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The role of data visibility in the control and automation of modern supply chains - A model predictive control case study in Ferrari

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Abstract – Nowadays, many companies still conceive their logistic operations as a simple material replenishment of production plants and don't invest money to structure their supply chain and make processes more efficient. In addition, the high complexity and the emerging uncertainties that are characterizing a more globalized, dynamic, and interconnected world stimulate businesses to innovate the management of their supplier network. Unexpected events, such as COVID-19 and the semiconductor crisis, have put companies in research for solutions that look to improve and strengthen the partnership with their suppliers. Digitization represents one of the most innovative and disruptive challenges in today's supply chains. Indeed, the increasing amount of data retrievable from logistic and production processes today is yet not exploited enough in comparison with its potential benefits. Companies still work by silos and prefer to hide their information rather than sharing them with their partners. This research investigates the role of data visibility, in order to demonstrate its benefits in a complex supply chain. By collaborating with Ferrari on a Supplier Relationship Management (SRM) project, this paper presents the design of a supply chain control tower through Model Predictive Control. By simulating a Model Predictive Control (MPC) optimization model on a small part of Ferrari's supplier network, the coordination, efficiency, and sustainability of the supply chain are assessed through a comparison with the current state and by evaluating the network's performances in different logistic scenarios. Although this solution is presented as a decision-support tool, it is thought of as a key technology for the future development of autonomous supply chain operations.

Keywords: Data visibility; supply chain integration; model predictive control; supplier relationship management; supply chain control tower; centralized autonomous agents

1. Introduction

Supply chains today are complex, dynamic, and unpredictable fields in the world of industry, as they are highly prone to uncertainty and affected by social, political, and natural phenomena. More demanding customers require companies to constantly innovate to create and sustain a competitive advantage (Rebelo et al., 2019). Over the recent years, firms increased their product differentiation, and adapted their business strategies towards a higher customization. This change carried along new needs in the operations, such as a better use of IT and a more structured organization of production activities. Along with this trend, the rise of globalization and the development of mobility solutions have expanded logistic flows' on an international scale. On the one hand, it has leveraged the opportunities for businesses to get access to resources and clients all over the world, but on the other, it has augmented risks of stock-out and block of production lines due to more uncertainties affecting different nations and stakeholders. The widely known semiconductor crisis, for example, has created disruptions over many

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supply chains, showing their fragility and the high level of complexity to be managed. For these reasons, there is a need for logistic flows to be more reactive and predictive.

In companies, also the logistics departments have undergone a tremendous change: from purely operational functions that reported to sales or manufacturing and focused on ensuring the supply of production lines and the delivery to customers to a central, independent supply chain management (SCM) function (Alicke et al., 2016). The focus of SCM has been shifted thanks to innovative solutions that are changing the operations between suppliers and clients.

An important role in this transition can be played by digitization. A digital transformation of supply chain processes can guarantee a higher acknowledgment and control of the logistic operations along tiers and the development of a structure that can react quickly to market uncertainties. The introduction of emerging digital technologies, such as IoT, advanced robotics, and data analytics, are altering traditional ways of working and are requiring companies to rethink the design of their supply chain. Besides the need to adapt, businesses have the opportunity to reach the next level of operational effectiveness, leverage innovative logistic flows, and initiate a transition to supply chain digitization (Alicke et al., 2016). A major step in this regard is data visibility: the exchange of process information between partners allows multi-machine coordination and performance monitoring and enables the detection and, consequently, solves problems in the system faster. This could ultimately pave the way for the automation of the decision-making processes through both logistics and production.

However, data cannot show its whole potential if not managed with a collaborative and transparent mindset. Many companies have started to implement integrated processes, but very often, this is still done in silos (both horizontally and vertically), and not all information is leveraged to achieve the best result possible (Alicke et al., 2016). Although businesses are concerned about data leakage and, therefore, tend to augment privacy and protection, the key to success for any supply chain is an efficient exchange of information, which boosts the agility of the entire process (Schrauf & Berttram, 2016) and helps develop solid relationships between partners, reducing the seamless split between clients and suppliers.

In this perspective, the introduction of Supplier Relationship Management (SRM) strategies has brought important solutions to the improvement of information flows within complex logistic chains. SRM is focused on joint growth and value creation with the suppliers based on trust, open communication, empathy, and a win-win orientation, with the aim of enhancing supply chain performance and reducing costs to achieve a higher competitive advantage (Oghazi et al., 2016). The goal of the project currently under study in Ferrari is to introduce an SRM platform to create a uniform communication channel for all buyer-supplier interactions in which they can constantly exchange data and information. In this way, the buyer has the opportunity to predict any risk to its assembly processes and prevent critical issues caused by missing parts in the production lines.

The characteristics of Ferrari are its low volumes and highly customized and handcrafted products. This gives the opportunity to analyze the impact of data visibility in a supply chain marked by a high diversification of suppliers, which are mostly small-to-medium-sized companies with a historical relationship with Ferrari and whose revenue is mostly owned by the Prancing Horse. However, this choice doesn't usually match with a structured cooperation method, as these partnerships usually lead to a traditional rather than progressive process management, that stays highly flexible and low structured. Many suppliers tend to guarantee the production continuity of Ferrari's assembly line but focus on making their own interests, hiding problems in their processes, and limiting the communication and visibility with the client. As a consequence, they do not follow the client's orders and prefer to produce the daily need. If this method, on the one hand, does not compromise Ferrari's yearly volumes, it may become an issue if the company wants to increase its production throughput.

This paper aims to investigate the potential of data visibility in automating the decision-making processes in supply chain operations and develop a solution that exploits data sharing between tiers to create a centralized Model Predictive Control (MPC) control tower that, based on Ferrari's demand, can compute the optimal choices that govern the material and information flow throughout the chain. This research project aims to answer the following main research question:

"How can data visibility reduce the seamless split between manufacturers and suppliers and enhance the control and automation of supply chain processes?"

This research is based on the SIMILAR approach, which consists of seven phases: (1) **S**tate the problem, (2) **I**nvestigate alternatives, (3) **M**odel the system, (4) **I**ntegrate, (5) **L**aunch the system, (6) **A**ssess Performance, (7) **R**e-evaluate (Pollet & Chourabi, 2008).. The paper is organized as follows. In Section 2, the state-of-the-art solutions are displayed in a literature review, where the current digital technologies are implemented in different supply chains and a classification of MPC model applications for supply chain control towers. Section 3 presents the current state of the process in order to understand the quantitative impact of the research problem on supply chain operations. The modeling of the system is presented in Section 4, where the design phase of the supply chain control model is explained by describing in depth the development of an MPC scheme applied to Ferrari's supply chain. Furthermore, the future state of the system will be introduced, along with the model KPIs, to assess supply chain performance. Following, the model is applied to the current and the future state, where two different versions of MPC will be compared to demonstrate the benefits of a centralized solution over a decentralized strategy. A few scenarios are simulated within a restricted group of suppliers through Ferrari's database. In Section 6, the control models are verified in order to guarantee their validity, and the results will be finally presented and explained. Finally, the research questions will be answered in the conclusion.

2. Literature review

2.1. SRM and supply chain control towers

Supply chains are complex structures characterized by highly interconnected systems whose behavior affects the performance of the entire system. When making decisions, logistic managers need to consider not only operational parameters but also the dynamics of the market, which brings high uncertainty to the whole system. For this reason, companies are working to develop technologies that can better integrate the information flow with their suppliers to strengthen the coordination through the supply chain. SRM provides the foundation upon which supplier management, risk, performance, and sourcing strategies are based and helps organizations monitor and better plan the major supply shifts. The exchange of data can also be exploited to implement supply chain control towers that can help managers make decisions for their business operations by computing real-time choices on both a short- and long-term horizon regarding the material and information flow. Control towers are software offering key value-adding services that improve the material flow in the Supply Chain network and exploit the collection of data by designing personalized dashboards focused on monitoring order status, stock, and supplier performance. The goal of this innovation refers to gaining control of the information flows around transportation, inventory, and order activity and managing those activities from a single location (Kolehmainen, 2013). This facilitates a coordinated network to manage complexity and execute at levels that cannot otherwise be managed easily by humans (Liotine, 2019). Important changes and innovations brought by a supply chain control tower that differentiates them from ERP systems based on IBM (2022) and Verwijmeren (2017) are: (a) *Real-Time Order Planning:* a control tower captures key data in real-time, such as delivery time, inventory availability, and transportation costs, to improve customer service levels; (b) *Exceptions Management:* establishing end-to-end supply chain visibility and correlating data across siloed systems with external event information helps to better predict disruptions. Smart alerts provide insights into the upstream and downstream impact of events in the supply chain and induce a company to work on the exception; (c) *Granular Visibility and collaborative information sharing:* a control tower would ideally provide granular visibility into the details of each order. Furthermore, a better collaboration through data exchange helps the supply chain to increase its responsiveness to unplanned events and global disruptions, driving its overall efficiency and performance; (d) *Optimization of the logistic effort:* improving data visibility along the supply chain enhances better management of the logistic processes and helps to prioritize a business' effort and resources. Supply chain digitization is not a rapid process, as it usually requires a high resettlement of the IT infrastructures, a certain level of coordination between the stakeholders for the on-boarding, and it needs to be coupled with the education of the end-users, from the single employees to the suppliers themselves. According to Jones (2022), control towers can be deployed in four levels:

Level 1 - Visibility: monitoring the stock of finished and semi-finished products, tracking the transports and foreseeing the future supply helps the whole supply chain to increase robustness and responsiveness.

