Stochastic Model Predictive Control of Supply Chains of Perishable Goods

Bernardini, F. P.; Maestre, J. M.; Velarde, P.; Negenborn, R. R.

DOI
10.1016/j.ifacol.2025.09.519

Publication date
2025

Document Version
Final published version

Published in
IFAC-PapersOnline

Citation (APA)
Bernardini, F. P., Maestre, J. M., Velarde, P., & Negenborn, R. R. (2025). Stochastic Model Predictive Control of Supply Chains of Perishable Goods. *IFAC-PapersOnline*, *59*(11), 25-30. https://doi.org/10.1016/j.ifacol.2025.09.519

Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 59-11 (2025) 25–30

Stochastic Model Predictive Control of Supply Chains of Perishable Goods ⋆

F. P. Bernardini * J. M. Maestre ** P. Velarde *** R. R. Negenborn ****

* *Dipartimento di Ing. Industriale e dell'Informazione, Università di Pavia, 27100 Pavia, Italy, (e-mail: federicopietro.bernardini01@universitadipavia.it).*
** *Departamento de Ingeniería de Sistemas y Automática Universidad de Sevilla, 41092 Sevilla, Spain (e-mail: pepemaestre@us.es)*
*** *Department of Engineering, Universidad Loyola Andalucía, Spain, (e-mail: pavelarde@uloyola.es)*
**** *Department of Maritime & Transport Technology, Delft University of Technology, 2628 CD Delft, The Netherlands (er.r.negenborn@tudelft.nl)*

Abstract: This work presents a stochastic model predictive control approach to optimize the management of a meat supply chain with uncertain demand. The proposed approach considers the temperature-dependent deterioration of meat products and the multi-stage nature of the supply chain, including producers, warehouses, retailers, and customers. The management problem is formulated as a mixed-integer optimization problem, where the objective is to minimize the total cost of the supply chain while satisfying customer demand and quality requirements. The approach uses scenario-based optimization to account for different uncertainty sources. The results show that the proposed method effectively balances the conflicting objectives of minimizing costs and meeting demand and quality requirements while accounting for uncertainty.

Keywords: supply chain, model predictive control, stochastic control, optimal control.

1. INTRODUCTION

One-third of all food produced for human consumption is lost or wasted, which annually amounts to 1.3 billion tons of food and economic costs of 940 billion USD (Flanagan et al., 2019). Only the meat industry generates approximately 263 million tons of food waste, with more than 20% of global production being lost

To address food waste in the meat industry, there is a need for quality-aware methods that enable the monitoring and control of critical quality parameters throughout the supply chain (Read et al., 2020). These methods can detect and prevent quality issues early, ensuring that only safe and high-quality products reach the market (Ren et al., 2022; Sprong et al., 2019). Additionally, quality-aware control methods can provide the data and insights needed to identify bottlenecks, optimize processes, and make informed decisions, thus reducing waste and improving the efficiency of the supply chain. In particular, quality control methods such as monitoring temperature, storage conditions, and the means of transportation can help ensure that the product remains within safe temperature ranges and prevent spoilage, thus extending the shelf life and allowing for longer selling times.

Since meat is a highly perishable product with a relatively short shelf life, it must be sold quickly after production. The shelf life of meat depends on several factors, including the quality of the meat and the storage conditions, because higher temperatures lead to faster product deterioration (Raab et al., 2011; Bruckner et al., 2012). Therefore, maintaining appropriate storage temperatures throughout the meat supply chain is critical to ensure the product remains fresh and safe for consumption. Indeed, several recent works have formulated the optimization of the supply chains with perishable goods, e.g., (Jonkman et al., 2019) optimizes agro-food supply chains, considering factors such as seasonality, perishability, processing and (Jouzdani and Govindan, 2021) focuses on the sustainability of the supply chains using a multi-objective mathematical program that optimizes cost, energy consumption, and traffic congestion. Also, a framework to reduce food waste in food supply chains by connecting risks with food waste is presented in (Paciarotti and Torregiani, 2021). The optimization of the meat supply chain can be found in works such as (Schmidt and Moreno, 2022), which develops a decision support tool for optimizing traceability and is based on a multi-objective mixed-integer linear program that minimizes total batch dispersion, operating costs, and carbon emissions. Furthermore, the scheduling of a meat supply chain using a mixed integer linear program that considers real-time quality and temperature information is presented in (Sprong et al., 2019).

The main contribution of this work is to extend the supply chain planning method proposed in (Sprong et al., 2019) into a Model Predictive Control (MPC) framework, an advanced control strategy widely used in industrial processes due to its ability to deal explicitly with non-linearities, delays, and constraints on the variables system, to name a few (Camacho and Bordons, 2013). In this context, MPC can be applied to manage and control various processes, including economics, storage, and logistics. Since the standard formulation of MPC does not deal

⋆ This project has received funding from the C3PO-R2D2 project (PID2020119476RB-I00) funded by MCIN/AEI/10.13039/501100011033.

