



Push-pull digital thread for digital transformation of manufacturing systems

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ABSTRACT

Current digitalized manufacturing systems do not yet achieve the goal of smart manufacturing: precise control and agility under unexpected disruptions. Push-Pull Digital Thread is a solution concept to enable contextual data and knowledge exchange across operational and functional units in a manufacturing enterprise. The extraction of decision reasoning and functional information can be facilitated by Large Language Models processing information obtained from a decision maker at the point of decision. This concept shows a potential to address critical limitations in previous endeavours for smart manufacturing systems by building a semantically searchable and sharable knowledgebase in manufacturing systems and beyond.

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1. Introduction

Various concepts of smart manufacturing have been proposed, studied, and pursued during the past few decades with various catch phrases from Intelligent Manufacturing Systems (IMS) in 1980's, Computer Integrated Manufacturing (CIM) in 1990's, and most recently Industry 4.0. Significant digitalization in design and manufacturing processes and their operational integration with enterprise resource planning (ERP) have resulted in substantial enhancement in production quality, machine utilization and overall system productivity. However, when socio-economic challenges such as the COVID-19 pandemic and resulting global supply chain disruption occurred, significant vulnerabilities of current manufacturing systems were exposed.

Regarding why digitalized, best practice manufacturing systems do not yet provide benefits of the smart manufacturing such as precise control and agility under unexpected disruption, many industry leaders and researchers state that current manufacturing systems are "well-digitalized but not digitally transformed." It is suggested that true digital transformation goes beyond process level digitalization and should functionally integrate the entire organization of the enterprise surrounding manufacturing, especially decision makers. In the MIT Sloan Management Review [1], Kane defines "Digital Transformation" as continual adaptation to a constantly changing environment by building a technical and operational foundation and responding in the best possible way to unpredictable and ever-changing customer expectations, market conditions and local or global events. From the business consulting point of view, IBM promotes "Cognitive Manufacturing" to achieve digital transformation of

manufacturing enterprises by exploiting big data, AI, automation, hybrid cloud and other digital technologies to make faster and smarter decision-making, and real-time response to market disruption [2], also explored in [3].

The goals of digital transformation have been studied by the CIRP community. Monostori et al. [4] suggested smart manufacturing systems require flat and flexible organizations, prioritizing life-long learning of both employees and information processing systems. Abramovici et al. [5] proposed semantic data management for an interdisciplinary, globally distributed development and continuous reconfiguration of smart products and manufacturing systems. Laroche et al. [6] defined the challenge of smart manufacturing systems as knowledge reuse and proposed a new way for structuring knowledge and managing contextual information. Kadar et al. [7] addressed the application of a semantic data model for virtual factories to support the design and the performance evaluation of manufacturing systems, while exploiting the interoperability between various Digital Enterprise Technology tools.

A digitally transformed manufacturing system is an agile system which responds in the best possible way to any random disturbances. From the point of engineering systems, this can be achieved by providing precise feedback control loops to accommodate the effect of disturbances. Therefore, this paper focuses on major challenges to address missing links of well-digitalized manufacturing systems in closing the loop effectively and responding to unpredictable disturbances. There are three inherent structural problems for manufacturing systems to be digitally transformed:

- 1) The culturally one directional decision/data/knowledge flow from design to manufacturing in most manufacturing systems hinders fast and agile closed loop control. [8]

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- 2) Data gathering, exchange and knowledge-sharing across functional units is limited by protectionism (silos), resulting a very slow feedback control. [9]
- 3) Most reasoning grounds for decisions are unstructured data, which cannot be effectively represented in the current ERP systems, and thereby not being reusable in the future decisions. When the decision maker leaves the position, most knowledge will be lost. [10]

This paper discusses the problems above and suggests a new paradigm for decision data and knowledge extraction, archiving and a bi-directional communication and exchange platform across the manufacturing system to enable precise control of manufacturing systems. A case study using conversational AI to facilitate the extraction of decision reasoning information demonstrates how such a paradigm may be implemented.