Level 2 - Alerts: the supply chain control tower sends out alerts regarding bottlenecks or out-of-stock to the logistic stakeholders, who will be able to prioritize their efforts towards the components that bring a high risk to production continuity.

Level 3 - Decision-support: the supply chain has reached digital maturity, processes are fully mapped and all suppliers are integrated. Transactions are executed within the control tower, and the users make decisions based on the recommendations of intelligent agents.

Level 4 - Autonomous: the intelligent agents embedded in the execution layer run the supply network without human intervention through high-tech digital solutions such as Artificial Intelligence and Machine Learning.

While several vendors propose solutions that aim to cover Levels 1 and 2 of the supply chain control tower integration, the aim of this research is to investigate how Big Data, communication networks, digital infrastructures, and control strategies can push an SRM system to become a decision-support tool or eventually be able to coordinate autonomously an entire logistic process between tiers or, in large-scale, the entire supply chain.

2.2. Supply chain control models and MPC

MPC is a popular solution in the industrial world and has been widely used by the literature to design supply chain control strategies. An overview of all the case studies examined in this paper is presented in Table 1.

Table 1. Literature overview of MPC models applied in supply chain case studies

Reference	Control Strategy	KPIs	SC tiers	Sector	Market Data	Current State	Multiple scenarios
(Perea-Lopez et al., 2003)	Centralized MPC Distributed MPC	Profit maximization	4	Generic	×	×	×
(Braun et al., 2003)	Decentralized MPC	Stock monitoring Order monitoring Min demand variations	3	Semiconductor	×	×	×
(Wang et al., 2004)	MPC + move suppr.	Stock monitoring	-	Semiconductor	×	×	×
(Lin et al., 2005)	Min Variance Control	Stock monitoring Backlog minimization Min demand variations	-	Generic	×	×	×
(Dunbar & Desa., 2007)	Distr. nonlinear MPC	Stock monitoring Min unfulfilled order Order monitoring Min demand variations	3	Generic	✓	×	✓
(Jingshuang et al., 2008)	Distributed MPC	Stock monitoring Min demand variations	-	Generic	×	×	×
(Maestre et al., 2009)	Centralized MPC Distr. non-coop. MPC Distr. cooper. MPC	Stock monitoring Min demand variations	2	Generic	×	×	✓
(Maestre et al., 2011)	Distributed MPC	Stock monitoring Max demand satisfaction	N	Generic	×	×	×
(Miranbeigi & Jalali, 2011)	Decentralized MPC	Stock monitoring Min transport costs Backlog minimization Min demand variations	4	Generic	×	×	×
(Wang & Chen, 2014)	Centralized MPC	Stock monitoring Min demand variations	4	Automotive	×	✓	×
(Hipólito et al., 2020)	Centralized MPC	Stock monitoring Overdue goods Overproduction Transport minimization	3	Food	×	×	✓

Maestre et al. (2009) compare the performance of centralized MPC, distributed non-cooperative MPC, and distributed cooperative MPC. Results show that coordinated distributed MPC is the most time-efficient solution for reaching optimal performance, which is focused on keeping the stock and the unfulfilled orders close to a reference value. Another distributed MPC solution is proposed by Maestre et al. (2011), where independent agents must negotiate to make a cooperative decision to control the stock levels. Perea-Lopez et al. (2003) present a Mixed-Integer Linear Programming (MILP) model for supply chains, implemented with an MPC scheme and a rolling horizon approach. In this case study, the model represents the logistic flow as a whole, from the raw material warehouse to the end-consumer, and is tested with three different strategies: a centralized and two decentralized approaches, where the objective is to optimize the manufacturing and distribution costs. The paper underlines how a central coordinator is able to better coordinate its resources and reduce costs by balancing the distribution network and the plant. Miranbeigi and Jalali (2011), Wand et al. (2014), and Wang et al. (2004) demonstrate how an MPC controller, with real-time updates to demand variations, enhances the supply chain performance and deals with uncertainty and stochasticity. A food supply chain case study is displayed in Hipólito et al. (2020), where a centralized MPC framework is proposed as a decision-support tool to address the logistics management of perishable goods. In Dunbar and Desa (2007), a distributed nonlinear Model Predictive Control strategy is designed for an application in a large supply chain comprised of cooperative dynamic sub-systems. By communicating states and by using move suppression systems, the MPC controller penalizes any "disagreement" between the subsystems on a coupled variable. The study presented by Braun et al. (2003) is based on the application of a decentralized MPC scheme on a semiconductor supply chain. This six-node example suggests that the MPC strategy can be readily extended to handle complex systems in a robust manner. Results show that a control-oriented approach may require significantly lower safety stock levels compared to industry heuristics while still maintaining high customer satisfaction levels. In Jingshuang et al. (2008), an optimization-based distributed MPC scheme is applied to a dynamic supply chain network, with the aim of satisfying the customer orders with minimum inventory over a specified rolling time horizon. A move suppression term that penalizes the rate of change in the transported quantities increases the robustness of the control system. Finally, a Minimum Variance Control (MVC) approach is undertaken by Lin et al. (2009) to maintain an inventory level that is just enough to satisfy customer demand, avoiding the formation of the bullwhip effect. Simulation results show that this strategy can be successful with both stationary and variable demand.

In this paper, Model Predictive Control is applied to an automotive supply chain study case, and its performance is assessed through several KPIs by analyzing two different control strategies in various scenarios. Differently from the literature, in this paper, the future state is compared with a simulation of the "as is" condition in order to show the benefits of data visibility on supply chain operations. In particular, a supply chain control tower, governed by a single centralized MPC agent, is evaluated against a decentralized MPC scheme designed to simulate the behavior of the current state of Ferrari's supply chain. The use of real market data allows us to analyze the concrete impact of the proposed solution on the logistic KPIs. The model is designed to optimize, at the same time, stock levels, backlogs, the supplier service level, and order variation over the chain. Finally, for the first time, the MPC models are tested over multiple scenarios: the ability to recover from an initial backlog, the capability to react to a material shortage, and a variation of the OEM (Original Equipment Manufacturer)'s production mix are analyzed and compared. The goal is to show how a digital supply chain is more robust and efficient to the dynamic behaviour of today's markets.

3. Case description

3.1. Ferrari's current state

The analysis of Ferrari's processes was essential to understand the logistics of an automotive business that presents an extra complexity caused by a high product customization and a variable range of components ordered and produced along its supply chain. In the current state, Ferrari weekly updates its supply program, sending its demand to the suppliers in the form of both a confirmed quantity in a defined frozen period and a forecast over a long-term horizon, subject to change week by week depending on the production mix. Once the programs are received, it is the supplier's duty to guarantee on-time deliveries. However, due to various factors in the supply chain, it might happen that suppliers deliver the material late or just in time for assembly, which not only lowers their service levels but, in the case of critical components, may even put at risk the client's production flow. These scenarios may induce an increase in the car's production lead time and delays in the delivery to the end customer. The reasons for these issues can be various: they might range from issues at the supplier's plant, such as production stops, scrapped pieces, and operators' absenteeism, to abnormal events in the transport and handling operations, such as traffic jams, delays at customs clearance, inventory variations, and obsolescence. Furthermore, the past years have shown how modern supply chains, relying on globalized flows and, therefore, multiple local factors, are highly subject to disruptions: more recent examples are the semiconductor crisis that created huge rises in demand with low offers, contributing to the creation of bullwhip effects, the blockage of the Suez canal by the container ship Ever Given, and ultimately the pandemic, which anesthetized the Asian industry sectors for weeks. These events have uncovered the fragility of globalization and unveiled the importance of reactivity in decision-making between buyers and suppliers. For this purpose, open communication and data sharing have become important levers in the supply chain competitiveness in the market.

By observing the current state of the process, it was possible to identify the points of improvement in Ferrari's logistics, which have an effect on the supply chain and on the assembly line. They have been selected according to the Lean methodology TIMWOODS (Pannel, 2020).

Transportation: Lack of coordination often causes high backlogs and increases the probability of missing pieces in the assembly line. As a consequence, the frequency of urgent transport increases, which makes supply chains less efficient and sustainable.

Inventory: A supplier that does not follow the programs may become uncontrollable also for the delivery of extra quantities, which, if accepted, risks excessively filling up the warehouse with useless material, increasing the risk of losses and obsolescence.