10.1016/j.ifacol.2025.09.519

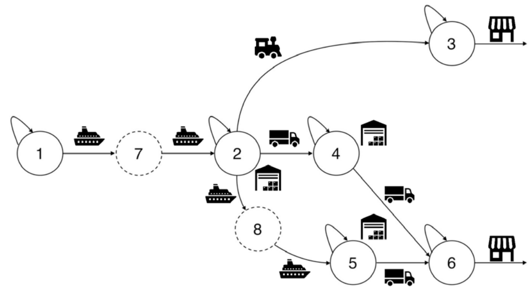

Fig. 1. Example of a supply chain. There is one producer (node 1), three warehouses (nodes 2, 4, 5), and two retailers (nodes 3, 6). The remaining nodes (nodes 7 and 8) are auxiliary and implement transport delays.

explicitly with uncertainties in a probabilistic sense, a stochastic MPC formulation that handles the unpredictability in the meat supply chain is necessary (Mesbah, 2016). This ensures that the control strategy is robust to unexpected changes, e.g., in the demand, thus improving closed-loop performance.

The remainder of this paper is organized as follows. Section 2 describes the Irish lamb meat supply chain, including the different stages and actors involved in producing, processing, and distributing meat products. In Section 3, the proposed stochastic MPC formulation is developed, which considers multiple demand scenarios, cooling cost, product quality, and logistics aspects. Section 4 shows and discusses the simulation results, highlighting the advantages and limitations of the proposed approach. Finally, Section 5 draws some conclusions regarding the effectiveness and potential impact of the designed stochastic MPC approach on the efficiency and sustainability of Irish lamb meat supply chains.

2. DESCRIPTION OF THE MEAT SUPPLY CHAIN

The supply chain must move a set $\mathcal{I} = \{1, 2, \ldots\}$ of meat units across a graph $\mathcal{G} = \{\mathcal{N}, \mathcal{E}\}$, where $\mathcal{N} = \{1, 2, \ldots\}$ is the set of nodes representing suppliers, warehouses, retailers and delays, and $\mathcal{E} \subseteq \{(n,m)|(n,m) \in \mathcal{N}\}$ is the set of available links for meat transportation. Also, let us define $\mathcal{N}_r \subset \mathcal{N}$ as the set of the nodes representing the retailers in the supply chain.

The movement of units across the graph $\mathcal{G}$ is mathematically defined as a discrete-time system as

$$x_{\mathcal{G}}(k+1) = A_{\mathcal{G}} x_{\mathcal{G}}(k) + B_{\mathcal{G}} u_{\mathcal{G}}(k) + E_{\mathcal{G}} \omega_{\mathcal{G}}(k), \quad (1)$$

where $x_{\mathcal{G}} = [x_i]_{i \in \mathcal{I}}$ is an integer state vector that represents how many units there are in the graph, $u_{\mathcal{G}} = [u_{ij}]_{(i,j) \in \mathcal{E}}$ is an integer input vector indicating how many containers move between nodes and $\omega_{\mathcal{G}} = [\omega_r]_{r \in N_r}$ is an integer disturbance vector representing the customer demand. $A_{\mathcal{G}}$ and $B_{\mathcal{G}}$ are matrices defined according to the graph structure, containing elements in the set $\{-1, 0, 1\}$.

To ensure the proper movement of meat units across the supply chain, the following constraints are considered:

$$x_{\mathcal{G},\max} \geq x_{\mathcal{G}}(k) \geq 0, \quad (2)$$

$$G_{\mathrm{eq1}} u_{\mathcal{G}}(k) = G_{\mathrm{eq2}} u_{\mathcal{G}}(k-1), \quad (3)$$

$$G_{\mathcal{G}} u_{\mathcal{G}}(k) \leq 1, \quad (4)$$

Equation (2) ensures that there are no negative meat units at the nodes of the network. Likewise, this constraint also forces the controller to satisfy the demand at nodes $r \in N_r$. Constraint (3) is added to force that shipments only remain a one-time step at delay nodes. Equation (4) establishes that a given meat unit can only advance one node per time instant.