2. Push-pull digital thread: a new knowledge sharing concept

There are at least three levels of closed loop control in manufacturing systems, some of which are not digitalized and require manual intervention. At the machine-level, data from sensors and controllers are mostly structured (numerical or graphical) and effectively used to control machines and processes. IoT (Internet of things) and deep learning further enhance the controllability of machines with minimal human intervention, which is being widely adopted at the present time and requires no further discussion here. At the operation level, any abnormal operation or faulty execution of production can be monitored and alerts an operational decision maker to make necessary corrections. A decision maker needs to pull necessary information or related data from the previous operations and suppliers to complete the manual (non-digitalized) feedback control. Finally, function-level feedback control is the most complex level, which often requires intervention from the top to force/allow cross-functional (or siloed) data exchange and information sharing. For example, trouble shootings which require design changes usually take longer time to close the loop and to issue engineering design change orders (ECOs). Making this long feedback loop to be digitally transformed is potentially the key to achieving the goal of digitally transformed manufacturing.

The following factors make this feedback loop difficult to be closed digitally. Firstly, the current design data flow from design to manufacturing in most manufacturing systems is unidirectional and does not carry functional aspects of product designs. Fig. 1 shows data and information flow in a typical manufacturing enterprise. In the two-dimensional data communication space of a manufacturing enterprise, horizontal design data translations do not carry functional information of products. The current push type data flow with little sharing of functional decision grounds inevitably results in slow, non-digitalized, manual case-by-case feedback control. From the point of a manufacturing enterprise, vertical information flow stems from the recognition of market demand along socio-economic-scientific challenges, such as pandemic outbreaks or accelerating climate change, which then translates into more detailed concepts of

products and their specific product designs. Most top-down decisions flow without providing enough functional reasoning grounds of decisions, which also require long time to close this loop.

If the pushed data, such as design specifications and geometry from design to manufacturing, can include underlying functional requirements and design reasonings, then troubles found during manufacturing can be rapidly diagnosed and corrected in many cases before taking a function level feedback loop. Or, if the manufacturing decision makers can pull necessary functional aspects of the design on demand, fast track closed loop control may become feasible by identifying the stake holders correctly. “Push-Pull Digital Thread (PPDT)” is a solution concept proposed in this paper to enable the feed-forward (push) and feed-back (pull) exchange of relevant and necessary contextual data and functional knowledge across the operational and functional units of a manufacturing enterprise digitally. While the concept of a digital thread, as shown in Fig. 2, has been depicted and pursued by many researchers to link design, performance, product, and supply chain data for smart decision makings in manufacturing [11], no concrete implementable form of digital thread has been reported yet. Further, no concept of push-pull type (bi-directional) digital thread has ever been proposed, which is potentially the key paradigm shift needed to implement the concept of digital threads.

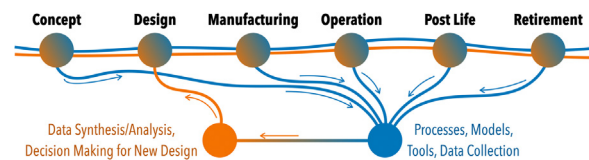


Fig. 2. Conceptual depiction of digital thread for engineering design, adapted from [11].

The Push-Pull Digital Thread (PPDT) has three functional blocks:

- 1) Extraction of contextual knowledge and reasoning data of any decisions (including design) from the decision maker at the instant of decisions (or close to it before any lapse of memory, position change or retirement of the decision-making personnel).
- 2) Representation of functional aspects of decision reasoning basis (such as “what” “how” and “why”) quantitatively into distributed feature vectors using statistical language models which can be semantically searched and pulled when necessary.
- 3) Building enterprise-wide intranet to share functional representation of decisions. Proper security protocol should be employed to enable push-pull data exchange without leaving out any key stakeholders in the loop, while keeping the know-hows and past decision reasonings within the enterprise in perpetuity.