Waiting: Missing components for the assembly causes supply chain inefficiencies in the production flow. Cars that need to be stopped create a time waste, an increase in costs for extra-work recoveries, and may cause delays in the delivery to the customer.

Overprocessing: Lack of data visibility causes a higher burden of daily activities for logistic employees. Phone calls or emails to ask about stocks and capacity are another form of waste. From a measurement conducted in the logistics department, the average time spent daily by material planners for non-value-adding activities caused by supplier backlog adds up to 3 hours.

Skills: Competent resources spending much of the working day on non-value-adding activities are non-utilized talent for the company and a waste of potential for innovative projects on supply chain operations.

3.2. The analogy with Decentralized MPC

In this section, it is explained how businesses that lack of coordination within a supply chain can be associated with a decentralized MPC strategy. This analogy is made both to model the current state and to evaluate its potential application for automated supply chain control to compare with a centralized control strategy. DMPC can simulate the way businesses currently interact within the network. In this scheme, every company consists of its own MPC agent that looks for the optimal system inputs that maximize the company's own objectives. Like businesses operating by silos, in this configuration, nodes do not communicate any type of information (states, variables, or computed choices) with each other. A graphical representation of a DMPC structure is displayed in Figure 1.

4. Supply chain model

4.1. The model

Since Ferrari's supply chain is composed by a wide network of suppliers, which makes it a complex system with a high amount of variables, the focus of the study is related to the supply of the dashboard. This Part Number (PN) is formed by many sub-components, produced in different parts of the world. Due to computational constraints and for the sake of simplicity, for this simulation, the supply chain was reduced to a total of 5 companies: the OEM (Ferrari itself), TAM, the dashboard Tier-1 supplier, and three Tier-2 suppliers: ProPlastic, which produces the dashboard's cover, Mtronic, which supplies the electronic board, and EBOVx, which manufactures the Thin Film Transistor (TFT) displays. In order to comprehend the scope of this simulation, it is important to focus on the choices made for the design of this model. For this reason, it is crucial to have a complete vision of the supplier process, from the arrival of inbound material to the shipping of the finished product.

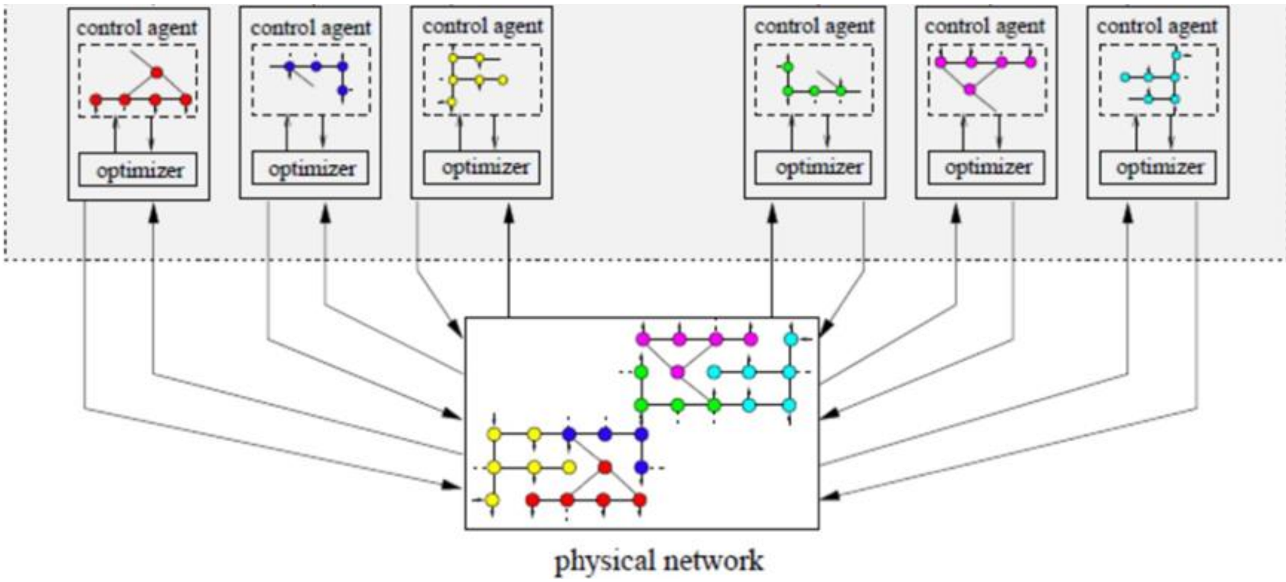

Figure 1. Decentralized MPC scheme

Being able to look into the supplier's stocks and production capacity gives a broader perspective of the supply chain operations and facilitates a better coordination on the decisions to be made.

As a MPC controller is characterized by an optimization algorithm, this section shows how the OEM's supply chain has been represented into an optimization model. First, the sets and parameters of the model are presented. These data have been taken from Ferrari's suppliers and can be considered reliable for this simulation. Following, the model variables are listed and described. The system equations and constraints are then explained in detail.

4.1.1. Model environment

Indices

i	Index of the material produced or transported
k	Index of the supply chain node
k'	Index of the node upstream of node k
k''	Index of the node downstream of node k
l	Index of the production line
n_k	Index of the tier level along the supply chain
r	Index of the material consumed
t	Index of the discrete time instant

Sets

N	Network of companies in the supply chain

L_k Set of production lines at node k

M Set of products

T^{n_k} Set of companies at Tier-n

Parameters

$z_{k,k''} = \begin{cases} 1 & \text{if node } k \text{ delivers to node } k'' \\ 0 & \text{otherwise} \end{cases}$

LT_i^k Production lead time of product i at node k

OF_i^k Order frequency (days) at node k for product i

$\rho_{r,i}$ Consumption rate of material r on product i

$\tau_{k,k''}$ Transit time between node k and node k''

V_l^k Production capacity of process unit l at node k

LB_i^k Logistic batch of product i at node k

PB_i^k Production batch of product i at node k

FD_i^k Program frozen days of product i sent by node k

$e_k^i = \begin{cases} 1 & \text{if product } i \text{ is an inbound material at node } k \\ 0 & \text{otherwise} \end{cases}$

$o_k^i = \begin{cases} 1 & \text{if product } i \text{ is an outbound material at node } k \\ 0 & \text{otherwise} \end{cases}$

$S_{ref,k}^i$ Target stock value of product i for node k

4.1.2. System variables

States

S_k^i Stock level of product i at node k

B_k^i Backlog of node k for product i

Ou_k^i Unfulfilled order of product i sent by node k

$Q_{i,l}$ Quantity of product i produced by process unit l

P_k^i Production throughput of product i at node k

C_k^r Consumption of material r at node k

O_k^i Order sent by node k to suppliers of product i

d_k^i Demand of product i requested by the client to node k

$x_{k,k''}^i$ Delivery of product i from node k to node k''

$lb^i_{k,k''}$ Batches of product i shipped from node k to k''

pb^i_k Batches of product i produced at node k

Sv^i_k Floating stock level of product i at node k

$tt^i_{k,k''}$ Shipment of product i from node k to k''

oo^i_k Batches of product i ordered by node k

$p^l_i = \begin{cases} 1 & \text{if product } i \text{ is being processed by line } l \\ 0 & \text{otherwise} \end{cases}$

$f^k_i = \begin{cases} 1 & \text{if product } i \text{ is being ordered by node } k \\ 0 & \text{otherwise} \end{cases}$

4.1.3. System equations

$$S^i_k(t+1) = S^i_k(t) + e^i_k\left(\sum_{k'\in N}\left(z_{k',k}x^i_{k',k}(t+1)\right) - C^i_k(t+1)\right) + o^i_k\left(P^i_k(t+1) - \sum_{k''\in N}\left(z_{k,k''}x^i_{k,k''}(t+1)\right)\right), \quad \forall i \in M, l \in L_k, k \in N \tag{1}$$

$$Ou^i_k(t+1) = Ou^i_k(t) + O^i_k(t+1) - \textstyle\sum_{k'\in N} x^i_{k',k}(t+1), \forall i \in M, l \in L_k, k \in N \tag{2}$$

$$B^i_k(t+1) = B^i_k(t) + d^i_k(t+1) - \textstyle\sum_{k''\in N} x^i_{k,k''}(t+1), \forall i \in M, l \in L_k, k \in N \tag{3}$$

$$Sv^i_k(t+1) = Sv^i_k(t) + o^i_k \cdot \left(P^i_k(t+1) - \textstyle\sum_{k''\in N} z_{k,k''} \cdot tt^i_{k,k''}(t+1)\right), \forall i \in M, l \in L_k, k \in N \tag{4}$$

Equations 1, 2, 3, and 4, respectively, represent the stock, unfulfilled order, backlog, and floating stock balance of product i with the inbound deliveries and outbound shipments. In particular, for Ferrari, the car assembly part is neglected, and the dashboard consumption represents the production demand, while for Tier-2 suppliers, the inbound received material is not taken into consideration (infinite raw material assumption), and therefore, the unfulfilled orders are set to zero. Equation 4, oppositely to the stock balance (Equation 1, which is updated only when a new amount of material is delivered, shows the physical finished product availability in the supplier warehouse, which is consumed once the material is *shipped*.

