks and upgrading the supply chain technology promises more adaptability Martínez-Arellano et al. (2023).

From a manufacturer's perspective, efficient supply chain management is crucial for running smooth production processes Battesini et al. (2021). The focus is to understand and optimize the operational and strategic dynamics within the supply chain. The early decisions made during the planning and designing of the system contribute significantly to the subsequent implementation and operational capabilities, thereby influencing the ability to respond effectively to disruptions. Operational and strategic considerations have a significant role in shaping a firm's response strategies Fan et al. (2020). Resource allocation is guided by rules translated from the policies, while philosophies – such as Lean principles – direct key aspects like storage strategies, and are essential in addressing disruptions. This paper delves into the importance of coordinating changes within the supply chain. It emphasizes the need for a comprehensive understanding of options and limitations at the business level, proposing the concept of "dynamic responsiveness". Through semantic models and ontological reasoning, the paper introduces a structured and automated approach to decision-making and resource utilization, particularly in navigating changes or disruptions within the supply chain.

This paper introduces a four-step semantic approach to effectively generate responses to supply chain disruptions, as shown in Figure 1. The approach consists of semantic modelling, ontological reasoning, and sourcing preferencing. Modelling the firm facilitates a way to formally capture the impact on materials, products, or processes Pal and Yasar (2020). Semantic reasoning is then applied to understand the affected elements in the manufacturing process and direct the working search space. Sourcing preferences, including internal, external, or a combined approach, are considered in the final steps to assess and prioritize the responses. This semantic approach provides a structured and comprehensive framework for assisting the manufacturer with a data-driven decision-making tool for supply chain disruptions Sudan et al. (2023).

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The paper outlines three responding strategies – Internal Response, External Response, and Combined Approach – each influencing the response approaches to supply chain disruptions. The first, a firm will look to explore the present options within its existing capabilities, increasing onsite raw material inventory and enhancing internal manufacturing capabilities by acquiring new ones. This is more suitable for short-term disruptions, as it is quicker to build inventories than factories Yan et al. (2023), and helps avoid the re-occurrence of that incident. The second response strategy proves more beneficial when the business is entirely disrupted and relies on external strategies. The final approach combines the merits of internal and external options to address partial disruptions, creating a more flexible response. These strategies provide an effective guide in formulating responses specific to the nature and extent of the disruption Tang (2006).

The ontology model is illustrated with a practical use case, modelling a battery manufacturing value chain. The multi-level ontology is applied to model disruptions, and to capture capabilities, processes, and resources across different supply chain levels. The use case tests the loss of a critical supplier of raw material scenario. By following the four-step approach, this work demonstrates how ontology contributes to developing a digital representation capable of generating disruption responses. The advantage of using this approach is its scalability, allowing to explore a large set of scenarios and responses that are more complex in reality.

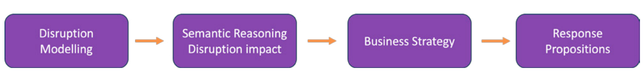

Fig. 1. The overarching process for inferring solutions to disruptions from the ontology models.

2. METHODOLOGY

As introduced in the previous section, semantic modeling is at the core of the proposed approach. Building on the work by both Martínez-Arellano et al. (2023) and Kazantsev (2024) the semantics of processes, capabilities, and resources are captured, and a new ontology model is proposed to model disruption elements as well as response strategies Järvenpää et al. (2018). The framework for generating responses and establishing the relations between the models results in a structured set of responses that allow data-driven decision-making in the scenario of a disruption as shown in Figure 2.

The constructed ontology includes (i) 444 classes, the most important ones being Disruption, Capacity, Capability, Process, Resource, Company/Organization, and ProductElement; (ii) 397 properties that define relationships between classes, such as: *hasInputCapability*, and (iii) seven semantic SPIN rules to infer combinations of responses to meet demand change. To develop a semantic reasoning approach, the following four steps to supplier disruption were defined:

(1) Capturing the supply disruption related to material, product, or process. This step requires modelling in the ontology of the type of disruption that has occurred. By doing so, then the relationships (object properties) of the disruption within the ontology can be used to support step 2.
(2) Semantic reasoning. Using inference in the form of SPIN rules allows the identification of the products and processes that are affected by the disruption and to what extent this will determine the solution search space (i.e., solutions available at the disrupted nodes).
(3) Consideration of the sourcing preference of the business. Every manufacturing firm has sourcing preferences when searching for responses to supply disruption. Hence, three strategies (internal, external, and combined) were defined to structure the output from ontology towards the desired sourcing preference:

Internal Response - The manufacturer explores the options available within its current capabilities. This will include using the raw materials inventory (safety stock), increasing the internal capability to manufacture (new machinery, overtime work), or acquiring this capability, considering technology policies, cost, capacity policies, and facility constraints. If no options can handle the disrupted element directly, alternative solutions that replace the element type can be searched. For example, using a different type of raw material or looking at another process that can deliver the same capability.