3. Decision reasoning knowledge extraction

Authors have recently reported “Design Reading,” a method for enabling data-driven design by extracting and representing contextual design reasoning data and functional requirements from past design documents [12,13]. “Design Reading” applies machine learning-based Natural Language Processing (NLP) to extract a structured hierarchy of functional requirements and design parameters, top to bottom, along the text passages. Deep learning-based (NLP) models such as Google’s BERT were fine-tuned to perform the task of Question-Answering to extract and structure conceptual design reasoning information from textualized descriptions of existing designs, as shown in Fig. 3. “Design Reading” demonstrated that extracting functional reasoning could be automated, however, only if past design and decision reasonings could be well described in textualized design documents. Design documentation in practice, however, is often ill-structured and designers usually skip the functional and conceptual reasoning in their post-design documentation. Therefore, “Design Reading” can be successful only if well described design documentation is available.

Design reasoning knowledge often remains unstructured, informal, qualitative, and contextual in nature. Furthermore, contextual

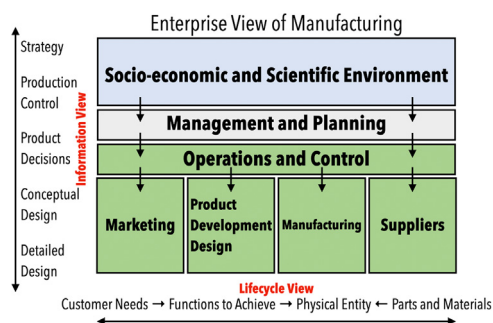


Fig. 1. Unidirectional information and data flow of most enterprises with manufacturing.

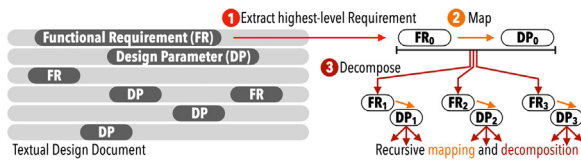


Fig. 3. Process for extracting functional structure from text document, adapted from [12].

information from decision-makings at all levels of an enterprise are neither well documented nor required for later retrieval in most industrial systems. The key finding in this paper is that decision (including design) reasoning and functional information exist most clearly at the instant of decision making. The decision maker's memory will disappear gradually over time and is lost to the enterprise when the decision-maker retires or changes positions. By aggregating them into a searchable database at the instant of decision making (or not long after), design and manufacturing decision reasoning knowledge can be computationally represented and accessible for the Push-Pull Digital Thread (PPDT). This knowledge can be *pulled* by any future decision makers in the closed loop control of the manufacturing system, used to guide future engineering decision-makings (*reusable*), and *pushed* to the affected operational units. A function graph from the extracted knowledge will guide where to push data without missing any key stake holders, while keeping know-hows and past decision reasonings within the enterprise.

Fig. 4 shows how to extract decision reasoning and functional information from a decision maker using a Large Language Model trained on chat completion. The structure of the information captured at the point of decision would extract the essential ingredients of decision reasoning grounds in “what (functional requirements)”, “how (design parameters)”, “why (decision basis)”. The next section will demonstrate how conceptual reasoning knowledge can be captured directly from the point-of-decision with a case study on Engineering Change Orders (ECOs) of vehicle door weatherstrip design in an automotive manufacturing enterprise.

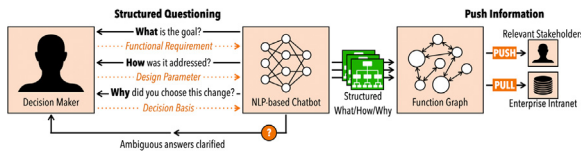


Fig. 4. Information capturing process from a decision maker.

4. A case study on engineering change orders (ECOs) for vehicle door weatherstrip design

Manufacturing troubleshooting may require design changes which would take long periods of time to resolve, in weeks if not months. Digitally transforming this feedback loop will shorten the feedback control time in the future similar cases. Push-Pull Digital Thread uses both structured questioning and flexible semantic-based interaction to map “what, how, why” information from decision-makers. It initiates this step by introducing an interview stage to accompany each ECO, conducted by a Large Language Model trained on chat completion akin to a Virtual Design Assistant (VDA) [14]. In this case study, an implementation of OpenAI's GPT-3.5 [15] is assigned the role of VDA to facilitate a conversational decision reasoning extraction interaction. GPT-3.5 is a generative language model based on a Transformer neural network architecture, as is Google's BERT implemented in the “Design Reading” system. Prior to the interaction, the VDA is provided with an instructional input enumerating the information to target over the course of the exchange. This initialization and the resulting interaction between a design engineer are presented in Table 1.

