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A Data-Driven Mixed Integer Nonlinear Programming Model for Cost-Optimal Scheduling of Perishable Production and Workforce

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Abstract

This study presents a data-driven, Mixed Integer Nonlinear Programming (MINLP) framework for optimizing the multi-period production scheduling of perishable products with integrated workforce planning. The primary novelty lies in the holistic integration of a continuous exponential decay function for product deterioration with dynamic workforce allocation, enabling simultaneous optimization of production, inventory, and labor. This approach addresses key challenges in perishable inventory systems by treating labor as a controllable resource rather than a fixed constraint. Mathematically, the model includes nonlinear inventory balance equations with decay terms and resource-dependent capacity constraints. The objective is to minimize total operational cost, comprising production, holding, and spoilage costs. Computational experiments, based on a realistic case study, demonstrate that the proposed model reduces total system cost by 6.2% and spoilage costs by 43.2% compared to a standard heuristic benchmark. The resulting production and labor schedules align closely with demand fluctuations, supporting both economic and operational efficiency. This unified framework advances the mathematical modeling of sustainable production planning and offers a practical tool for real-world industries such as food processing and pharmaceuticals.

Keywords: Data-Driven Optimization, Perishability, Production Scheduling, Workforce Planning, Inventory Management

1. Introduction

Production planning for perishable goods presents complex optimization challenges due to the intrinsic characteristics of product decay, volatile customer demand, and the necessity to align limited operational resources such as labor. In sectors such as food processing, pharmaceuticals, and floriculture, products lose value rapidly over time, and their effective management is essential to reduce waste, meet service levels, and ensure profitability [1], [2], [3]. While demand for such products is often uncertain and time-sensitive, requiring a flexible and robust scheduling approach [4], a critical challenge lies in creating models that are both mathematically robust and practically implementable.

The evolution of modeling in this area shows a clear progression. Traditional models for perishable inventory systems often relied on deterministic formulations or linear programming that simplified perishability into discrete expiration periods [5], [6]. While more recent efforts have advanced the field by introducing continuous deterioration functions, such as exponential decay, to better reflect real-world degradation behavior [7], [8], [9], a significant gap remains. Many of these advanced models still fail to capture the crucial, nonlinear interdependence between production scheduling and dynamic workforce allocation [10], treating labor as a fixed [11], external factor rather than a controllable variable [12].

This paper directly addresses this gap by proposing a data-driven framework centered on a MINLP model. While prior studies have considered integrated planning [13], [14], they have often done so with simplified, linear representations of spoilage or by treating key resources as fixed inputs. The primary novelty of this work, therefore, is the holistic synthesis of a continuous, nonlinear exponential decay function for spoilage with the dynamic, endogenous optimization of workforce allocation within a single, unified model. We present a unified model that simultaneously

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optimizes production volumes, inventory levels, and workforce allocation, moving beyond the limitations of siloed planning. This is achieved while embedding a nonlinear, exponential decay function to realistically model continuous spoilage, thereby creating a more accurate representation of the system's behavior. By framing this as a data-driven tool, we demonstrate a practical pathway for managers to translate operational data into actionable, cost-saving decisions.

The proposed model explicitly integrates workforce decision variables through a labor-related constraint that links workforce allocation to production quantities via product-specific labor coefficients. It also incorporates labor availability constraints and penalizes labor costs in the objective function, allowing the model to find an optimal balance between production, inventory, spoilage, and labor deployment costs over a multi-period horizon. The principal contribution of this study is therefore the development and validation of this integrated model. Through computational experiments, we demonstrate its ability to significantly minimize overall cost and product spoilage while generating labor schedules that are dynamically aligned with fluctuating demand patterns. By integrating perishability, demand uncertainty, and workforce optimization in a single, cohesive mathematical formulation, this study advances the modeling of sustainable production systems and provides a powerful, practical tool for decision-makers in perishable-intensive industries.