External Response - The manufacturer might be disrupted entirely and not be able to carry out its activities without the use of external strategies. For example, a material, part, or another service not available internally might require looking for a different supplier. In addition to the constraints mentioned in (1), the business might have specific policies around the supplier options due to quality tolerances or policies regarding the percentage of the process or service that can be outsourced.

Combined Approach - the manufacturer might be in the position of only partially being able to address the impact of the disruption and open to exploring both internal and external options. In this

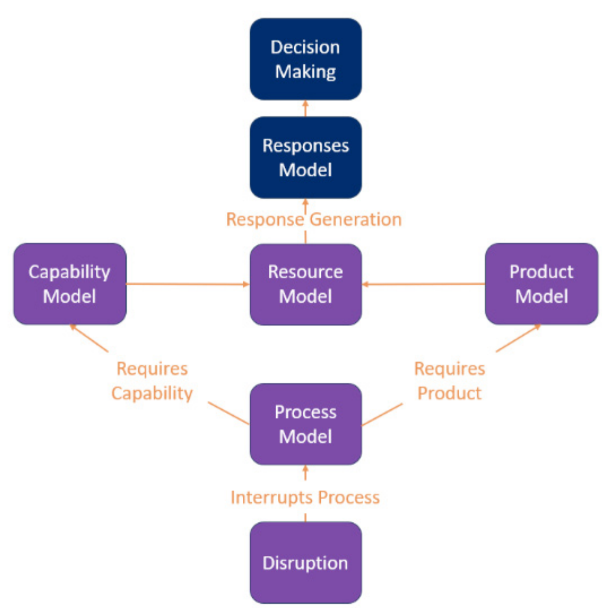

Fig. 2. Elastic Manufacturing Ontology Framework.

case, solutions that complement internal strategies can be searched for. For example, responding to a process service disruption by increasing the internal capacity (machinery, people, and materials) and complementing the unmet volume through contract production.

(4) Response proposition. Given the preferred response approach of the manufacturer, solutions available are selected and presented to the decision-maker. Each identified solution is characterised through different metrics that allow us to understand the impact and benefit of such a solution. These metrics include cost, environmental impact, and time.

The electric vehicle industry provides a compelling case for the necessity and utility of the multi-level ontology approach, as the production of electric vehicles involves a high degree of complexity and variability. This includes various models and specifications, rapidly evolving technologies, and integrating diverse components such as batteries, electric motors, and advanced driver-assistance systems Schuh et al. (2020).

3. USE CASE: DISRUPTION OF RAW MATERIAL IN BATTERY MANUFACTURING

In this section, the concepts captured in the ontology are written with capital letters and italics, the object and data properties starting with small letters and in italics, while the individuals are denoted using the `Courier` font.

A running example: a loss of a critical supplier in battery manufacturing

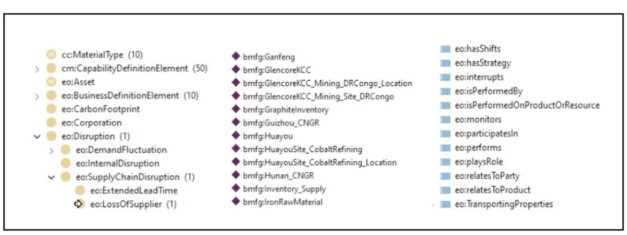

Fig. 3. Classes (orange circles), Instances (purple diamonds), and Properties (blue boxes) used to define manufacturing responses to a battery cell disruption.

The example considers an electric vehicle producer who acts as (i) a manufacturer of lithium electric batteries; (ii) an assembler of these electric batteries and (iii) a battery integrator with electric vehicles. The producer produces the battery cells in-house and further assembles them into battery packs. To produce a lithium cell, several raw materials are needed, including lithium, cobalt, aluminium, and copper. Hence, the supply chain consists of various suppliers of these raw materials. Following Liu et al. (2021), the manufacturing of a lithium battery consists of the following processes to capture the material required and capabilities for the manufacturing operation (see Figure 4). First, raw materials like lithium, cobalt, and graphite are extracted from mines and then undergo refining processes to ensure they meet the specifications for battery production. The production starts with the manufacturing of cathode and anode electrodes by coating the refined materials onto metal foils and drying them to form electrode sheets. Concurrently, a separator, typically made of polythene or ceramic material, is produced to keep the cathode and anode apart while allowing the flow of ions. Second, in the assembly stage, electrode sheets and separators are combined with electrolyte, a conductive solution, to form a cell stack. The stack is then enclosed in a casing and sealed to prevent leakage. The sealed cell undergoes an initial charge and discharge cycle to activate the electrochemical reactions and stabilize its performance, a process known as a formation. Third, each battery cell undergoes rigorous testing to ensure quality, safety, and performance meet industry standards. In the fourth and final step, multiple cells are connected, and a battery management system is added to monitor and control the cells' charging and discharging, forming a complete battery pack ready for use in various applications.