Consider the case of assembling weather strips on the front door sides of a generic model car of Hyundai Motor Company. Door side mounted weatherstrips were designed to be inserted with a dedicated insertion tool, which the workers of the respective final assembly factory rejected due to poor workability. The closure design team

Table 1

Design decision extraction using an AI language model.

The following is the record of an interaction between a Virtual Design Assistant (VDA) powered by an AI language model GPT-3.5, and a real-world automotive closure design engineer who decided the ECO presented in this case (Eng).

System Initialization Instructions: You are an assistant and want to understand the problem, the key design parameters involved, what solutions were possible, the reason why they chose a certain solution, and any unintended effects on other systems.

Eng (human): I just made a change to the design of my product

VDA (AI chatbot): What was the main goal of this design change?

Eng: We wanted to redesign the weatherstrip component so that it would be easier for assembly workers to insert it manually.

VDA: What were the key design parameters that were considered in making this change?

Eng: The key design parameter is the peak force required from the worker when manually inserting the weatherstrip. The peak force must be reduced.

VDA: What were some possible solutions that were considered to address this design parameter?

Eng: There were three options. We could add a lubricant such as soap. Or, we could change the weatherstrip's cross section geometry. Or alternatively we could change the material of the weatherstrip.

VDA: Which solution did you choose and why?

Eng: We did not add a lubricant because that increases cost and assembly time.

VDA: So, which of the other two options did you choose? Did you change the cross section geometry of the weatherstrip or its material?

Eng: We changed the material. Changing the cross section geometry would require a new extrusion die which is expensive. Changing the material hardness just requires simple validation.

VDA: Did this change in material have any unintended effects on other systems within the product?

Eng: It's possible that a softer weatherstrip may detach from the door more easily over the lifetime of repeated use.

VDA: That's a valid concern. Did you conduct any tests or simulations to ensure that the new material's performance meets the required performance standards of the product?

Eng: We did CAE simulations and experimental testing to verify the new hardness value was optimal for the redesigned weatherstrip.

VDA: That's great to hear! Did you also consider any potential manufacturing changes that would be required to accommodate this new material?

Eng: We think there should be no manufacturing issues resulting from the change in material.

VDA: That's good to know. Do you have any plans to validate the usability of this redesigned weatherstrip with human factors testing?

Eng: We will introduce the new weatherstrip design to the factory and test if the assembly workers can easily insert it now.

VDA: Sounds like a good plan. Overall, it seems that you have carefully considered the key design parameters and evaluated various solutions before making a change to the weatherstrip component. Additionally, you have taken appropriate steps to validate the new material's performance and will be testing its usability in the factory - this demonstrates a good design process.

was requested to make manual insertion of the door weatherstrip easier (Fig. 5).

The closure design group reviewed three options to reduce insertion force: 1) size reduction of the mushroom shape at the bottom part of the weather strip; 2) using lubricants for insertion assembly; 3) change of the weatherstrip solid elastomer material to reduce hardness. The decision maker considered that option 1 was not acceptable since the weatherstrip design was standardized in the same car family and could not be customized for a specific factory and that option 2 could not become a sustainable solution. Option 3 was adopted after various numerical simulations and testing to ensure easy insertion while not risking easy detachment during the opening and closing of doors. The implementation without knowledge sharing took 10 weeks for this ECO, which would be shortened with the PPDT to realize agile manufacturing.

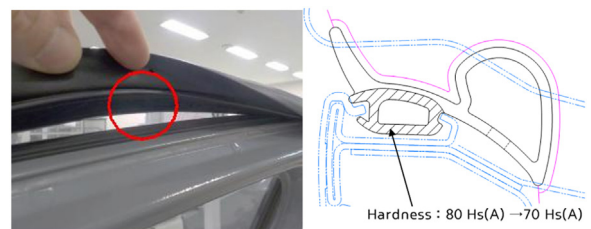


Fig. 5. Door side weatherstrip of Model Z [Courtesy Hyundai Motor].