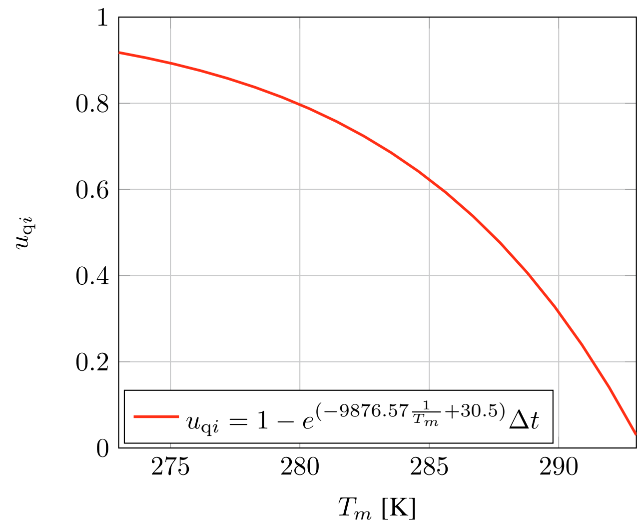

Fig. 2. Exponential relationship between control variable u_{qi} of a unit i and cooling temperature T_m at node m expressed in Kelvin degrees, using a $\Delta t = 24$ hours.

Finally, note that this formulation gives supply chain planners flexibility to consider alternative transportation modes and a comprehensive range of potential destinations for their products, as shown in the example of Figure 1. Also, more constraints can be included to represent specific events that disrupt transportation, e.g., to indicate that no containers can be transported through a specific link at a certain time.

2.1 Meat Quality & Refrigeration

Meat units are assumed to have homogeneous quality, which decays at varying rates, depending on factors such as their size and origin. The deterioration model employed here —designed for Irish lamb— is detailed in (Mack et al., 2014). In particular, a quantitative measure of the deterioration of a unit of meat at node $m \in \mathcal{N}$ over Δt hours is given by the decrement experienced by its Quality Index (QI):

$$\Delta QI(\Delta t) = e^{(-9876.57\frac{1}{T_m}+30.5)}\Delta t, \quad (5)$$

where $T_m \in [2, 20]$°C is a constant refrigeration temperature at node m, expressed in Kelvin degrees, during Δt.

Using Equation (5), a discrete-time model for each unit $i \in \mathcal{I}$ is formulated as

$$x_{\mathrm{q}i}(k+1) = x_{\mathrm{q}i}(k) - \Delta x_{\mathrm{q}i}(k), \forall i \in \mathcal{I}, \quad (6)$$

where $x_{\mathrm{q}i(k)}$ is the quality of unit i at time step k and $\Delta x_{\mathrm{q}i}(k) = e^{(-9876.57\frac{1}{T_m}+30.5)}\Delta t$ is the variation of quality of unit i during time step k. As a reference, consider that a unit in perfect condition has the initial quality $x_{qi}(0) = 30$. Also, the considered step time is $\Delta t = 24\,\mathrm{h}$.

Here, T_m acts as a control variable for quality drop Δx_{qi}. However, this nonlinear relationship with the quality drop is not convenient for the problem formulation. Therefore, the change of variable

$$u_{\mathrm{q}i} = 1 - 24e^{(-9876.57\frac{1}{T_m}+30.5)}$$

is introduced, so that Equation (6) becomes an integrator, i.e.,

Table 1. Transportation Parameters

Meaning	Symbol	Simulation Value
Barge cost	P_{barge}	370 €
Train cost	P_{train}	1340 €
Truck cost	P_{truck}	1870 €
Barge CO_2 emission cost	E_{barge}	3.60 €
Train CO_2 emission cost	E_{train}	2.55 €
Truck CO_2 emission cost	E_{truck}	7.20 €
Reward for satisfied demand	P_q	10 000 €
Penalty for unmet demand	μ	500 €
Penalty for meat waste	ξ	500 €
Max cooling cost	τ	9.60 €

$$x_{qi}(k+1) = x_{qi}(k) + u_{qi}(k) - 1. \tag{7}$$

Thus, the decision variable becomes the quality of the meat unit *preserved* at time instant k. As shown in Figure 2, the proposed change of variable is easy to invert. Not only does it avoid introducing a non-linearity into the problem, but it also makes the cost function convex, as will be shown later. Notice that this is the approach employed by Hammerstein models to preserve linearity (Degachi et al., 2020).

Therefore, the overall quality in the supply chain can be represented by the linear model

$$x_{\text{q}}(k+1) = A_{\text{q}} x_{\text{q}}(k) + B_{\text{q}} u_{\text{q}}(k), \tag{8}$$

where $x_{\text{q}} = [x_{\text{q}i}]_{i\in\mathcal{I}}$ is a state vector that aggregates the quality levels, $[u_{\text{q}i}]_{i\in\mathcal{I}}$ is the input control variable, and A_{q} and B_{q} are matrices built based on Equation (6).