4.1.4. Constraints

Non-negative constraints

$$S^i_k, Ou^i_k, B^i_k, Sv^i_k, x^i_{k,k''}, p_{i,k,l}, Q_{i,k,l}, P^i_k, C^i_k, d^i_k, O^i_k, pb^i_k, lb^i_k, ti^i_{kk''}, oo^i_k, f^i_k \geq 0, \ \forall i \in M, l \in L_k, k, k'' \in N \tag{5}$$

4.1.4.1. Supplier production

$$p_{i,k,l}(t) \leq o_k^i, \forall i \in M, \forall k \in N, \forall l \in L_k \tag{6}$$

$$\sum_{i \in M} \sum_{t^*=t-LT_k^i+1}^{t} p_{i,k,l}(t^*) \leq 1, \forall k \in N \setminus \{\text{ Ferrari }\}, \forall l \in L_k \tag{7}$$

$$Q_{i,k,l}(t) \leq p_{i,k,l}(t) \cdot V_l^k, \forall i \in M, \forall k \in N \setminus \{\text{ Ferrari }\}, \forall l \in L_k \tag{8}$$

$$P_k^i(t) = \sum_{linL_k} Q_{i,k,l}\left(t + LT_k^i\right), \forall i \in M, \forall k \in N \setminus \{\text{ Ferrari }\} \tag{9}$$

$$C_k^i(t) = \rho_i^r \sum_{linL_k} Q_{i,k,l}\left(t + LT_k^i\right), \forall i \in M, \forall k \in \{\text{ Ferrari, TAM }\} \tag{10}$$

$$\rho_i^r \cdot \sum_{linL_k} Q_{i,k,l}\left(t + LT_k^i\right) \leq S_k^r(t), \forall i \in M, \forall k \in N \setminus \{\text{ Ferrari }\}, \forall l \in L_k \tag{11}$$

$$P_k^i(t) = PB_k^i \cdot pb_k^i(t), \forall i \in M, \forall k \in N \setminus \{\text{ Ferrari }\} \tag{12}$$

4.1.4.2. Material flow

$$x_{kk''}^i(t) \leq M \cdot o_k^i \cdot e_{k''}^i, \forall i \in M, \forall k, k'' \in N \tag{13}$$

$$tt_{kk''}^i(t) \leq Sv_k^i(t), \forall i \in M, \forall k \in N \setminus \{\text{ Ferrari }\}, \forall k'' \in N \tag{14}$$

$$x_{kk''}^i\left(t + \tau_k^{k''}\right) = tt_{kk''}^i(t), \forall i \in M, \forall k \in N \setminus \{\text{ Ferrari }\}, \forall k'' \in N \tag{15}$$

$$x_{kk''}^i(t) \leq LB_k^i \cdot lb_{kk''}^i(t), \forall i \in M, \forall k \in N \setminus \{\text{ Ferrari }\}, \forall k'' \in N \tag{16}$$

4.1.4.3. Information flow

$$O_k^i(t) \leq M \cdot e_k^i, \forall i \in M, \forall k \in N \tag{17}$$

$$d_k^i(t) = \sum_{k'' \in N} z_{kk''} \cdot O_{k''}^i, \forall i \in M, \forall k \in N \setminus \{\text{ Ferrari }\} \tag{18}$$

$$f_k^i(t) \leq e_k^i, \forall i \in M, \forall k \in N \setminus \{\text{ Ferrari }\} \tag{19}$$

$$\sum_{t^*=t-OF_k^i+1}^{t} f_k^i(t^*) \leq 1, \forall i \in M, \forall k \in N \setminus \{\text{ Ferrari }\} \tag{20}$$

$$f_k^i\left(t + OF_k^i\right) = f_k^i(t), \forall i \in M, \forall k \in N \setminus \{\text{ Ferrari }\} \tag{21}$$

$$O_k^i(t) \leq M \cdot f_k^i(t), \forall i \in M, \forall k \in N \setminus \{\text{ Ferrari }\} \tag{22}$$

$$O_k^i(t) \leq LB_k^i \cdot oo_k^i(t), \forall i \in M, \forall k \in N \tag{23}$$

Constraints 6 and 7 define the WIP requirements in the optimization model, which must be associated to the component's manufacturer and must respect the lead times of the production line in terms of time occupation. Constraint 8 sets each supplier's production capacity of every line and component, while Constraints 9 and 10 respectively define the throughput of a finished product and the consumption of every component used to make it. In Constraint 11, a product is allowed to be manufactured only if all its components are available on stock. Constraints 13 and 14 respectively norm that the delivery of a component is permitted only if the arc between the shipping and receiving node is activated, and if there is enough finished product stock in the warehouse. The equation in Constraint 15 defines the association between delivered material and shipped material, which is based on the transit time between the supplier and the client. Constraint 18 implies that every supplier's demand is created by the generation of a client's order. In Constraints 17 and 19, the feasibility of the order is set up, while Constraint 22 allocates orders based on their frequency and delivery schedules, as defined in Constraints 20 and 21. Finally, Constraints 12, 16, and 23 deal with the setting of the number of batches for respectively every production, shipment, and order.

4.2. Future State

The aim of this project is to improve the information flow between the OEM and its suppliers to bring more efficiency to the process and avoid any risk of stock-out and production stop. By observing the current state, there are three supply chain needs addressed with this project:

- **Suppliers capacity and bottlenecks:** Real-time monitoring of suppliers' production capacity in order to improve partner collaboration, make the production planning more efficient, and anticipate any risk of backlog and shortages.
- **Order management:** Complete integration of order management with the suppliers by gaining information about their ability to absorb the OEM's demand in the short and long term.
- **Inbound logistics management:** Improve suppliers' stock visibility, control the inbound material flow, and work through exception management and alert generation.

In the future state, the focus of the proposed solution is the digital exchange of data between clients and suppliers, which allows them to gain visibility and better coordinate logistic operations. In this sense, the improvement of the information flow would help to increase the performance of the material flow operations over tiers. However, data has much more potential than increasing awareness over the chain. The goal of this paper is to demonstrate how data visibility could not only improve the efficiency of a complex supply chain but even pave the way for the automation of the logistic operations between clients and suppliers in terms of both material and information flow. In this way, the role of a supply chain control tower gains value as it becomes a decision-support tool for logistic managers. It enables them to identify faster the bottlenecks in the system and intervene promptly to solve issues in their supplier network. In order to analyze the impact of this innovation, here is described how this solution could reduce the inefficiency in the system, by using the TIMWOODS methodology, in analogy with the discussion of the current state in Section 3.

- **Transportation:** as data exchange leads to the automation of the decision-making process, it is expected that higher punctuality of suppliers reduces the number of urgent transports and the extra costs currently undertaken. Moreover it also helps the supply chain to reduce its environmental footprint.
- **Inventory:** Data visibility and automation also enhance the reduction of extra quantities shipments and extra batch management, which has an impact on the risk of scrapped pieces and packaging material costs.
- **Waiting:** Data visibility reduces the amount of missing pieces on production lines and the amount of time for a product to waste time in the process. Finally, it also increases the service levels towards the end-consumer.
- **Overprocessing:** the increase in transparency and the automation of decision-making reduces material planners' non-value-adding activities. In a future perspective, the operational role of the material planner is limited to monitoring the correct processing of the automated operations.
- **Skills:** companies can benefit from this innovation to exploit their resources in a more efficient manner by raising their work to a tactical or even strategic level.

In order to achieve complete data visibility over supply chain processes, it is necessary to have an agent able to keep an eye on the whole network in order to totally control and optimize the chain. Centralized Model Predictive Control (CMPC) is the solution chosen for this study case. A centralized controller has visibility over the whole supply chain, measures all variables in the network, and determines actions or set points for all the system's actuators (the supplier's shipments and the client's orders). Oppositely to a decentralized controller, it optimizes at every iteration a single objective function that encloses the goals of all the companies involved. A representation of a CMPC scheme is displayed in Figure 2.

4.3. Simulation KPI's

Since MPC is an optimization problem, it is also necessary to investigate the performance of the system under study. The main goal of every business is always to make the highest money with the lowest costs. Supply chains are a central part of a business because they involve production and, therefore, direct income for the businesses involved.

