Digital Twin Framework for Machine Learning-Enabled Integrated Production and Logistics Processes

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DIGITAL TWIN FRAMEWORK FOR MACHINE LEARNING-ENABLED INTEGRATED PRODUCTION AND LOGISTICS PROCESSES

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Abstract. This paper offers an integrated framework bridging production and logistics processes that employs a machine learning-enabled digital twin to ensure adaptive production scheduling and resilient supply chain operations. The digital-twin based architecture will enable manufacturers to proactively manage supply chain risk in an increasingly complex and dynamic environment. This integrated framework enables "sense-and-respond" capabilities, i.e. the ability to sense potential supplier and production risks that affect ultimate delivery to the customer, to update anticipated customer delivery dates, and recommend mitigating steps that minimize any anticipated disruption. In its core functionality this framework senses disruptions at a supplier facility that cascade down the upstream supply chain and employs the predictive capabilities of its machine learning-based engine to trigger and support adaptive changes to the manufacturer's MES system. Any changes to the production schedule that cannot be accommodated in a revised schedule are propagated across the downstream supply chain alerting end customers to any changes.

Keywords: Production Scheduling, Supplier Risk, Digital Twin, Machine Learning.

1 Introduction

In manufacturing companies today, MES and SCM information systems often work independently without any built-in feedback between systems. The information originating in either of these systems, even if potentially affecting the other, is typically not transparent across systems and latency issues can be a problem. The resultant information silos, then, may not use the most current information for decision-making. As a result, once the factory floor learns about any supply chain or supplier disruption, it is often too late to be accommodated systematically and seamlessly and can require manual rescheduling of planned production tasks. Bridging MES and SCM systems for disruption management and mitigation requires two-way information flows in order to achieve efficient utilization of resources and improved downstream deliveries.

With sense-and-respond capabilities, a manufacturer is better able to manage unexpected delays and disruptive events and avoid the latencies in response that drive inefficiencies. The approach described herein responds to the need for a concrete and practical approach that links production control to logistics risk due to supplier issues, transport delays, and other unexpected disruptions on the manufacturer's own factory floor. First, this framework integrates the flows of information about anticipated disruptions across the supplier and production processes bridging the siloes that separate them today. With this data as input, the model leverages the digital twin construct to create a virtual model of the production system that drives a machine learning engine to predict order completion and customer delivery dates. By implementing machine learning within a digital twin framework, it is possible to continuously update the model with real-time data instead of relying on offline adjustments to the production schedule or expert knowledge. Finally, the approach is practical in that it does not require sharing of confidential or proprietary data by supply chain partners, requiring only internal process data at the manufacturer, historical supplier performance data, contracted supplier delivery dates and actual, scheduled shipment arrival dates at the end customer.

2 Related Research

2.1 Disruption Management

Recent research has focused on data-driven tools that enable manufacturers to proactively manage supply chain disruptions to better manage risk and achieve resiliency [1,2,3]. The overarching goal of many of these efforts is to develop tools that sense impending supply chain risks and respond with agility—or what is referred to as "sense-and-respond" capability. Data-driven methods have been tasked with disruption and attendant risk management in a range of applications related to the framework described herein including procurement and supplier sourcing, transportation and logistics, and shop-floor production control—applications where sufficient data is typically available for model training and validation. With respect to scheduling of production systems that rely on the synchronized arrival of many parts and components, delays can be accommodated up to a break-down point beyond which the schedule fails and service targets are not met. Melançon et al. [4] developed a system that uses machine learning to send alerts when conditions on the supply chain such as combinations of events or small deviations lead to service failures. The system anticipates conditions and raises alerts in time for planners to take corrective action, but not so early that the issues would naturally be taken care of in the next production plan. With respect to supplier risk, Cavalcante et al. [5] combine simulation and machine learning to select suppliers and evaluate on-time delivery as an indicator of supplier reliability. Estimating transport delays of materials is critical to production scheduling for optimized operations. Birkel et al. [6] provide an overview of the challenges of applying predictive analytics in transport logistics. Ouedraogo et al. [7] address transport risk for multi-modal container transport, while Van der Spoel et al. [8] address a gap in the literature concerning arrival vs. travel/journey time prediction for overland trucking. Viellechner and Spinler [9] compare machine learning methods for predicting delays in ocean container shipments. Servos et al. [10] compare the performance of different machine learning methods in predicting disruptions and delay in the multimodal transport of containers.