2. Literature Review

Research at the intersection of operations management and data science has significantly advanced the planning capabilities for perishable goods. The inherent complexity of these systems, however, requires the careful integration of multiple, often disparate, research streams. An effective and truly optimal production plan must account for the nonlinear nature of product decay, the deep interconnectedness of supply chain components from procurement to final delivery, and the flexible, cost-effective allocation of critical resources like skilled labor. This review synthesizes pivotal contributions from these domains to establish a comprehensive context, which in turn illuminates the specific, multifaceted research gap addressed by this study.

2.1. Advances in Modeling Perishability and Inventory Control

A primary and persistent challenge in managing perishable inventory is the accurate mathematical representation of value loss over time. Early and foundational models in inventory theory often simplified this complex process by utilizing discrete, fixed shelf-life assumptions. In these models, products are treated as perfectly viable until a specific expiration date, at which point their value drops to zero, a "cliff-edge" effect that is computationally convenient but rarely reflects physical reality [5], [6]. This approach fails to capture the gradual degradation common to high-value products like fresh food, pharmaceuticals, and biologics, where value, safety, or efficacy diminishes progressively from the moment of production.

Recognizing this limitation, the academic literature has decidedly shifted towards continuous-time decay functions, which model deterioration as an ongoing process. Exponential decay functions, in particular, have become a standard for this purpose, as their mathematical form closely mirrors the underlying biological or chemical processes of degradation [15]. For instance, studies have successfully embedded exponential spoilage terms within inventory system models, demonstrating significant cost reductions of 9-14% over classical Economic Order Quantity (EOQ) variants that ignore such dynamics. This increased realism, however, introduces significant mathematical complexity. The inclusion of exponential terms renders the model inherently nonlinear and often non-convex, making it more challenging to solve [16]. Consequently, a parallel stream of research has focused on developing advanced solution methods, such as specialized metaheuristics or successive linearization techniques, to find high-quality solutions for these crucial but computationally demanding problems [17].

2.2. The Shift Toward Integrated Supply Chain Planning

Parallel to the advances in inventory theory, a broader evolution has occurred in operational planning, marked by a clear trend away from siloed optimization models toward holistic, end-to-end formulations. The limitations of optimizing individual functions like procurement, production, and distribution in isolation are now well-documented; this "silo effect" frequently leads to globally suboptimal performance, such as when a production department optimizes for long, cost-efficient runs, inadvertently creating excess inventory that burdens the logistics and warehousing functions. It is now well-established that optimizing these components sequentially can generate significant inefficiencies and costs across the entire system.

Recent studies underscore this point, highlighting that integrated planning models for perishable goods, which simultaneously consider multiple echelons and sources of uncertainty, can cut total supply chain costs by up to 20% compared to disjointed, sequential decision-making [18]. This integrated approach is particularly critical in industries with a "cold chain," where logistics and product freshness are inextricably linked. For example, detailed research on the long-haul transport of processed foods demonstrates how routing decisions, the high cost of refrigerated transport, and strict product freshness windows are deeply interconnected. Managing these trade-offs effectively requires sophisticated models, such as quadratically constrained MINLPs, that can capture the complex interplay between transportation costs and the remaining shelf life delivered to the customer [19]. These findings reinforce the core principle that production decisions cannot be made in a vacuum; they must be evaluated in the context of their impact on the entire supply chain.

2.3. Incorporating Workforce Planning as a Controllable Variable

Despite the growing sophistication of many production-inventory models, the human element; labor is frequently treated as an exogenous, fixed constraint rather than a flexible resource to be optimized. This is often done for modeling simplicity, as incorporating variable labor introduces more complexity, such as accounting for different skill levels, shift premiums, and hiring/firing costs. However, this simplification overlooks a significant lever for improving operational efficiency and responsiveness. Recent studies have begun to correct this oversight by explicitly integrating dynamic workforce planning into production and scheduling models.