Service levels are a widely used KPI used by OEMs to monitor the performance of their suppliers. The main impact on these parameters is given by delivery punctuality: the orders should be satisfied in the times indicated by the programs, and backlogs should be minimized. At the same time, the client should guarantee a minimum variation of the ordered quantity over time in order not to create a bullwhip effect over the supply chain and possibly cause disruptions. Additionally, as another issue caused by globalization is the logistic environmental footprint, another goal for supply chains is the reduction of transport, causing high emissions. Finally, warehouse stock is also important, as it has a direct impact on a business' finances. The KPIs extrapolated from the model are the following:

- **Supplier backlog:** a normalized index of the backlog over the whole supply chain is computed as described below. The efficiency of the supply chain increases when this value is low.

$$\text{Backlog index} = \frac{\text{Backlog}}{\text{Logistic batch}} \tag{24}$$

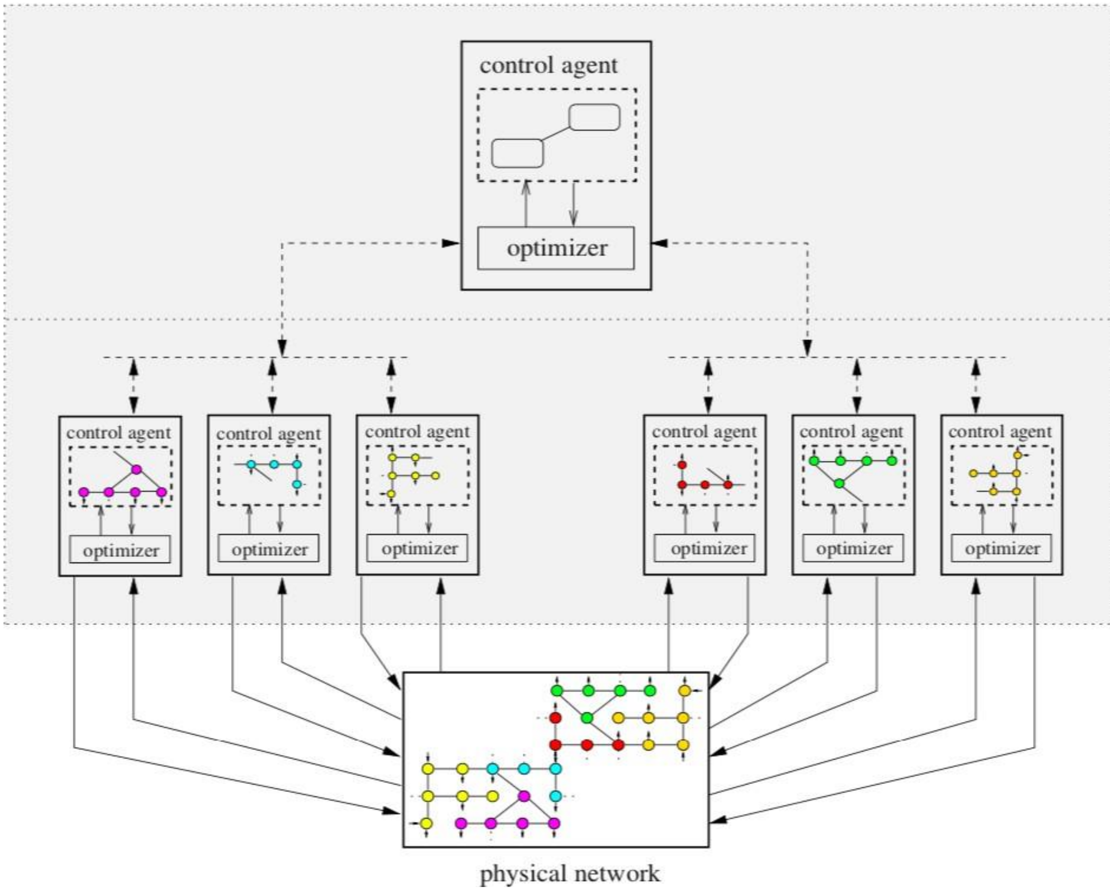

Figure 2. Centralized MPC scheme (Negenborn et al., 2010)

- **Material stock:** The stock trend is compared with the target defined by the company. The efficiency of the warehouse management over the supply chain goes along with the minimization of this value.

$$\text{Stock index} = \text{mean}\frac{(\text{Stock} - \text{Target stock})}{\text{Logistic batch}} \tag{25}$$

- **Order variation:** This index evaluates how much a client keeps its ordered quantity flat throughout time, which is essential not to increase the complexity over the chain. This value is represented by a percentage ratio and shows a better efficiency of the supply chain with low values.
- **Supplier punctuality:** This KPI analyses how the model allows a supplier to be on time with its deliveries. It is represented by the percentage ratio of the times an order O at time t is fulfilled with a delivery x of the same exact quantity. This value is higher if a supplier manages to follow the client's program.
- **Number of transports:** As another supply chain goal should be minimizing its impact on the environment, the simulation also measures the number of transports that are made over the running time, in order to evaluate which option makes the logistic operations more sustainable.
- **Simulation running time:** This performance index is chosen to compute the computational cost given by the two different control strategies in order to assess their time efficiency.

5. MPC simulation

The MPC model is simulated through a convex Mixed-Integer Quadratic Programming (MIQP) optimization problem. This program has been coded and simulated in Python in order to create a unique MPC algorithm customized for a supply chain application, and the model optimization has been solved by Gurobi.
Since Model Predictive Control consists of optimization cycles based on an objective function (as described in Section 2.2), the temporal dynamics of the model must be defined. Working days are chosen as the discrete-time measure unit. Then, it is crucial to define the simulation parameters:

- **Prediction horizon (H_p):** In every iteration of the MPC, it represents the number of discrete time steps along which the model predicts the output states of the model.
- **Control horizon (H_C):** In every iteration of the MPC, it represents the number of discrete time steps along which the model computes the optimal input actions.
- **Simulation time (T_{sim}):** The number of iterations chosen to run the MPC control.

In this simulation, the running time T_{sim} has been set to 120 working days (around 6 months), while H_p and H_C (that have the same value) are set to 15 days (around 3 weeks). The simulation code has been written and structured as an MPC algorithm, characterized by a number of iterations equal to the simulation time. Every iteration corresponds to an optimization cycle of the MPC problem, running with the receding horizon principle over H_p.

Objectives

The performance of a supply chain can be assessed by focusing on the efficiency of the logistic network, which should consist of minimized waste throughout the process, extra-flow operations, and overprocessing.
To summarize, these are the terms included in the MPC model's objective function:

- **Minimization of the backlog B:** Every supplier must be committed to eliminate the backlog towards their clients in order not to compromise their production continuity.
- **Minimization of the unfulfilled orders Ou:** In analogy with the supplier's commitment to minimize the backlog, the aim for the client is to not have any material still to be received from the suppliers.
- **Minimization of order quantity variation ΔO:** Clients should minimize the order quantity variation, finding a compromise between safety stocks and frozen order periods, in order not to create entropy and complexity within the supply chain.
- **Supplier punctuality ΔXO:** This term equals the difference between the received quantity x and the program order O; the aim is to incentive the supplier to deliver the quantity once, and in the times and quantity indicated by the program in order to also reduce the number of transports.
- **Minimization of the warehouse capital S:** According to the warehouse's volumetric capacity and the material's or product's price, the model aims to keep the stock close to a chosen target (S_{ref}).

Comparing the terms of the performance function with the KPIs presented in Section 4, it can be observed that the unfulfilled order index is not included in the KPIs. Indeed, for this study, client unfulfilled orders are equal to the supplier backlog, as the supply is single-sourcing. In opposite cases, this term could be included in the KPIs analysis. Since these terms have a different impact on the validity of the model, they are coupled with a weight w.

5.1 DMPC current state model

The current state of Ferrari's supply chain is a logistic network where there is a lack of communication of data and information between the different nodes. In order to recreate this scenario with mathematical modeling, the focus of the design shifts to the objectives of the system and of the behavior assumed in the simulation by the different actors involved. For this reason, in the design of a DMPC controller, every company behaves like an independent control agent who aims to satisfy his own goals without paying attention to the efficiency of the entire system.

The objective function for the MPC optimization problem of the current state, as a consequence, is specific for every company and is here displayed:

$$J_k = \min\left[\sum_{j=1}^{H_p}\sum_{i\in M}\left(w_k^S\cdot\left(S_k^i(t+j)-S_{ref,k}^i\right)^2+w_k^B\cdot\left(B_k^i(t+j)\right)^2+w_k^{Ou}\cdot\left(Ou_k^i(t+j)\right)^2+\sum_{k''\in N} w_k^{\Delta XO}\cdot\left(\Delta XO_k^i(t+j)\right)^2\right)\right],\ \forall t\in(0,\dots,T_{sim}-1) \tag{26}$$

This choice increases the computational cost of the simulation, as the number of optimizations, at every iteration, must be equal to the number of nodes in the logistic network. Since in the current state companies work by silos and focus only on the optimization of their processes, the only data that is shared is of course the physical quantity arriving from the upstream nodes. In fact, in reality, it often happens that the quantity shipped not only does not correspond to the programs, but also it is not communicated to the client, who figures it out either observing the quantity in transit, or notices it only once the material has been received. As the simulation starts from the upstream tiers to the OEM (Ferrari), at every time step, every inbound material is set equal to what has been decided by the control agent upstream in the logistic flow.