2.2 Digital Twin

The digital twin is a virtual version of physical products, assets, processes and systems constructed for the purpose of "testing" in the virtual world prior to implanting in the real-world. One can think of the digital twin as an information mirroring concept that is able to "reflect" the behavior and real-time state of a physical object with sufficient accuracy that the manufacturing processes and production operations can be analyzed, predicted and optimized. Enabled by real-time data capture and sharing in an IIoT environment, dynamic changes can be communicated quickly between the physical and virtual worlds. One of the most researched applications of the digital twin has been modeling the product lifecycle (PLM) to capture all stages of product realization to create a comprehensive reference model to enable better product design and engineering, manufacturing and, ultimately, service [11,12]. Fewer, but a growing number, of research has focused on production control and management—the application of relevance here. Janesch et al. [13] combine a model-based digital twin and a data-driven digital twin with machine learning to explore the life cycle of manufacturing systems. Leng et al. [14] developed a digital twin-driven approach for rapid reconfiguration of automated manufacturing systems. Other applications have addressed the generation of designs for an automated flow shop manufacturing system [15] and digital twin-based production lines [16]. Min et al. [17] provide a machine-learning enabled digital twin-based framework for production optimization in the petrochemical industry.

2.3 Machine Learning for Production Control

The explosion of data-collection on the factory floor offers new opportunities to make intelligent data-driven decisions for production control. An assessment of the state-of-the-art of machine learning in production planning and control is provided by Cadavid et al. [18] and Weichert et al. [19]. Meiners et al. [20] offer an approach that implements machine learning to analyze data generated along the process chain for complex patterns that can inform improvements. Related to the framework proposed herein, and given its importance in meeting customer delivery requirements, prediction of lead times has received attention. Employing a digital twin of the processes, with online connection to the manufacturing execution system (MES) for frequent retraining of the models to keep the prediction model up to date, Gyulai et al. [21] compare analytical and machine learning models for a flow-shop environment. Mezzogori et al. [22] employ statistical and neural network techniques to predict lead times in a 6-machine job shop. Using the current workload and the expected lead time of entry jobs, the authors use artificial neural networks (ANNs) to predict reliable delivering dates. Cycle time prediction, another key indicator of delivery reliability, has also been addressed. Predicting cycle times can be challenging because process flows may include hundreds of process steps, routings through the factory, and possible equipment failures. Can et al. [23] apply genetic programming, an artificial intelligence (AI) technique, to develop predictive models of process cycle times based on system status information gathered in real-time from manufacturing execution systems.

3 Machine Learning-Enabled Digital Twin Framework

This paper develops a machine learning-enabled digital twin framework for production control and disruption management. As supply chains become leaner and more unforgiving of disruption, AI-enabled tools are being called upon to not only anticipate disruptive events but also to monitor and recognize disruptions in real time, to understand the supply chain's vulnerability to disruption, to determine the impact of any delays on production, and to recommend mitigating actions. The proposed framework addresses key sources of potential disruption that affect the execution of customer order and its delivery to the end customer. As shown in Fig. 1 below, production supply chain disruptions due to the supplier can include delays in inbound material arrival, production down time, and transport delays to the manufacturer and end customer. The supplier, manufacturer and end customer share order quantities and contracted delivery dates through their information systems, but do not formally share information related to delays that may impact downstream operations. The challenge for manufacturers is to exploit information currently available to them to reduce delays and improve resiliency.

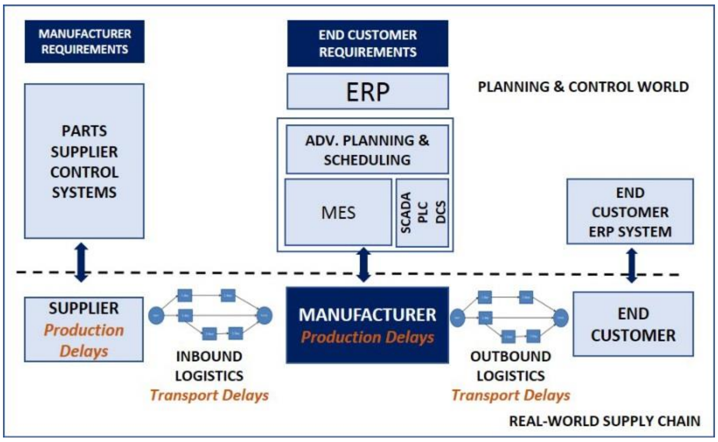

Fig. 1. Typical supply chain for a manufacturer with an upstream supplier and downstream customer with siloed information systems and potential disruptions.