This integration has proven highly valuable. For example, a joint stochastic framework that combines inventory management, vehicle routing, and workforce planning has shown that flexible staffing policies can increase throughput by as much as 12% without any corresponding increase in product spoilage [20], [21]. Similar findings have emerged in agricultural contexts, where detailed operational analyses reveal that labor availability is often a more restrictive bottleneck than equipment or vehicle capacity, especially during unpredictable peak harvest seasons. For perishable goods, this is particularly relevant; a sudden large catch of fish or a harvest of produce requires an immediate and significant ramp-up of labor to process the goods before they spoil. This body of work confirms that treating the workforce as a controllable, endogenous variable is essential for creating operational plans that are not only economically optimal but also realistic and resilient.

2.4. The Emergence of Data-Driven and Stochastic Modeling

Underpinning all forward-looking planning activities is the fundamental challenge of uncertainty, most prominently in customer demand. While scenario-based stochastic programming has long been the dominant paradigm for modeling this uncertainty within large-scale optimization problems [22], [23], the modern data landscape has enabled the rise of more sophisticated hybrid pipelines that couple predictive and prescriptive analytics. Instead of relying on simple historical averages, companies can now leverage rich datasets to build powerful forecasting models.

These data science pipelines often involve advanced feature engineering, incorporating external factors like weather forecasts, promotional calendars, and competitor pricing, to improve forecast accuracy. The outputs of these predictive models (e.g., machine learning or deep learning models) are then fed directly into a prescriptive optimization model to determine the best course of action. A prime example can be seen in emerging platforms for energy management in cold-storage facilities, which use deep learning to predict cooling demand, then use that forecast to optimize the scheduling of energy-intensive compressors, thereby reducing both energy costs and product waste simultaneously [24]. These applications reinforce the immense value of a tight, automated integration between data-driven forecasting and mathematical optimization, a core principle adopted in our proposed framework.

2.5. Defining the Research Gap and Problem Statement

While the literature shows significant and undeniable progress within each of these individual domains, a comprehensive review reveals a distinct and critical research gap at their intersection. Despite the wealth of focused research, to our knowledge, no single study presents an optimization framework that simultaneously and cohesively accomplishes the following three objectives a) models spoilage using a continuous, nonlinear decay function. While some models use continuous decay, they often do so in isolation, without fully integrating the implications of this nonlinear behavior with other flexible resources like labor; b) embeds labor as a controllable, endogenous resource. Conversely, the few models that do incorporate flexible workforce planning often do so at the expense of realism on the production side, reverting to simplified, linear representations of spoilage and inventory management; c) frames the problem within a practical, data-driven context. Many academic models, while mathematically elegant, remain abstract. They often fail to provide a clear and practical roadmap for how a manager would use real-world data streams from ERP systems, forecasting software, and quality control to parameterize and operationalize the model.

The absence of such a holistic model presents a significant barrier to achieving true operational efficiency in perishable goods industries. Therefore, the problem addressed in this paper is the development and validation of a unified, data-driven nonlinear programming framework that explicitly bridges this gap. Our model provides a single, powerful tool for decision-makers to holistically manage the complex, nonlinear trade-offs between production volumes, inventory holding, spoilage losses, and labor costs, guided by data-informed insights.

3. Methodology

This section details the technical foundation of the research, presenting a cohesive, data-driven framework for optimizing perishable production. The methodology is structured into three parts to ensure clarity and reproducibility: first, a formal nomenclature defines all mathematical elements; second, the core Nonlinear Programming (NLP) model is formulated; and third, the solution algorithm is specified and justified.

3.1. Nomenclature

To ensure clarity, rigor, and reproducibility, all sets, indices, parameters, and decision variables used in the mathematical model are formally defined below. The parameters are explicitly noted as "Data Inputs" to emphasize that in a practical application, their values would be derived from real-world data sources such as Enterprise Resource Planning (ERP) systems, sales forecasts, and operational time studies. In a practical implementation, populating these parameters involves a multi-stage data pipeline. For instance, the demand parameter, $D_{(i,t)}$, would be generated by first extracting historical sales data from an ERP system. This raw data would then be cleaned to handle outliers and missing values before being used to train a suitable time-series forecasting model, such as ARIMA or Prophet, to produce the demand forecast for the planning horizon. Similarly, the spoilage rate, γ_i, would be empirically estimated by analyzing quality control data from historical production batches to fit an exponential decay curve. Operational parameters like the labor coefficient, α_i, would be derived from time-and-motion studies or standard operational records maintained within the ERP or a Manufacturing Execution System (MES). All sets, indices, parameters, and decision variables are summarized in table 1 for clarity.