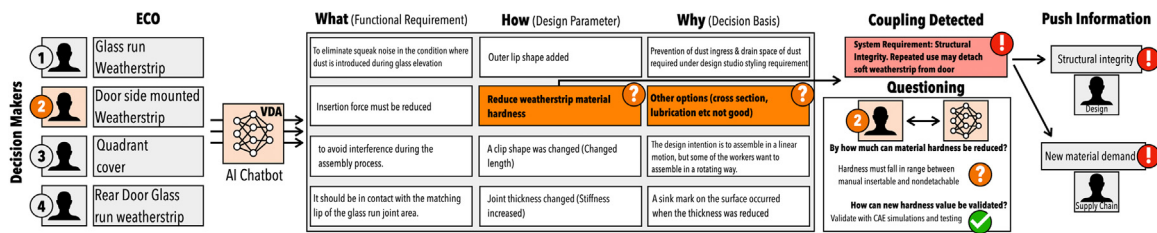


Fig. 6. Engineering change order case study: example of point-of decision design reasoning extraction using Large Language Model.

When a design is updated or modified to fix design-related manufacturing problems, an Engineering Change Order (ECO) is formally issued in a manufacturing enterprise. Typically, an ECO is accompanied by a data entry step to the master database, performed by the decision-maker, but current ERP templates are inflexible to include unstructured data, and the entered data can be brief or incomplete with reasoning which is the critical functional information of highest value. The typical ECO in this problem currently has the following information: part number and name, short description of the problem and history of specification changes in bullets, date of application, which cannot provide contextual feedback to the affected parties of the enterprise and the reuse of the past reasoning knowledge.

Capturing decision-making reasoning is critical to enable reuse and sharing for a smart manufacturing enterprise. The extraction of decision reasoning and functional information from a decision maker at the point of decision is performed by an interactive “question and answering” session between the VDA (human interviewer simulating VDA chatbot in this paper) and the decision maker of the closure design team. Table 1 shows a summary of knowledge extraction. The information extracted is then abstracted and semantically embedded into an enterprise-wide database to be semantically searchable and cross-referenced on-demand as shown in Fig. 6.

5. Discussion and conclusion

The following points must be addressed soon to implement the concept of Push-Pull Digital Thread (PPDT) in real manufacturing systems.

- 1) At each node of manufacturing system, any decision maker's reasoning information needs to be extracted and archived via user-friendly interaction with a chatbot. Large parameter language models such as GPT [15] with conversational capability can be fine-tuned for the specific manufacturing industry to include the functional reasoning ontology. Interviewing immediately after decision making will require minimal time and easy interaction for interviewees.
- 2) The decision maker should be able to identify the push destinations of the decision. Although apparent for most decisions, sometimes critical push destinations may be omitted or inconsistent, resulting in serious operational failures. The PPDT can also assist the decision maker to push identified functional coupling (push thread). At the same time, any future decision makers in the entire enterprise system can semantically search on-demand or cross reference the current decision reasoning and linked quantitative data such as simulation, analytics, test results, material specifications and drawings (pull thread).
- 3) Access to the database should be controlled and protected by the data security protocol set by the company.

This paper proposes a concept for how to address important missing links and ingredients in current efforts toward smart manufacturing systems by building a contextual and semantically searchable knowledgebase across the manufacturing enterprise. Software architecture framework has been built to develop an enterprise-level knowledgebase, compatible with the existing enterprise resources planning (ERP) tools.

Push-Pull Digital Thread (PPDT) concept has potential to enable fast and agile closed-loop control of manufacturing systems. This will also enable the utility of Big Data; all past decision reasonings, successes or failures, which will greatly boost the speed and precision of future manufacturing decisions. A complete digital transformation of manufacturing will require a holistic socio-technical approach, and the PPDT concept provides a framework for digitally integrating decision makers across domains in a system. This concept can be also applied to integrate decision reasoning at vertical levels of an enterprise for sharing coherent strategic decisions. When this concept can digitally transform current digitalized manufacturing systems, the manufacturing industry will finally achieve the tangible benefits of smart manufacturing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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