The *Machine Learning-Enabled Digital Twin Framework*, comprised of three modules, is illustrated conceptually in Fig. 2 below. The *Supplier Risk Prediction Module* uses historical data of supplier performance to reveal patterns of delays, either events in the supplier's factory or logistics delays in shipping to the manufacturer. Machine learning models in the *Digital Twin Learning Engine* use the updated supplier arrival dates to predict updates to the production schedule and any changes in planned order completion dates. Expected order completion dates are then input to a *Customer Transit Module* that optimizes the best route from a cost/time perspective for shipment of the order to the end customer given the expected disruption and associated delay.

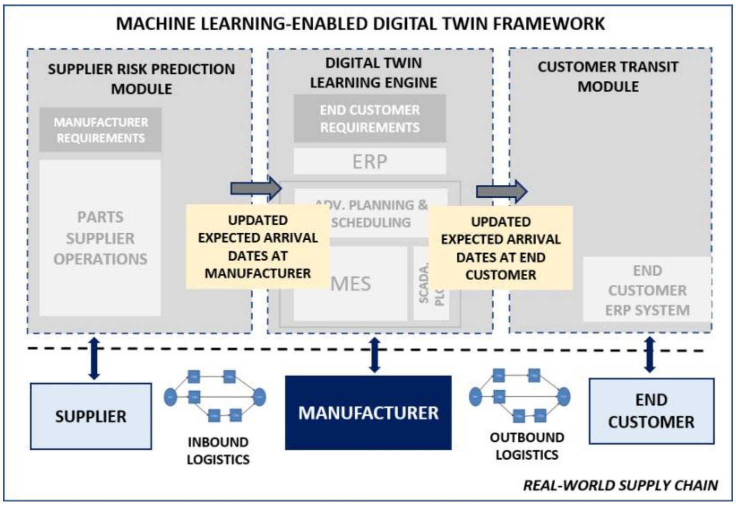

Fig. 2. *Machine Learning-Enabled Digital Twin Framework* predicts and adjusts for production and logistics disruptions that cascade from supplier through to end customer.

4 Integrated Production and Logistics Processes

4.1 Supplier Risk Prediction Model

Machine learning has shown promise in predicting supplier (non-)performance and in managing supply risks, enabling manufacturers to adopt a proactive rather than reactive response to anticipated supply chain disruption. Supply risk manifests when the actual arrival date of the shipment at the manufacturer is expected to exceed the contracted delivery date. To enable proactive response, the *Supplier Risk Prediction Module* implements machine learning to (1) classify orders that are of high and low risk of experiencing delays beyond the promised arrival date and/or (2) predict the arrival date of that shipment based on the supplier's previous experience with orders of similar characteristics. The machine learning model is trained using several years of historical data downloaded from the manufacturer's (or supplier's) ERP and other available databases, supplemented by simulated data as necessary, to provide a best prediction of the actual arrival date. Training input data include parameters such as *Supplier Name, Shipment ID, Shipment Volume, Shipment Description, Shipment Type, Order Date, Receive-By Date, Planned Ship Date, Contracted Arrival Date, Shipment Origin/Destination*, and *Carrier/Mode*. Once trained, the fitted Supplier Risk Prediction Module provides the manufacturer with the predicted arrival date which can be compared against the contracted date to provide a measure of supplier risk. The output of the *Supplier Risk Prediction Module*, i.e. predicted arrival date at the manufacturer (regression) or a days-late indicator (classification), is then passed to the *Digital Twin Learning Engine*.