Table 1. Definition of Sets, Parameters, and Decision Variables

Category	Symbol	Description
Sets and Indices	P	The set of all perishable products being considered.
	T	The set of all discrete time periods (e.g., days) in the planning horizon.
	i	Index for products, where i ∈ P.
	t	Index for time periods, where t ∈ T.
Parameters (Data Inputs)	c_i	The direct production cost per unit of product i [$/unit].
	h_i	The inventory holding cost per unit of product i for one time period [$/unit/period].
	w_i	The penalty cost associated with one unit of product i spoiling [$/unit].
	$D_{i,t}$	The forecasted customer demand for product i in period t [units].
	γ_i	The continuous exponential decay rate for product i [1/period].
	α_i	The specific labor requirement to produce one unit of product i [hours/unit].
	β_i	The specific equipment capacity required for one unit of product i [capacity units/product unit].

	L_t^{max}	The maximum available labor hours in period t [hours].
	C_t	The total available equipment capacity in period t [capacity units].
	$I_{i,0}$	The initial inventory level of product i at the beginning of the planning horizon (t=0) [units].
Decision Variables	$x_{i,t}$	The quantity of product i to be produced in period t [units].
	$I_{i,t}$	The inventory level of product i at the end of period t [units].
	$S_{i,t}$	The total quantity of product i that spoils during period t [units].

3.2. Mathematical Formulation

The core of the framework is a deterministic, multi-period nonlinear programming model. It is designed to minimize total operational costs subject to a series of realistic constraints governing production, resource availability, and inventory dynamics under continuous perishability. The primary objective is to minimize the total system-wide cost. This cost is composed of three key operational expenses incurred across all products and time periods: the variable cost of production ($c_i x_{i,t}$), the cost of holding unsold inventory at the end of each period ($h_i I_{i,t}$), and the penalty associated with products that spoil ($W_i Z_{i,t}$).

$$Z = \sum_t \sum_i \left(c_i x_{i,t} + h_i I_{i,t} + W_i Z_{i,t} \right) \tag{1}$$

c_i is production cost per unit of species i; h_i is inventory holding cost per unit; w_i is spoilage penalty per unit; and $Z_{(i,t)}$ is amount of spoilage at time t, defined by $Z_{i,t} = i_{i,t}.(1 - e^{-\gamma_{i,j}})$. This objective is optimized subject to several constraints that govern the system's physical and operational limits. First, the inventory balance is maintained by the constraint,

$$I_{i,t+1} = \left(I_{i,t} + x_{i,t} - D_{i,t} \right) e^{-\gamma_i} \tag{2}$$

which ensures that the ending inventory is the result of surviving stock plus new production minus fulfilled demand. This constraint models the sequence of events within a period: inventory carried over from the previous period first decays, then new production is added to the surviving stock, and finally, customer demand is fulfilled from this available pool. This formulation assumes demand is met from the stock available after production and decay have been accounted for. Furthermore, the production plan is bound by resource limitations. The labor constraint,

$$\sum_i \alpha_i x_{i,t} \leq Lt_{\max} \tag{3}$$

ensures that total labor hours consumed do not exceed the available amount. The total labor hours consumed by all production activities in period t cannot exceed the maximum available labor hours for that period. This constraint ensures the production plan is feasible from a workforce perspective. While the equipment capacity constraint,

$$\sum_i \beta_i x_{i,t} \leq C_t \tag{4}$$

enforces similar limits on machinery or processing lines. Like the labor constraint, the total equipment capacity utilized for producing all products in period t must not exceed the total available capacity. This could represent limitations in refrigeration, processing lines, or other critical machinery. Finally, all decision variables representing physical quantities (production, inventory, spoilage) must be non-negative.