Finally, the product is considered unacceptable when its QI is below 16. Therefore, it is required

$$x_{\text{q}i}(k) \geq 16, \forall i \in \mathcal{I}. \tag{9}$$

Constraint (9) sets the minimum value for the quality of a unit in the supply chain: if violated, the unit must be discarded. Likewise, the following constraint

$$0 \leq u_{\text{q}i}(k) \leq 0.9, \forall i \in \mathcal{I}, \tag{10}$$

limits the preservation of quality. In particular, $u_{\text{q}i} = 0$ means that the meat is not refrigerated. On the other hand, $u_{\text{q}i} = 0.9$ sets the maximum quality that can be preserved and indirectly the maximum refrigeration effect. *Remark:* To improve the readability of the quality values, of Equation (5), these variables have been scaled by 10.

2.2 Costs

Economic costs related to transportation, cooling, food waste and unmet demand are considered (see Table 1).

Transportation costs: Transportation modes are by barge, train, or truck. For each method, two different costs can be distinguished:

- P_{mode}: it is associated to the actual transportation (fuel, vehicle maintenance, among others),
- E_{mode}: it is associated with the CO_2 emission released.

Here $\text{mode} \in \{\text{barge}, \text{train}, \text{truck}\}$. Thus, every time a meat unit passes through a link, it is necessary to pay these penalties. Since these movements are given by $u_{\mathcal{G}}$, a linear penalty is defined:

$$J_T(k) = R_T u_{\mathcal{G}}(k), \tag{11}$$

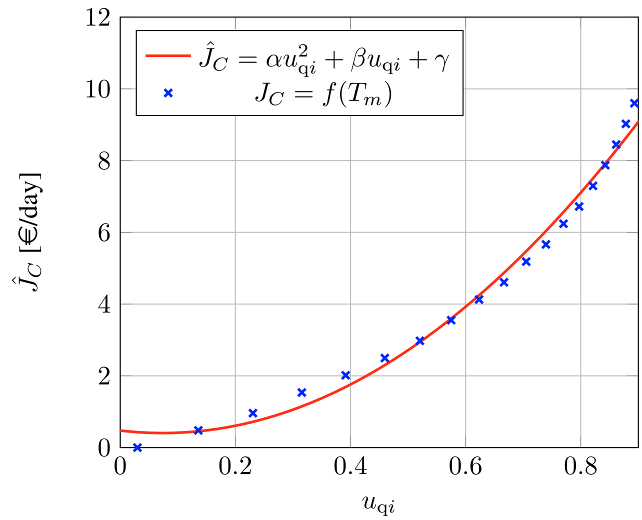

Fig. 3. Quadratic relationship between the cooling cost $\hat{J}_C$ in €/day and the quality drop $u_{\text{q}i}$ of a unit i. The parameters values are $\alpha = 12.7018$, $\beta = -1.8708$ and $\gamma = 0.4742$.

where R_T is a row vector that takes into account the transportation costs given the supply chain structure.

Cooling cost: The lower the refrigeration setpoint, the higher power consumption and cost. Figure 3 shows the relationship that links the cooling cost per day $\hat{J}_C$ and the quality preserved u_{q}, which is based on (Sprong et al., 2019), and the quadratic fit $\hat{J}_C = \alpha \Delta x_{\text{q}i}^2 + \beta \Delta x_{\text{q}i} + \gamma$ employed to introduce it in the cost, yielding:

$$J_C = {u_{\text{q}}}^T R_C u_{\text{q}} + Q_C u_{\text{q}}, \tag{12}$$

where R_C is a diagonal square matrix containing the quadratic coefficients α, and Q_C is a row vector containing the linear coefficient β for each container in $\mathcal{I}$.

Waste cost: Meat may need to be discarded, e.g., if the retailer cannot make it on time due to its degradation. The following penalty is therefore introduced

$$J_W(k) = R_W u_{\mathcal{G},\text{disposal}}(k), \tag{13}$$

where $u_{\mathcal{G},\text{disposal}}$ is a vector with a number of elements equal to the number of nodes from which units can be discarded, paying the disposal cost ξ. Matrix R_W indicates the cost for discarding a unit of meat in a certain node, which is set by parameter ξ.

Unmet demand cost: An auxiliary binary variable $u_r(k)$ indicates whether the quantity of meats units delivered at time step k to retailer $r \in \mathcal{N}_r$ is enough. If this quantity does not satisfy the demand of retailers, the penalty to be paid is μ. This cost is implemented as

$$J_D(k) = R_D u_n(k), \tag{14}$$

where R_D is a matrix that takes into account the cost for each retailer in $\mathcal{N}_r$ and $u_n = [u_r]_{r\in\mathcal{N}_r}$.

$$0 \leq u_n(k) \leq u_{n,\max}, \forall n \in \mathcal{N}_r, \tag{15}$$

sets the upper and lower limits for control variable $u_n(k)$.