STEP 1. Disruption Modelling in the ontology

The focal entity in the ontology is the battery manufacturing firm. It is the central hub for all supply chain activities and production operations. A critical cobalt raw material supplier is `Glencore`, which is modelled as an individual. The asserted data in the ontology includes previously defined classes, the individuals of the raw materials, suppliers, processes, capabilities, and resources, and object and data properties that set off the relations between the aforementioned entities. This allows for inferences that provide solutions in response to a disruption in the manufacturing process. Figure 3 shows some of the entities required to build the Battery manufacturing semantic ontology that can mimic the supply chain of batteries.

STEP 2. Semantic reasoning, understanding the impact on products and processes

Through semantic relationships, it is possible to understand the impact of a given asserted disruption and infer potential responses to such disruption. Hence, following the inference of the impacted process, the impacted product and capability required to perform the process are subsequently inferred. The class Loss Of A Supplier is linked to a particular supplier (individual), i.e., a company that plays the role of supplier in a supply chain. The first step is to check which products (including raw materials) are exchanged in the supply chain. The spin rules in Tables 1 and 2 find all the manufacturing processes related to the Loss Of Supplier indicated in Table 3 and then the products on which these processes are performed. The combined business capability that can be attached to these is `BatteryManufacturingCapability`. This capability can be attached to various suppliers and further specified with the required battery parameters. Spin rules are used to link the ontology entities based on the asserted data. For example, spin rules link the resources to the disruption instance and generate the responses as solutions to counter the disruption related to the affected process and product. A response represents the options a company might pursue, which uses the asserted information to infer possible solutions to the disruption.

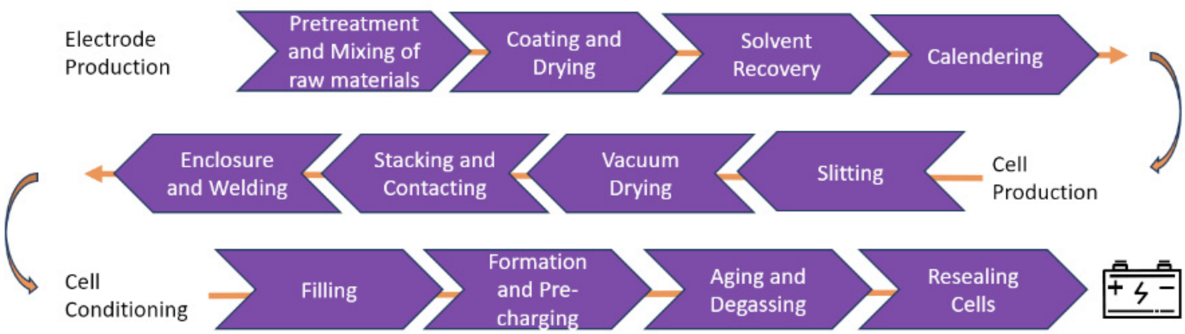

Fig. 4. Schematic of manufacturing stages for a Lithium battery.

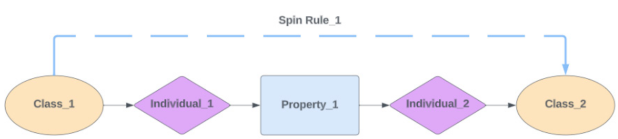

Fig. 5. A meta-model of ontological reasoning using a Spin rule to infer new properties (responses)

The responses are generated based on inferences between the aforementioned properties and those in the resource model.

Table 1. Code (spin rules) for deriving disrupted process and product

SpinRule_1: Infers Disrupted Process	SpinRule_2: Infers Disrupted Product

CONSTRUCT {
?this eo:interrupts ?process
 	
}
WHERE {
?this eo:relatesToParty ?party
?party eo:performs ?process
 	
?process
rdf:type/(rdfs:subClassOf)*
eo:Process
}
	CONSTRUCT {
	?this eo:relatesToProduct ?product
	}
	WHERE {
	?this eo:interrupts ?process
	?process eo:hasOutput ?product
	?product
	rdf:type/(rdfs:subClassOf)*
	pm:Product
	}

Table 2. Code (spin rules) for deriving Internal and External Responses.