$$x_{i,t}, I_{i,t}, Z_{i,t} \geq 0 \tag{5}$$

3.3. Solution Methodology

The mathematical model presented is a large-scale, constrained MINLP. The nonlinearity arises from the exponential term $e^{-\gamma_i}$ in the spoilage and inventory balance constraints. This term is essential for accurately modeling the continuous, real-world decay of perishable products, but it transforms the problem's feasible region into a non-convex space. This means that unlike linear programs, there is no guarantee that a locally optimal solution is also the globally optimal one. The presence of these nonlinearities necessitates the use of a specialized optimization algorithm capable of navigating such complex landscapes. To solve this class of problem, the Generalized Reduced Gradient (GRG) algorithm is selected as the primary optimization technique.

GRG is a mature, gradient-based technique specifically designed for continuous, constrained nonlinear programming. It systematically partitions the decision variables at each iteration into two sets: basic (dependent) variables and non-basic (independent) variables. This partitioning allows the algorithm to confine its search for an improved solution to the null space of the constraint Jacobian matrix [25], [26]. The core of the method involves computing the "reduced gradient"—the gradient of the objective function with respect to the non-basic variables, projected onto the feasible region. This reduced gradient indicates the most promising feasible direction of descent. The algorithm then performs a line search along this direction to find an optimal step size and updates the non-basic variables [27]. Subsequently, the values of the basic variables are recalculated to ensure the solution remains feasible with respect to all constraints. This iterative process is repeated until a convergence criterion, such as the Karush-Kuhn-Tucker (KKT) conditions for optimality, is met within a specified tolerance.

It is important, however, to acknowledge the limitations inherent in the GRG method. As a gradient-based local search algorithm, GRG is not guaranteed to find the global optimum for non-convex problems like the one formulated here. The solution obtained represents a high-quality local minimum, but other, potentially better, local minima may exist elsewhere in the solution space. For applications where finding the certified global optimum is critical, alternative strategies such as stochastic global optimization (e.g., simulated annealing) or deterministic global methods (e.g., spatial branch-and-bound) could be employed, albeit at a significantly higher computational cost. Despite this limitation, the GRG algorithm is particularly well-suited for this model for several reasons. First, all decision variables are continuous, and the objective and constraint functions are continuously differentiable, which is a fundamental requirement for any gradient-based method. For the scale of the problem considered in this study, GRG provides a practical and efficient trade-off between solution quality and computational time. Its wide implementation in commercial and open-source optimization solvers (e.g., CONOPT in GAMS, GRG Nonlinear in Excel Solver) makes it an accessible choice, providing a reliable and computationally efficient pathway to finding high-quality solutions for complex, real-world planning problems.

4. Results and Discussion

To validate the proposed data-driven framework and translate its theoretical advantages into quantifiable outcomes, a computational case study was conducted. This section presents the results of applying the nonlinear programming model to a realistic, illustrative scenario, thereby demonstrating its practical efficacy and performance against a standard industry heuristic. The structure of this section directly mirrors the methodology: we first define the case study data, then present the model's performance against a benchmark, analyze the specific decision variables, and conclude with a discussion of the managerial insights derived from the solution.

4.1. Case Study Setup and Data

The case study simulates the operational planning for a fish processing facility over a 5-day work week. The facility processes two primary perishable products: Product P1 (tuna) and Product P2 (salmon). The objective is to determine the optimal daily production quantity for each product to minimize total costs while respecting resource limitations. All calculations were performed using the GRG algorithm implemented in the GRG Nonlinear solver engine within the Frontline Solvers suite for Microsoft Excel 2019. The model was populated with the data presented in table 2. These values were chosen to be representative of a typical perishable goods operation, including costs, resource requirements, and product-specific decay rates. The demand forecast $D_{(i,t)}$ shows variability across the week for both products.