The proposed *Supplier Risk Prediction Model* is developed for a supplier who must coordinate the arrival of materials and sub-components to meet delivery commitments to the OEM. Supplier delays can range from frequent short-term delays of 12-48 hours to longer-term delays that may extend weeks. Supplier delays can affect 25% of deliveries to a customer depending on industry. In these cases, patterns of delivery delays specific to suppliers, or to types of products, or to products of specific materials can provide critical information for production scheduling. For this effort, we restrict our attention to historical delivery information, and information derived from it, to give insights into these patterns. If a particular supplier is habitually late with a certain type of order, the machine learning model can predict the length of the delay (c.f. 12 hours or 2 days) based on previous supplier behavior.

A number of machine learning methods will be explored including random forest, support vector machines, k-nearest neighbors and ANNs, or logistic regression for binary target outputs. In previous work, random forest has shown to be a good method for handling data imbalances when there are fewer delayed orders than on-time orders. Delivery delays are often further amplified by exogenous events that can be difficult to predict and assess such as possibility of transport strikes or seasonal severe weather. While this model does not address these rare disruptive events, such factors could be included in the model by creating an input parameter that captures the overall environmental risk as determined by the supply chain manager. In other work, the authors have explored extracting disruption event data via APIs or by web scraping and other methods using selected sources such as *NOAA's National Weather Service (NWS) Public Alerts* and the *Global Database of Events, Language, and Tone* that provides worldwide coverage and retrieval of geopolitical and business-related disruption information.

4.2 Digital Twin Learning Engine

Unexpected events are known risks in manufacturing. Typical disruptions are a) machine failure, b) urgent job arrival, c) job cancellation, d) due date changes, e) change in job priority, and f) shortage of materials. The latter event (f) also can be caused by a delay in the arrival of material. Typically, the manufacturer receives an alert with the new adjusted date of expected material availability. This event will trigger a rescheduling process for the manufacturing in the factory. Manufacturers currently have two policies for rescheduling. Updates can be made manually by a supervisor/operator, typically experienced, who can decide on corrective actions for the factory floor. The new schedule will be edited into the production plan and executed. This procedure can be applied if the overall production plan for the factory is not too complex and timing restrictions not too tight. Depending on the complexity of the production process, tightness of time-dependencies between orders, and production delays associated with switching between orders, manual correction of the schedule is not always feasible. In this case the factory floor schedule needs to be recalculated in consideration of all factory floor activities. In general, manual adjustments tend to have less severe consequences for completion times and fewer ripple effects for other orders on the same factory floor. However, the quality and reliability of manual rescheduling depends on the quality of prediction of the supervisor/operator.

Using estimated shipment arrival dates from the *Supplier Risk Prediction Module*, the *Digital Twin Learning Engine* systematically produces updated order completion dates and recommends mitigating changes to the production schedule at the OEM that minimize delays. The *Digital Twin Learning Engine* is comprised of two parts, the *Digital Twin* and the *Sense-and-Respond Machine Learning Model.* The *Digital Twin* mirrors real-world operations on the shop floor to include data from Enterprise Resource Planning systems (ERP) that manage orders received from the customer, Advanced Planning and Scheduling (APS) systems that create a master schedule for received orders, and Manufacturing Execution Systems (MES) that manage the execution of real-time, physical processes to fulfill customer orders by contracted delivery dates. The *Sense-and-Respond Machine Learning Model* learns the dynamic patterns of the production environment from historical ERP, APS and MES data. When a supplier delay or disruption is anticipated, the model predicts the impact of the disruption on the contracted order completion date and recommends a revised production schedule and order completion dates for affected and other orders. The model will recommend mitigating machine-task assignments to the MES. If no mitigating scheduling changes can be made, the model adjusts the date of expected production completion and alerts customers. The model can prioritize customer orders, as appropriate. Other strategies such as overtime production can also be considered. As shown in Fig. 3 below, the machine learning-enabled digital twin framework includes:

1) The "physical" factory to include all the physical assets such as machines and production equipment, robots, etc. needed to fulfill customer orders;
2) The "digital" factory to include the *Digital Twin* and *Sense-and-Respond Learning Model* and other data needed to determine delivery requirements; and
3) The mapping between the physical and digital worlds for real-time data exchange.