SpinRule_3: Infers Internal Response	SpinRule_4: Infers External Response

CONSTRUCT {
?this bmfg:InternalResponse ?response
}
WHERE {
?this eo:interrupts ?process
 	
?process
bmfg:requiresCapability
?response
?response
rdf:type/(rdfs:subClassOf)*
cm:Capability
}
	CONSTRUCT {
	?this bmfg:ExternalResponse ?response
	}
	WHERE {
	?this eo:relatesToProduct ?product
	?product bmfg:SuppliedBy ?response
	
	?response
	rdf:type/(rdfs:subClassOf)*
	bmfg:Suppliers
	}

STEP 3. Consideration of a sourcing strategy

The following step prioritizes the generated responses based on the strategy. The user decides whether an internal or external response alone is sufficient or a combined approach of responses would be required to recover from the disruption. In case the `CobaltInventory` - first - response is not sufficient to cover the total duration of the disruption, a combined approach would be required, and approaching other external suppliers would be essential. In the case where inventory and external suppliers do not cover the duration of the disruption, other responses will be considered. These include acquiring the lost capability of mining for Cobalt and changing the product chemistry to Lithium Iron Phosphate (LFO) batteries, if necessary.

Table 4 shows the inferred responses: `CobaltInventory`, which refers to the surplus inventory that can be used in situations of raw material supply disruptions; cobalt suppliers such as `Huayou` and `HunanCNGR`; cell suppliers such as `Panasonic` and `LG solutions`; additionally, in extreme cases of cobalt scarcity, manufacturing cells with different chemistry such as IronCells leading to `IronRawMaterial`; finally, acquiring the lost capability, `AcquireMiningCapability`, which embeds cobalt sourcing as an internal process that is not affected by the supply chain.

The aforementioned inference process for generating these responses is shown in Figure 6. In capturing the affected process and product, the lost supplier is linked to the process they perform. Based on the hasOutput relation, we can link the process to the product. Thus, the loss of any supplier links to the related process and product and, in our use case, links to `CobaltMining` and `CobaltRawMaterial`, respectively.

Table 3. Disruption Information

Disruption	Predicate	Inferred instance	Spin rule to execute
Loss of Glencore	Interrupts	CobaltMining	1
	RelatesToProduct	CobaltRawMaterial	2
	InternalResponse	CobaltInventory	3
	InternalResponse	AcquireMining Capability	3
	InternalResponse	IronRawMaterial	3
	ExternalResponse	CobaltSuppliers	4
	ExternalResponse	CellSuppliers	4