Overall Objective Function: Considering the elements previously defined, the objective function can be written as:

$$J(k) = J_T(k) + J_C(k) + J_W(k) + J_D(k). \tag{16}$$

2.3 Optimization Problem

By minimizing objective function J, the controller can determine the optimal assignment of containers from origins to destinations. To this end, it is possible to aggregate all the state vectors and matrices previously described into the discrete-time linear model

$$x(k+1) = Ax(k) + Bu(k) + E\omega(k), \tag{17}$$

where $x(k) = [x_{\mathcal{G}}^T,\, x_{\mathrm{q}}^T]^T$ contains information about the meat units location in the supply chain and their quality, $u(k) = [u_{\mathcal{G}}^T\, u_{\mathrm{q}}^T\, u_n^T]^T$ is the control action vector, $\omega(k)$ is the disturbance related at the demand of meat at time instant k, A is the state matrix, B is the input-to-state matrix, and E is the disturbance matrix.

State and control constraints are aggregated as

$$x \in \mathcal{X}, \tag{18}$$

$$u \in \mathcal{U}. \tag{19}$$

Based on this model, MPC computes a sequence of control actions over a prediction horizon N_{p} by solving an optimization problem. Only the first component of the control sequence is applied to the system, that is, $u(k)$, because the optimization problem is repeated at the next time step $(k+1)$ in a receding horizon fashion.

The optimization problem solved at time instant k is

$$\min_{u\{k:k+N_{\mathrm{p}}-1\}} \sum_{l=0}^{N_{\mathrm{p}}} J(k+l), \tag{20}$$

subject to (17), (18), (19), and $x(k) = \hat{x}_k$, where $\hat{x}_k$ is actual state of the supply chain.

3. STOCHASTIC MPC FORMULATION

Customer demand is considered a stochastic variable. One alternative to address this uncertainty is to employ Multi-scenario MPC (MS-MPC), which involves calculating a single control action for all possible scenarios considering their likelihood (Velarde et al., 2023; Maestre et al., 2021). Since MS-MPC does not characterize uncertainty using probability distribution functions, the optimization problem can be written as a deterministic program.

The optimization problem to be solved at each time instant k considers N_s scenarios to compute the control sequence and is formulated as

$$\min_{u\{k:k+N_{\mathrm{p}}-1\}} \sum_{j=1}^{N_{\mathrm{s}}} \rho^{(j)} \left(\sum_{l=0}^{N_{\mathrm{p}}} J(k+l) \right), \tag{21}$$

subject to

$$x^{(j)}(l+1) = Ax^{(j)}(l) + Bu(l) + E\omega^{(j)}(l), \tag{22a}$$

$$x^{(j)}(l) \in \mathcal{X}, \tag{22b}$$

$$u(l) \in \mathcal{U}, \tag{22c}$$

$$\omega^{(j)}(k) = \hat{\omega}_k, \tag{22d}$$

$$x^{(j)}(k) = \hat{x}_k, \tag{22e}$$

$$\forall l \in [0\,, N_{\mathrm{p}}],\ \forall j \in [1\,, N_{\mathrm{s}}],$$

where $\rho^{(j)}$ is the probability of scenario j. Therefore,

$$\sum_{j=1}^{N_{\mathrm{s}}} \rho^{(j)} = 1.$$

In addition to the stochastic behavior of retailer demand, additional constraints or even matrices A or B that depend on the scenarios can be considered to describe other problem-specific events, depending on the phenomenon described.

4. RESULTS AND DISCUSSION

This section presents the results of the simulation experiments designed to evaluate the performance of Perfect Forecast MPC (PF-MPC), MS-MPC, and Standard MPC (ST-MPC) under a 15-day supply chain scenario. Key performance metrics, including profit, cost breakdown, and delivery rates, are analyzed to highlight the strengths of MS-MPC in managing uncertainties.

4.1 Simulation Setup

The simulation replicated the operation of a supply chain network with eight nodes, including two destination nodes (3 and 6), where specific demand profiles were satisfied. Node 3 required deliveries on days 8 and 14, with demands of 1 and 2 units, respectively. Node 6 exhibited a more dynamic demand profile, requiring 2 units on day 3, 1 unit on day 7, 1 unit on day 10, and 5 units on day 15. These demand profiles were designed to represent realistic and variable retail requirements. Five containers of perishable goods were transported with initial quality ranging from $x_{q,0} = [30, 28, 26, 24, 22]$, and a minimum acceptable threshold set at $x_q \geq 16$ to ensure quality standards. The containers experienced natural degradation over time, necessitating precise control to minimize spoilage. Three predictive control approaches were tested:

- **PF-MPC:** Assumes perfect knowledge of future demand, enabling optimal planning without uncertainties.
- **MS-MPC:** Considers five demand scenarios with a prediction horizon of $N_p = 5$ days, capturing demand uncertainties.
- **ST-MPC:** Relies on the historical average demand for predictions, providing a baseline for comparison.