5.2 CMPC future state model

Data visibility is the key feature of a centralized MPC controller. By overlooking every company within the chain, the aim of this central agent is to optimize the operations within every node to increase the efficiency of the entire network. In this scheme, the supply chain works as a single entity, comprising companies that collaborate together to reach a common goal, while also satisfying their own objectives as much as possible. The downside of this solution, on the other hand, is a high computational cost, as the number of variables in the optimization model increases. This cost rises even more with the size and the complexity of the logistic network.

In the definition of the CMPC model, oppositely to a decentralized controller, every system's state will be part of a single objective function, that is defined as following:

$$J = \min\left[\sum_{j=1}^{H_p}\sum_{i\in M}\left(w_{Ferrari}^B\cdot\left(B_{TAM}^i(t+j)\right)^2+\sum_{k\in N}\left(w_k^S\cdot\left(S_k^i(t+j)-S_{ref,k}^i\right)^2+w_k^B\cdot\left(B_k^i(t+j)\right)^2+w_k^{Ou}\cdot\left(Ou_k^i(t+j)\right)^2+w_k^{\Delta O}\cdot\left(\Delta O_k^i(t+j)\right)^2+\sum_{k''\in N} w_k^{\Delta XO}\cdot\left(\Delta XO_k^i(t+j)\right)^2\right)\right)\right],\forall t\in(0,\dots,T_{sim}-1) \tag{27}$$

In this centralized configuration, the system is governed by a single supply chain control tower, that is able to constantly monitor every state of the process and make optimal decisions on all the material and information flows. This new methodology clearly differs from the current state and proposes a more structured, uniform and transparent logistics, where non-value adding activities are minimized and autonomous operations are promoted.

In fact, while today many decisions are made by humans, with a mainly unilateral communication (client → supplier), the future state would introduce a single platform, accessible by all the stakeholders of the chain, where decisions are automatically made by the computer; companies, through a simple monitoring activity, can either confirm them or propose new adjustments.

The states of the model are several, but can be mainly summarized in the stock, the backlog and the unfulfilled orders. The control variables, instead, are not only represented by shipments between nodes, the company's production and material consumption, but also include the client orders, that must respect a frozen day period (FDk = 10 days). It is important to mention that, oppositely to the DMPC simulation, where orders are predefined and set by every company, in the future state they are automatically computed based on Ferrari's demand, which is the only system disturbance.

5.3 Simulation scenarios

In order to demonstrate the validity of this innovation, the models are tested in four supply chain scenarios, where the dynamics of the logistic network are applied in different conditions, representing standard and critical situations. In this way, the two models can be compared by studying how they react to the variation of boundary conditions and to adversities. This analysis has the goal to prove how an integrated supply chain has a better capability and robustness to handle these complexities than the current state, where the operations are more decentralized and companies tend to be self-centered. The scenarios selected for this simulations are based on real or likely cases in an automotive supply chain. They are listed and explained below.

Scenario 1: Zero backlog

This scenario represents a standard condition where the supply chain is working efficiently and no problems are being faced. All suppliers have initially zero backlog towards their clients. Furthermore, no production issues or material shortages are experienced on both short- and long-term. The objective of this simulation is to show how the two MPC models react in a standard and controllable situation.

Scenario 2: Backlog recovery

In this scenario, all suppliers have accumulated an important backlog towards their clients, which creates a potential risk of Ferrari stock-out, due to supplier inefficiencies. This situation generates more urgency in the logistic operations and brings entropy to the system, which is expected to work more extra-flux in order not to stop Ferrari's production. The simulation aims to compare the ability and speed of the two models to recover the initial backlog.

Scenario 3: Material shortage

In this scenario, the system is put under stress with a serious risk of production blockage, due to a semiconductor shortage. This phenomenon is causing a 20-days stop of the electronic board production, which causes Tier-2 supplier to accumulate a high backlog towards its client. As this is a hot topic in today's logistic networks, it is interesting to compare the robustness of the two models to a market disruption, where the decision-making process is critical and decisive for the continuity of the production flow.

Scenario 4: Ferrari demand variation

Through this final scenario, Ferrari would like to analyze its supply chain sensitivity to a sudden variation of its production mix, which may create a bullwhip effect and augment the system complexity. The parameters guiding the simulation in this case are the disturbances $d_{Ferrari}$ and $O_{Ferrari}$, which are doubled after 6 weeks of simulation. The ability of the two MPC models to react and adjust their processes is assessed, to evaluate their robustness.

6. Results

6.1. Scenario 1: Zero backlog

The results of this simulation are displayed in Table 2.

Table 2. Scenario 1 KPI's

	DMPC	**CMPC**
Simulation time	23734 s (6.5 h)	5148 s (1.4 h)
Stock index	207.0	24.6
Backlog index	3.8	0.59
Supplier punctuality	76%	68%
Number of transports	175	156
Order variation	81%	75%

By observing the results, it can be inferred that the supply chain performs better in the centralized scheme: backlogs are lower over the whole simulation time, and warehouse target stocks are more respected than with the decentralized control architecture. Furthermore, although order variation is still high (75%), the CMPC controller improves the order distribution over the 6-month horizon, and it shows to have a lower environmental footprint, as transports are reduced by 10%. Finally, CMPC has also benefits in the computational cost, as the running time decreases up to 78%.

6.2. Scenario 2: Backlog recovery

The results for Scenario 2 can be summarized in the measured supply chain KPIs, presented in Table 3.

Table 3. Scenario 2 KPI's

	DMPC	**CMPC**
Simulation time	26059 s (7.2 h)	4823 s (1.3 h)
Stock index	219.0	32.7
Backlog index	12.1	10.8
Supplier punctuality	45%	35%
Number of transports	222	211
Order variation	81%	72%

In Scenario 2 the DMPC and CMPC models have been compared not only through their KPIs, but especially in their ability to recover from a high backlog set at the beginning of the simulation. A synthesis of this analysis is reported in Table 4, where the backlog recovery dates have been collected for every product.

This table shows that in the CMPC simulation, ProPlastic and Mtronic manage to recover the initial backlogs faster than with DMPC. However, an important struggle is recorded for the recovery of the dashboard backlog by TAM. This is due to a delayed production batch of Mtronic, that, since the dashboard order is a system disturbance and is fixed over time, does not allow a linear backlog recovery, which happens only at the sixth month of simulation. However, this issue does not compromise the production flow in Ferrari's factory. On the other hand, by analyzing Scenario 2's KPIs, the overall results favor the management of the centralized controller, as it reduces both the stock (-85%) and backlog index (-11%). As in the previous case, also the order variation, the number of transports and the computational cost improve in comparison with the DMPC scheme.

Table 4. Comparison between the months of complete backlog recovery for DMPC and CMPC model

	DMPC	**CMPC**
Dashboard - TAM	Jan 2023	May 2023
Cover - ProPlastic	Feb 2023	Jan 2023
Electronic board - Mtronic	Dec 2022	Nov 2022
TFT display - EBOVx	Variable	Variable

6.3. Scenario 3: Material shortage

The KPIs of Scenario 3 are presented in Table 5.

Table 5. Scenario 3 KPI's

	DMPC	CMPC
Simulation time	25285 s (7 h)	6585 s (1.8 h)
Stock index	190.8	24.8
Backlog index	34.8	1.4
Supplier punctuality	65%	67%
Number of transports	205	172
Order variation	81%	76%

From the results, it is clear how the centralized MPC controller performs better under all the indices measured. Stock targets are much more respected in the CMPC scheme, as the stock index decreases by 87%. This infers that, in spite of the shock caused by the shortage, the supply chain manages to not generate a bullwhip effect and handle the stocks efficiently. An important difference is certainly the output of the backlog index, which is reduced by 96%, mostly due to the different reaction of the model to the semiconductor disruption. CMPC shows to be better also with order variation, as it lowers by 5%, and to be the most sustainable solution, due to the 16% transport reduction. In this case, even the supplier punctuality benefits from the centralized strategy, raising of about 3%, demonstrating how this control tower performs better than the decentralized scheme in this critical scenario. Finally, even in this simulation, CMPC results the most cost-efficient solution, since the DMPC running time of 7 hours lowers down to less than 2 hours.

6.4. Scenario 4: Ferrari demand variation

The last scenario studies the models' sensitivity to sudden variations of the system disturbance: Ferrari's production demand. This situation is likely in a production process characterized by production mix variations, that may also experience changes in the takt-time. This is a case where the supply chain gets highly stressed, and suppliers may not be able to react to this change, especially if acknowledged under lead time. In this scenario, it was chosen to double the production demand on the 30th working day till the end of the simulation time. In the DMPC scheme, in order to keep the simulation as realistic as possible, are doubled the orders sent by all suppliers, while in the CMPC, only the demand and order relative to Ferrari are doubled, as the others are automatically computed by the control agent.