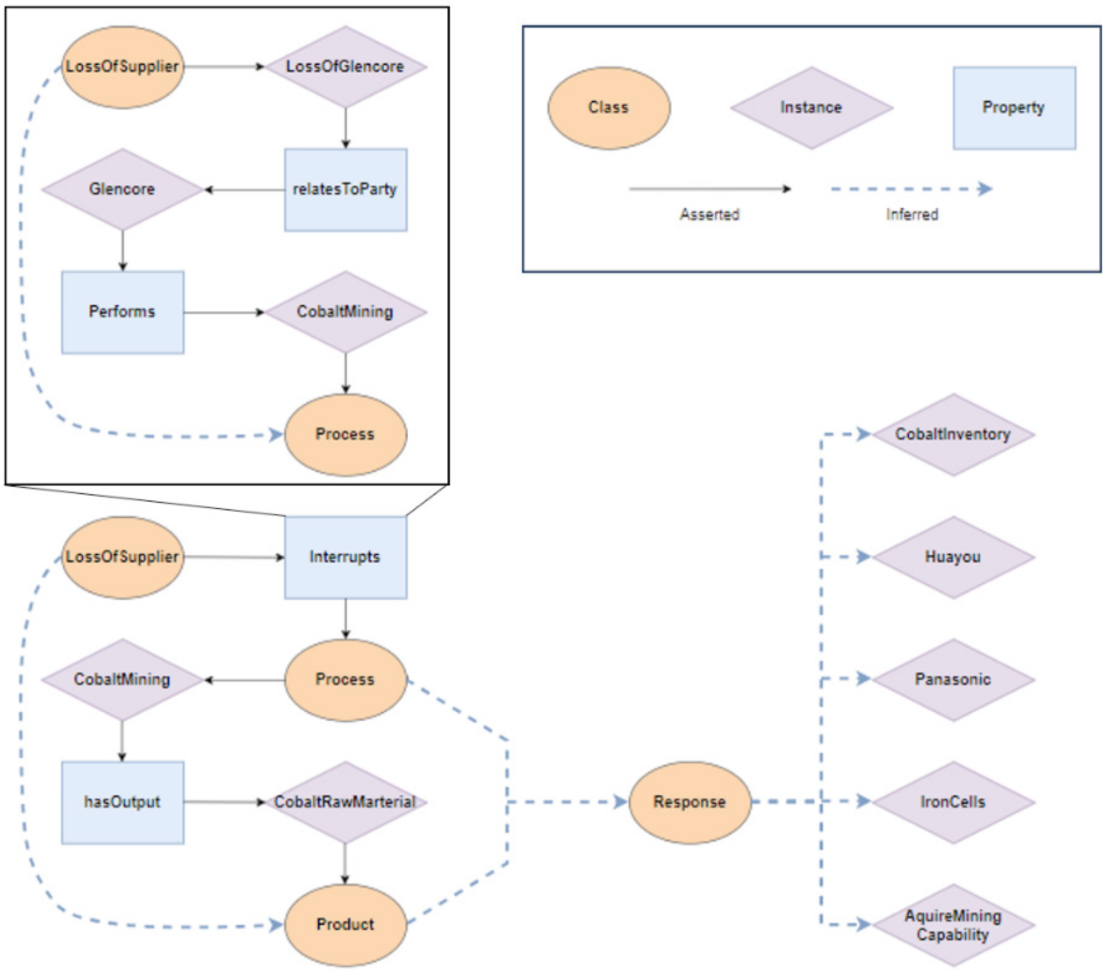

Fig. 6. Inferred impacted process and product, and the inferred responses.

STEP 4. Response proposition

For the case context, the product cost, carbon emissions, and time to deliver metrics are used to assess and guide the decision on the external supply options.

Table 4 shows the results from the SPARQL query, quantifying emissions, days to deliver, and type of product.

Table 4. Code for SPARQL query to quantify the Time for suppliers to deliver and their respective carbon emissions.

SPARQL Query

```
SELECT ?subject ?Product ?DistanceToSupplier
?EmissionsFactor ?TransportMode ?TimeToDeliver
((?DistanceToSupplier * ?EmissionsFactor) AS
?CarbonEmissions)
WHERE { ?subject bmfg:DistanceToSupplier
?DistanceToSupplier .
?subject bmfg:EmissionsFactor ?EmissionsFactor
.
?subject bmfg:TimeToDeliver ?TimeToDeliver .
?subject bmfg:TransportMode ?TransportMode.
?subject bmfg:Product ?Product.}
```

The multi-level ontology is used to assess the external response to make an informed decision based on the multiple external responses, which are assessed based on the cost of the product they supply, cobalt raw material (low cost) or readily manufactured cells (high cost); the time to deliver, based on the distance from the supplier; and the carbon emissions, based on transport mode and distance from the supplier. Each decision bears some maximum and minimum estimated Costs calculated from the low-level information, bears some Carbon footprint, has an estimated Time, and follows a specific Strategy to supply the lost raw material.

Table 5 shows Huayou as the suggested external supplier, supplying a low-cost product with the least carbon emissions and for the lower cost.

4. CONCLUSION

This paper presents a semantic ontology modeling a disruption in the supply chain for a battery manufacturer. The ontology enables the holistic capture of capabilities, resources, and external dependencies in the value chain of the manufacturer to coordinate a range of responses to the disruption. This response contributes to creating an elastic working environment that can facilitate matchmaking between disruptions and responses by identifying the processes and products impacted by the disruption. However, for the ontology to accurately identify and infer

Table 5. The output table to compare suppliers

Response	**Product**	**Distance To Supplier (kg)**	**Emissions Factor**	**Transport Mode**	**Time To Deliver (Days)**	**Carbon Emissions (kgCO2e)**
Huayou	**Cobalt**	140	0.4	Truck	**2**	**56**
Guizhou	**Cobalt**	1570	0.08	Train	5	126
Hunan	**Cobalt**	1180	0.08	Train	4	94
Panasonic	Cell	80	0.4	Truck	**2**	**32**
CATL	Cell	670	0.08	Train	4	**54**
LG solutions	Cell	360	0.4	Truck	**2**	144

a range of strategies, it is essential to establish a wide array of relations between the classes and instances of the model. Developing properties enhances our understanding of the chain and captures the necessary elements for building an accurate digital representation. Finally, the given framework could be both scaled and generalized, in other words, the ontology can be used to capture the impact for other suppliers and other manufacturing use cases.

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