To simulate real-world challenges, a disruption was introduced by limiting the capacity of the route between nodes 1 and 7 to one container per time step.

4.2 Performance Analysis and Discussion

Figure 5 and Figure 4 depict the container movements and total profit achieved using PF-MPC and MS-MPC, respectively. PF-MPC outperformed the other controllers with a total profit of $12,598.59$ €, due to its perfect foresight of demand, as seen in Table 2. MS-MPC achieved a slightly lower profit ($11,984.27$ €) but demonstrated higher adaptability to uncertainties by leveraging scenario-based planning.

Container Movements: As shown in Figure 5 (left panel), PF-MPC delivered containers efficiently, capitalizing on perfect knowledge. MS-MPC, depicted in Figure 4 (left panel), dynamically adapted to uncertainties, strategically routing containers to minimize penalties and disposal costs.

Profit Evolution: The right panels of Figures 5 and 4 illustrate the profit accumulation over time. PF-MPC consistently generated higher profits earlier in the simulation due to optimal delivery schedules. MS-MPC, while slightly delayed in profit

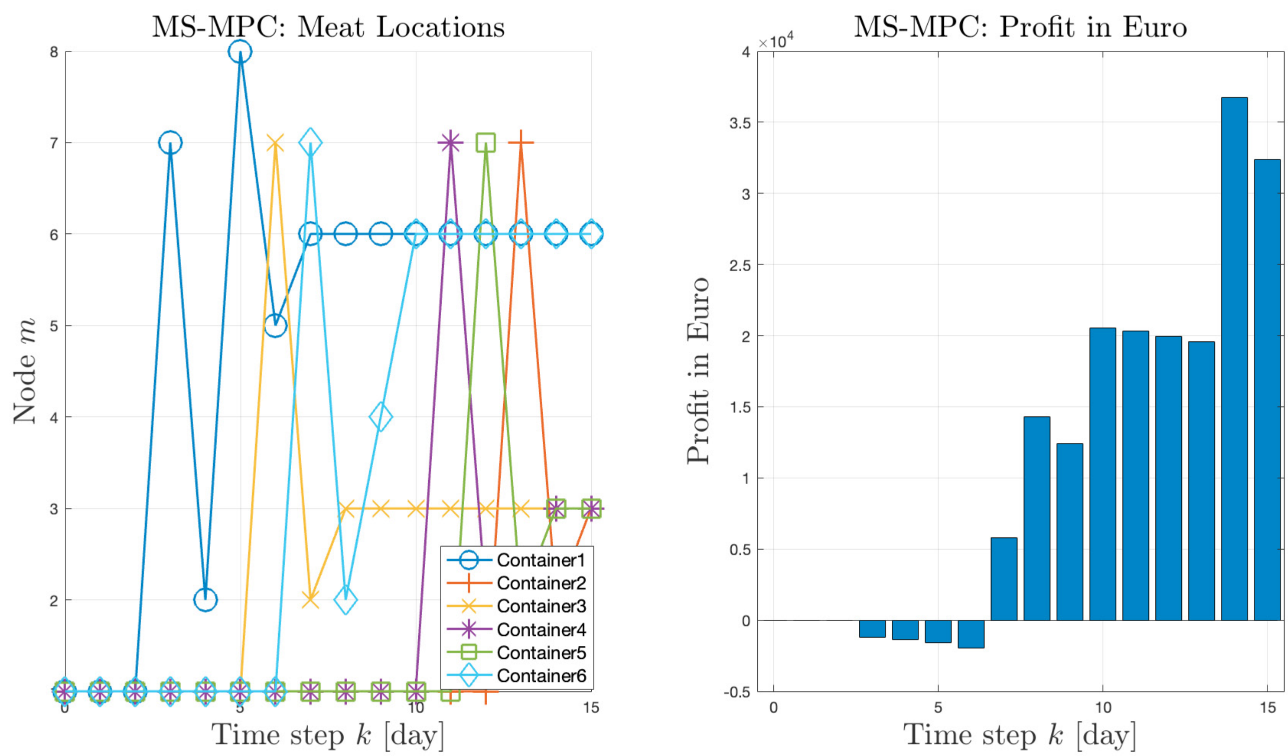

Fig. 4. Representation of container movements and total profit within the supply chain using an MS-MPC controller.