The optimization runs of both the DMPC and CMPC simulations result infeasible. This means that Ferrari goes out-of-stock with the dashboard, which may cause the stop of its production. This result is caused by an increase in demand without a parallel rise in the suppliers' production capacity. It shows how even a supply chain control tower is not able to react in an efficient manner to this sudden variation. However, this can still be considered a valuable result for the proposed innovation. In fact, supply chain control towers can be an innovative solution not only to monitor supplier performance but also to evaluate the impact of a planned decision over the supplier network. This improves the management of the supply chain, since it allows to make decisions by analyzing at an early stage their potential impact on the overall process. This approach may determine significant strategic decisions, such as supplier substitution or the activation of an additional supplier for a specific component that can guarantee the complete satisfaction of the demand. Therefore, it can be considered a step forward in the support of supply chain management activities and may acquire a major role in the future to increase the competitiveness of the supply chain on the market.

6.5. Model verification

In the model verification phase, the question to be answered is: "Is the model right?". In this section, a few tests of the DMPC and CMPC models are conducted in order to prove the correctness of the design.

Lead Time test

In the first verification test, the suppliers' lead times are all raised to 10 days. It is expected that such a high variation can cause issues for Ferrari's production flow. The results of the CMPC and DMPC simulations respect the predictions, as both models are infeasible under these conditions. The variation of the lead times causes the complete consumption of the initial dashboard stock at Ferrari and major delays in the Tier-2 components delivery to TAM, which is not able to timely replenish Ferrari's warehouse. This causes a stock-out at Ferrari's warehouse, and therefore, the model is infeasible.

Supplier capacity test

In the second test, the models are tested with a reduction of all suppliers' production capacity to only 1 piece per day. With this modification, it is expected that the suppliers will not be able to follow Ferrari's demand, which will lead to a rise of backlogs along the supply chain and can potentially compromise Ferrari's production continuity. Also, in this case, the simulation output respects the initial predictions, as the model outcomes are, in both cases, unfeasible solutions: the initial stock at Ferrari's warehouse is entirely consumed at the beginning of the simulation, and the reduced production capacity doesn't let suppliers keep pace with Ferrari's demand. This raises the backlogs between tiers and causes Ferrari to miss the assembly of the dashboard on the cars.

Prediction horizon analysis

After verifying the model through the capacity of the supply chain, the impact of the prediction horizon on the final results is assessed. By augmenting the visibility of the demand forecasts, it is expected that the MPC model can compute even better results. The KPIs will be assessed by running the CMPC and DMPC model with six different Hp values: 15, 20, 25, 30, 35, and 40, as presented in Figures 3-6.

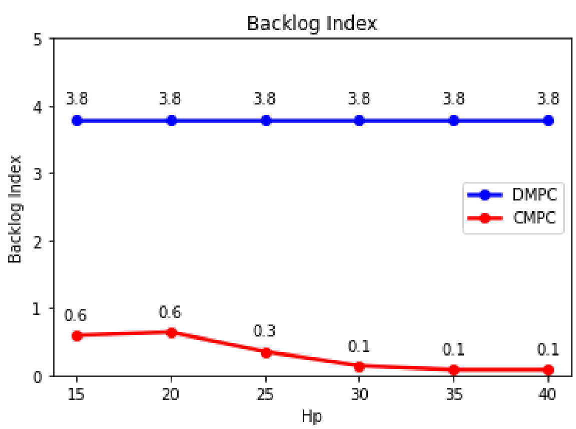

Figure 3. Backlog Index in function of H_p

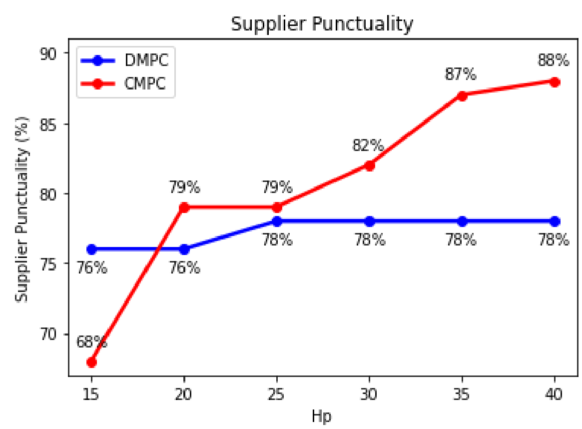

Figure 4. Supplier punctuality in function of H_p

The results show that data visibility over a longer horizon marks even more the difference between the DMPC and CMPC solutions. In fact, while with the DMPC architecture, there aren't major changes in the supply chain performance, a significant impact of the prediction horizon on the final output can be observed in the CMPC scheme: the backlog index reduces by 86%, supplier punctuality raises by 20%, and the number of transports drops down of 38%. Therefore, with longer-term visibility over the process, the centralized agent constantly increases its logistic performance compared to DMPC, which matches the initial expectations. However, it is also important to observe that the stock index and the order variation tend to rise with the increase of the prediction horizon. This can be considered another verification of the model's correctness. In fact, since these two KPIs have been associated with lower objective function weights, it can be expected that with a higher visibility the models satisfy the primary goals and oversee these two performance indices.

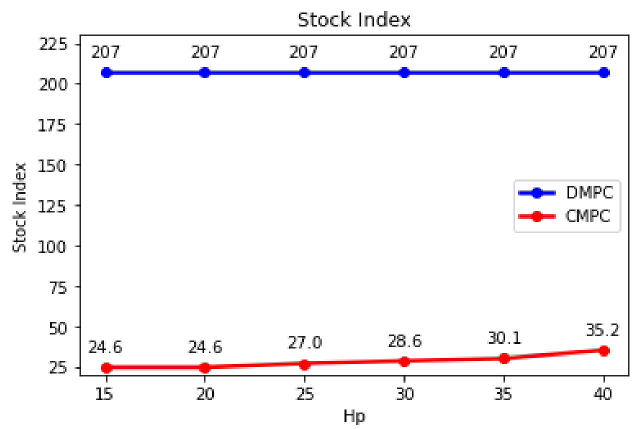

Figure 5. Stock Index in function of Hp

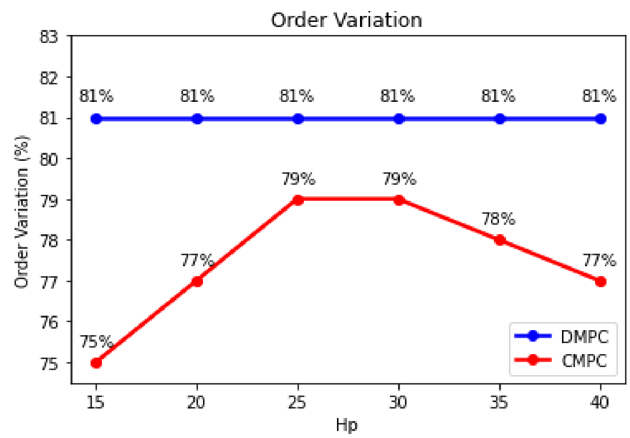

Figure 6. Order variation in function of Hp

6.6. Model validation

Validating a model means answering to the following question: "Is this the right model?". The CMPC strategy represents the future state envisioned for this process: a coordinated supply chain, where a single agent has a complete visibility over the entire process and makes autonomous decisions for every company. By considering the depth of the system modeling and the obtained results, it can be considered a valid application.

However, much of the logistic complexity characterizing a supply chain has been neglected in this paper. In fact, the model is a small representation of a very large automotive supply chain. Furthermore, as this works represents a prototypical digital tool used for research purposes, it cannot be considered complete, due to computational constraints. As a consequence, it was necessary to design the system by considering several assumptions that at the moment separate this model from practical and industrializable applications and are addressed for future research:

- **Stochasticity:** Every variable in real life is subject to a stochastic uncertainty (e.g, production capacity, warehouse stock, transport delays). In this study, for computational cost reasons, it was not possible to include stochasticity in the simulation.
- **Safety stocks:** This model does not consider the safety stock days set by every company for its suppliers.
- **Sourcing strategy:** In this model every client-supplier contract is single-sourcing. This model could eventually be adapted to alternative sourcing strategies.
- **Production mix:** The suppliers' production mix and therefore the factory operational constraints are not considered in this simulation as only one product for company is considered for this simulation.

Moreover, considering an extension of the model to the entire supply chain, the amount of variables and the complexity would raise exponentially. In this case, a CMPC architecture may experience some limitations, especially in terms of robustness and responsiveness. In fact, it is known from theory that centralized MPC does not respond well to sudden changes in the network and requires a high computational time for optimization in larger systems, such as a complete automotive supply chain. Therefore, it can be concluded that CMPC is valid control strategy in small systems, but is not cost-efficient in large-scale applications.