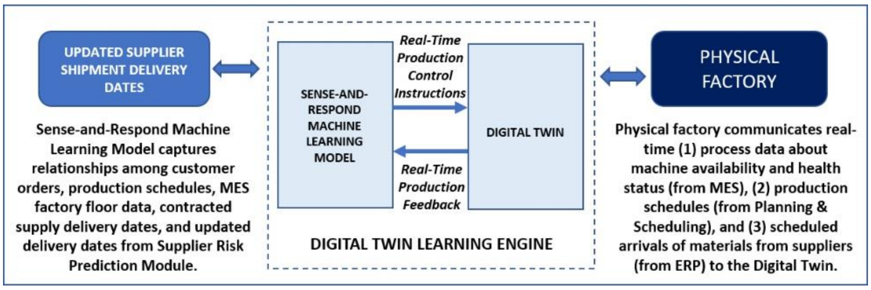

Fig. 3. The *Digital Twin Learning Engine* learns patterns of production on the factory floor.

The *Digital Twin Learning Engine* allows real-time updating of the MES and other systems based on predicted changes in arrivals of critical parts to the OEM rather than resorting to off-line adjustments to production control. The *Digital Twin* offers a continuous, interactive and real-time dialogue between the virtual and physical models of the factory floor. The *Digital Twin* is connected to relevant production systems such as MES, APS and ERP, receiving both current production schedules and timestamped snapshots of machine status and order information and assignments. Updated delivery dates from the *Supplier Risk Prediction Model*, plus real-time machine status updates and current production schedules, are input to the *Sense-and-Respond Machine Learning Model* which recommends adjustments in the production schedule, c.f. timing and sequencing of orders on specific machines. Training of the *Sense-and-Respond Machine Learning Model* can be accomplished using a number of machine learning algorithms such as support vector machines, AdaBoost optimizers, random forest or ANN. Model outputs are passed to the Digital Twin for verification and validation, and then returned to the "real" MES system for production schedule updating.

Communications between the *Sense-and-Respond Machine Learning Model* and the *Digital Twin* is achieved by information exchange using a shared database and several dedicated, automated services. The *Digital Twin* pulls data from (and pushes data to) a database that it shares with the other manufacturing management systems, e.g. ERP, MES, SCADA, etc., and which is also being continuously updated with predicted supplier delivery information flowing from the *Supplier Risk Prediction Model*. Auxiliary services prepare this information for consumption by the *Sense-and-Respond Learning Model*. The model then produces, as output, revised production schedules and machine assignments (or other pre-determined types of outcomes that the model has been trained to produce). Model outputs are consumed by another auxiliary service/software application that will store the result(s) in the shared database and can also transform the outputs into visualizations for human consumption and display on pre-programmed dashboards. The arrival of a new prediction into the shared database will trigger another service that will retrieve this information and feed it back to the *Digital Twin* to launch a new simulation to evaluate and validate that the recommended revised production schedule can respond to the delay(s) adequately and as intended. Once validated, this information is then updated in the manufacturing management systems for execution of the revised schedule on the factory floor.

4.3 Customer Transit Module

Updated estimates of order completion dates are passed to the *Customer Transit Module*. As noted earlier predicting shipment transit times and associated risks of disruption is a difficult problem, dependent on factors such as transport mode, routing, time of year/week/day, and external factors, most importantly weather and traffic. In this framework, the *Customer Transit Module* receives an estimated order completion date from the *Digital Twin Learning Engine* and projects an adjusted arrival date at the end customer. In this way, disruptions along the supply chain from supplier to manufacturing through delivery to the end customer are cascaded and incorporated into projected delivery date. Predicted transit times are modeled on a route-by-route basis, using historical data to estimate the transit time for future shipments using machine learning or optimization. Thus, the module consists of an ensemble of classifiers/models for different modes that are trained and tested using historical shipment data. The estimated transit time produced by the module and the baseline transit time established by the shipment planner are compared to determine any further delays. Depending on transport mode and geographic location, the predicted transit times can be adjusted for weather and traffic events obtained from public data sources such as weather stations, social media and news aggregators.

5 Conclusions

In this paper we respond to a gap in both practice and research by proposing a machine learning-enabled digital twin framework that bridges the gap between production process and logistics processes for the purpose of reducing supply chain risk due to disruptions in either the logistics or production environments at the supplier and manufacturer. Machine learning models provide updated estimates of expected delivery dates at each stage of the supply chain which can be applied in a digital twin simulated environment and folded into the manufacturer's MES system with recommended possible actions to mitigate those delays. Revised delivery dates can then be passed to the end customer in a seamless flow.

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