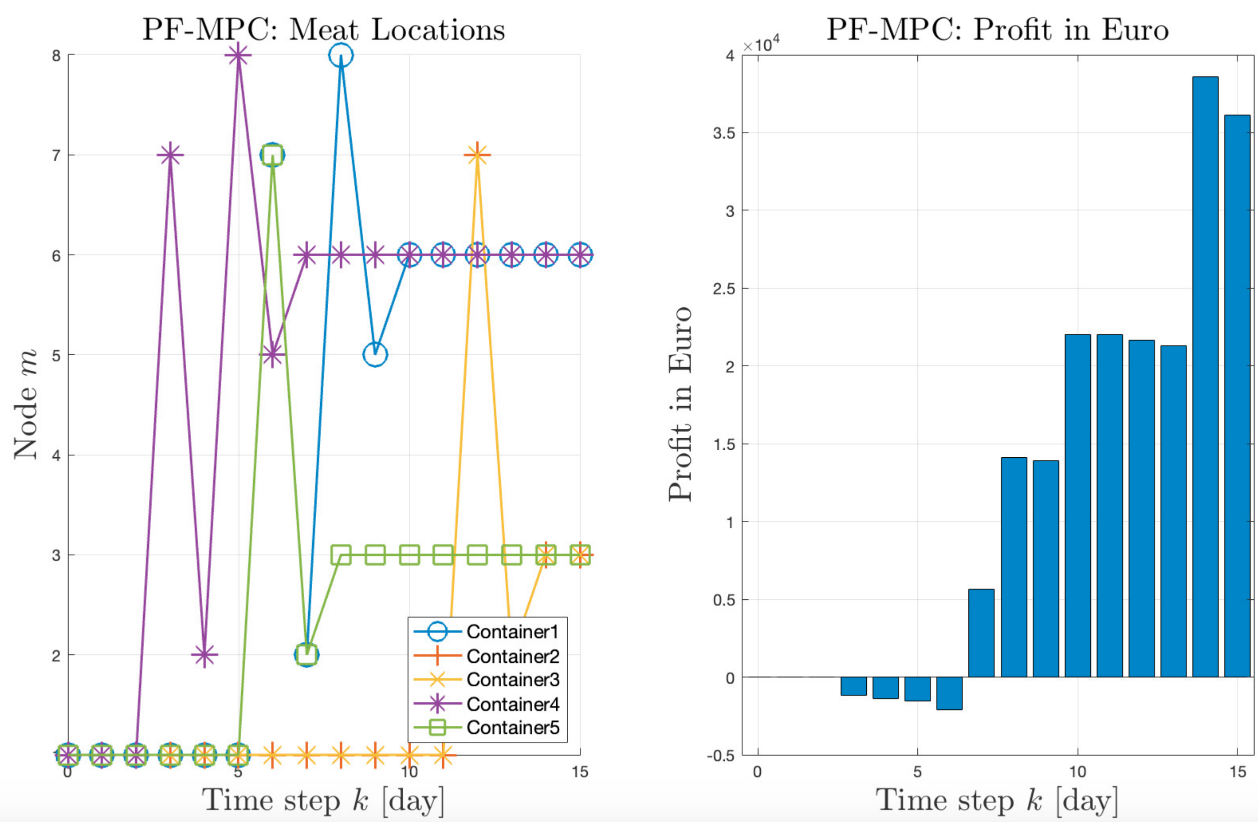

Fig. 5. Representation of container movements and total profit within the supply chain using a PF-MPC controller.

accumulation, maintained robust performance despite uncertainties.

Quality Degradation: Figure 6 shows the quality trends over the simulation period. Both approaches maintained quality above the minimum acceptable threshold ($x_q \geq 16$), ensuring no waste. However, MS-MPC's earlier deliveries reduced the

Table 2. Comparison of Performance Metrics for Different Controllers

Metric	PF-MPC	MS-MPC	ST-MPC
Total Profit (€)	12,598.59	11,984.27	10,984.27
Transport Cost (%)	48.37	44.66	39.71
Cooling Cost (%)	4.34	5.44	4.83
Penalty Cost (%)	47.29	43.66	44.37
Disposal Cost (%)	0.00	6.24	11.09
Cost per Delivered Unit (€)	3,700.71	4,007.86	4,507.86
On-Time Delivery Rate (%)	16.67	4.08	4.08

risk of spoilage compared to ST-MPC, though it lagged behind PF-MPC in preserving quality due to demand uncertainties.

The results demonstrate the potential of MS-MPC as a robust alternative to ST-MPC in managing supply chain uncertainties. While PF-MPC achieved the highest profit due to perfect foresight, MS-MPC provided a practical approach, balancing costs and quality preservation effectively in uncertain environments.