6.7. Discussion of the results

By analyzing the results of the four scenarios simulated in this section, it can be deduced that MPC has a better impact with a centralized strategy, in terms of logistic efficiency, robustness to uncertainties, computational cost and environmental sustainability. This result is underlined even more with the ability of the models to foresee the system states over a longer horizon, as demonstrated in Section 6.5. This demonstrates the benefit of data visibility in changing perspective from a silos mentality to a strong, collaborative supply chain that can gain competitiveness on the market. In this regard, the centralized MPC presents better KPIs in all the first three scenarios, thanks to a better coordination between the information and material flows, that minimize the resulting backlog and allow to keep the warehouse stocks closer to the prefixed targets. In Scenario 3, for example, it is clear how in the future state, buyers and suppliers considerably change their cooperating method in case of a material shortage. By observing the Figures 7-8, in the DMPC method, the controller prefers to adopt a Just-In-Case strategy, letting the buyer (TAM) receive as much electronic boards as possible, while the CMPC model prefers to keep the stock low for the Tier-1 (in order to stay closer to the target stock) and work on a Just-In-Time fashion, which increases the performance indices.

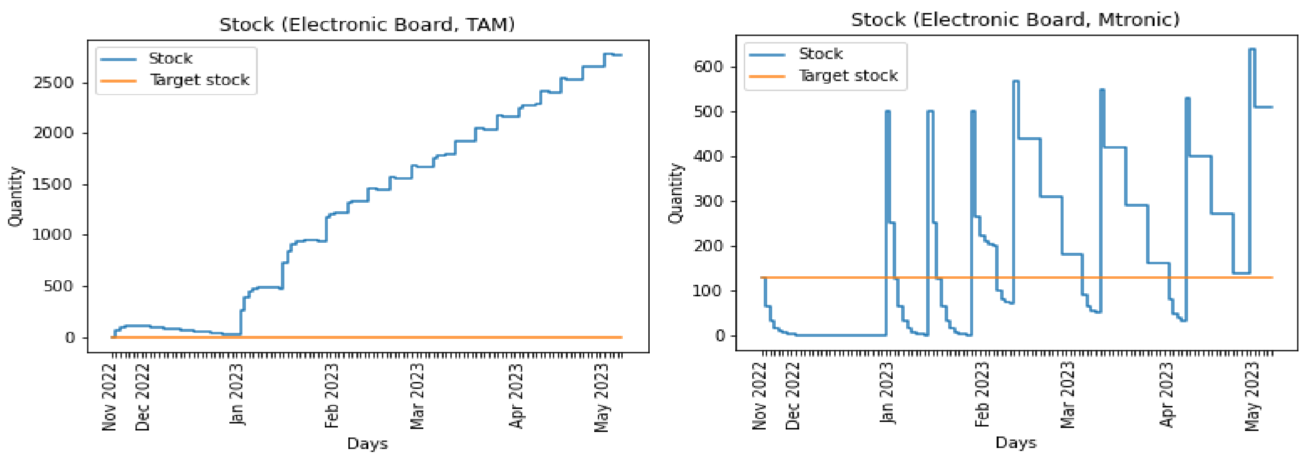

Figure 7. Electronic board stock at TAM and Mtronic, DMPC, Scenario 3

Moreover, the CMPC model demonstrates to be a better solution also in terms of computational cost and CO2 emissions. In fact, simulation times are much shorter than in the DMPC scheme, and transports are reduced thanks to less frequent emergencies and extra-flux operations.

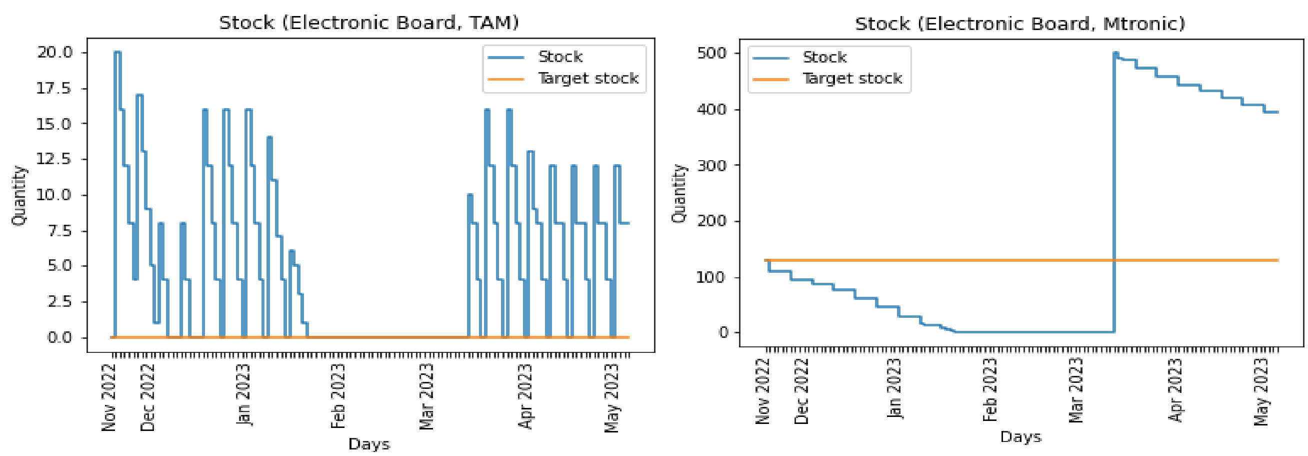

Figure 8. Electronic board stock at TAM and Mtronic, CMPC, Scenario 3

After the complete analysis of the final outputs and the comparison between the two MPC models, it can be inferred that SRM and supply chain control towers represent a high-value technology in the digital transformation of logistic operations. The centralized scheme is concluded to be the optimal solution of a supply chain application, as it guarantees a better decision-making support than a decentralized strategy, and represents the most avant-garde solutions in the path towards autonomous supply chain management.

7. Conclusion & future research

Rising supply chain complexities and uncertainties nowadays require buyers and suppliers to reduce the split in their logistic processes and build solid partnerships to gain higher competitiveness in the market. In this research paper, the role of digitization and data visibility within supply chains was investigated through the design of a centralized MPC agent, able to make autonomous optimal decisions for the material and information flow over the logistic network. This research work contributes to the scientific knowledge with a study case where, through the use of real market data, it presents the impact of a centralized MPC supply chain control tower on the current state of Ferrari's supply chain, simulated through decentralized MPC. These models were run over four scenarios, representing different conditions characterizing modern supply chains. The results show that CMPC has the best performance, as it manages to coordinate the logistics within tiers better, thanks to its ability to overlook all the supply chain processes. With these innovations, the controller is able to distribute the client's orders in an optimal way, depending on the boundary conditions affecting the system. Alerts generation can help to anticipate risks of shortage, rather than making quick decisions in emergency situations. In this way, the supply chain is structured to early predict when and where there could be an issue and intervene to solve it. Furthermore, businesses are able to control their stock levels in a more efficient way since the model tends to adjust the orders and shipments to the warehouses' target stocks. Moreover, the CMPC scheme shows to be the most sustainable and time-efficient strategy, as it reduces the number of transports throughout the network and is less computationally expensive than DMPC. As shown in Scenario 4, supply chain control towers can be a support also in the production scheduling strategies. Changes in production mix, or takt-time reductions, could be investigated with the suppliers in order to understand how it would impact the logistic network and evaluate their feasibility. Finally, by verifying the model with different prediction horizons, it can be concluded that the CMPC architecture gains an increasing performance with a longer-term visibility over the supply chain processes, which strengthens the validity of the study here proposed.

This research shows how digital transition strengthens partnerships between buyers and suppliers. A shared flow of information enhances trust and responsibility as businesses do not hide their processes but work with a more open spirit of collaboration. This ultimately improves suppliers' service level, guarantees lower delivery times to clients, and can lead to gaining a competitive advantage in the market.

However, many are still the challenges that could be integrated in the solution proposed in this paper. First, this simulation has been designed for a single component of Ferrari's supply chain. The extension to other PNs is a big challenge in terms of data availability and controllability. As CMPC is not robust and has a low responsiveness on a large scale, future research should evaluate the application of distributed MPC in this supply chain study case. Its advantage is that every single agent, by gathering a limited amount of information and having limited action capabilities, can execute a more effective control on its specific subsystem both in terms of responsiveness to change and low computational costs, still guaranteeing high performance. Furthermore, the logistic complexity applied to the model could be further increased by integrating safety stocks, multi-product production lines, and competitive supplier sourcing strategies into the model. Stochasticity is another important theme. In this paper, the sensitivity of the model has been tested through small variations of disturbances and parameters. In real applications, every variable has a range of uncertainty based on historical data and future predictions. On the other hand, it would inevitably raise the computational cost of the simulation. Another area of improvement is the simulation itself. In this paper, MPC has been run through a MIPQ optimization problem, which finds global or local optimum. Other optimization techniques (e.g. heuristics) are addressed for future research.

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resources and validation. All authors approved the final version of the manuscript and take responsibility for their respective contributions

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