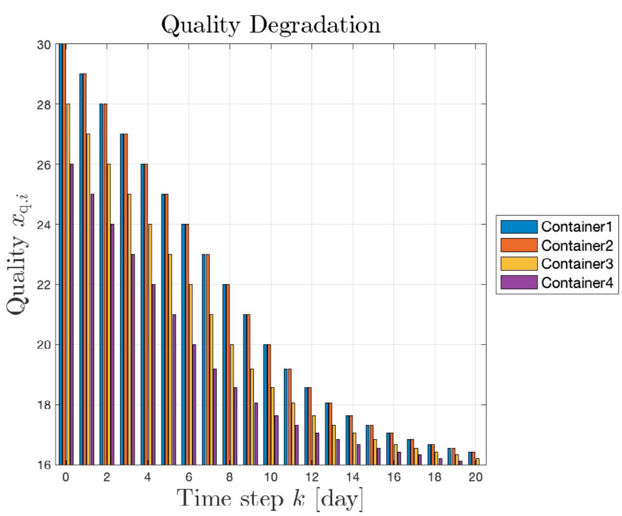

Fig. 6. Quality trends for containers during the simulation period.

5. CONCLUSIONS

Optimizing and managing the meat supply chain is inherently complex, involving multiple factors that influence quality, cost, and sustainability. The development of robust control strategies is essential for minimizing waste, ensuring food safety, and maintaining high-quality standards for perishable goods. This work introduced an MS-MPC approach to address the challenges posed by uncertainty in retailer demand. The MS-MPC method demonstrated its capacity to enhance supply chain robustness by effectively managing uncertainties, leading to improved reliability in delivery schedules and compliance with quality thresholds. By considering multiple demand scenarios, the MS-MPC framework successfully balances the competing objectives of meeting immediate demand and ensuring the long-term sustainability of the supply chain. These findings underline the potential of MS-MPC as a practical and scalable tool for real-world supply chain applications, particularly in environments characterized by demand variability and logistical constraints.

REFERENCES

Bruckner, S., Albrecht, A., Petersen, B., and Kreyenschmidt, J. (2012). Influence of cold chain interruptions on the shelf life of fresh pork and poultry. *International Journal of Food science & technology*, 47(8), 1639–1646.

Camacho, E.F. and Bordons, C. (2013). *Model predictive control*. Springer science & business media.

Degachi, H., Chanfreut, P., and Maestre, J. (2020). A nonlinear distributed model predictive scheme for systems based on hammerstein model. *IFAC-PapersOnLine*, 53(2), 3361–3366. 21st IFAC World Congress.

Flanagan, K., Robertson, K., and Hanson, C. (2019). Reducing food loss and waste. *Setting the Global Action Agenda*.

Jonkman, J., Barbosa-Póvoa, A.P., and Bloemhof, J.M. (2019). Integrating harvesting decisions in the design of agro-food supply chains. *European Journal of Operational Research*, 276(1), 247–258.

Jouzdani, J. and Govindan, K. (2021). On the sustainable perishable food supply chain network design: A dairy products case to achieve sustainable development goals. *Journal of Cleaner Production*, 278, 123060.

Mack, M., Dittmer, P., Veigt, M., Kus, M., Nehmiz, U., and Kreyenschmidt, J. (2014). Quality tracing in meat supply chains. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 372(2017), 20130308.

Maestre, J.M., Velarde, P., Ishii, H., and Negenborn, R.R. (2021). Scenario-based defense mechanism against vulnerabilities in lagrange-based dmpc. *Control Engineering Practice*, 114, 104879.

Mesbah, A. (2016). Stochastic model predictive control: An overview and perspectives for future research. *IEEE Control Systems Magazine*, 36(6), 30–44. doi: 10.1109/MCS.2016.2602087.

Paciarotti, C. and Torregiani, F. (2021). The logistics of the short food supply chain: A literature review. *Sustainable Production and Consumption*, 26, 428–442.

Raab, V., Petersen, B., and Kreyenschmidt, J. (2011). Temperature monitoring in meat supply chains. *British Food Journal*, 113(10), 1267–1289.

Read, Q.D., Brown, S., Cuéllar, A.D., Finn, S.M., Gephart, J.A., Marston, L.T., Meyer, E., Weitz, K.A., and Muth, M.K. (2020). Assessing the environmental impacts of halving food loss and waste along the food supply chain. *Science of the Total Environment*, 712, 136255.

Ren, Q.S., Fang, K., Yang, X.T., and Han, J.W. (2022). Ensuring the quality of meat in cold chain logistics: A comprehensive review. *Trends in Food Science & Technology*, 119, 133–151.

Schmidt, B.V. and Moreno, M.S. (2022). Traceability optimization in the meat supply chain with economic and environmental considerations. *Computers & Industrial Engineering*, 169, 108271.

Sprong, J., Lin, X., Maestre, J.M., and Negenborn, R.R. (2019). Quality-aware control for optimizing meat supply chains. In *2019 18th European Control Conference (ECC)*, 3867–3872. IEEE.

Velarde, P., Gallego, A.J., Bordons, C., and Camacho, E.F. (2023). Scenario-based model predictive control for energy scheduling in a parabolic trough concentrating solar plant with thermal storage. *Renewable Energy*, 206, 1228–1238.