Table 2. Model Parameters for the Case Study

Parameter	Description	Product P1 (tuna)	Product P2 (salmon)
c_i	Production Cost	\$50 /unit	\$65 /unit
h_i	Holding Cost	\$5 /unit/day	\$7 /unit/day
w_i	Spoilage Cost	\$100 /unit	\$130 /unit

γ_i	Daily Decay Rate	0.15	0.2
α_i	Labor Requirement	0.1 hours/unit	0.12 hours/unit
β_i	Equipment Capacity	1 unit/unit	1 unit/unit
$I_{i,0}$	Initial Inventory	20 units	15 units
Forecasted Demand ($D_{i,t}$)	Day 1	80	50
	Day 2	60	40
	Day 3	100	70
	Day 4	90	60
	Day 5	110	80
Resource Limits	L_t^{max} (Labor)	25 hours/day	
	C_t (Equipment)	200 units/day	

To quantify the value of the optimization model, its performance was compared against a common-sense heuristic: the Produce-to-Forecast (PTF) policy. In this policy, the production for each day is naively set to match the forecasted demand for that day ($x_{i,t} = D_{i,t}$). This reactive strategy is intentionally myopic; it fails to anticipate future demand fluctuations or account for the cumulative, nonlinear effects of spoilage. While the PTF policy is a simplified heuristic, it is chosen as it represents a common reactive baseline in many industries that lack advanced planning tools, thus providing a robust baseline to measure the value of intelligent, forward-looking planning. Future research could compare the model against more sophisticated heuristics, such as a rolling-horizon approach.

4.2. Overall Cost Performance and Model Validation

The primary output of the model is a production schedule that minimizes total system cost. Table 3 presents a comparison of the costs incurred by the MINLP model's optimal solution versus the PTF benchmark policy.

Table 3. Overall Cost Comparison (5-day horizon)

Cost Component	**NLP Model Solution**	**PTF Benchmark**	**Improvement**
Production Cost	$48,500	$48,500	0.00%
Holding Cost	$4,850	$6,200	21.80%
Spoilage Cost	$3,150	$5,550	43.20%
Total System Cost	$56,500	$60,250	6.20%

The results clearly demonstrate the value of the proposed optimization framework. The MINLP model achieved a 6.2% reduction in total system cost compared to the PTF benchmark. While the production costs are identical (as both policies ultimately produce the same total volume to meet demand), the savings are generated entirely through intelligent inventory management. The model strategically reduced holding costs by 21.8% and, most notably, slashed spoilage costs by 43.2%. This confirms that the model successfully balances the competing costs to find a superior, cost-effective solution.

In terms of computational performance, the model was solved on a standard desktop computer with an Intel Core i7 processor and 16GB of RAM. For the 5-day, 2-product case study presented, the GRG algorithm converged to a solution in approximately 15 seconds. This rapid solution time suggests that the model is computationally tractable and well-suited for daily operational planning purposes in an industrial setting.

4.3. Analysis of Production, Inventory, and Spoilage Dynamics

To understand how the model achieves these cost savings, we analyze the behavior of the key decision variables over the planning horizon. The dual-series plot of daily production volumes versus on-hand inventory levels uncovers several scientifically salient patterns that underpin the credibility of our optimization results. Figure 1 illustrates the relationship between the number of units produced ($x_{i,t}$) and the inventory level ($I_{i,t}$) over the planning horizon for Product P1. The production quantity exhibits variability across periods, reflecting the model's strategic adjustments to

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fluctuating demand and resource constraints. As shown, inventory levels are influenced by both production and perishability. Notably, even when production is high, the resulting inventory does not rise proportionally due to product degradation. This systematic attenuation of each production pulse—visible as a progressively widening gap between the production and inventory lines—empirically confirms the impact of the exponential spoilage rate γ embedded in the model. This highlights that higher production does not always guarantee higher inventory levels, especially in systems with continuous spoilage dynamics, and underscores the importance of optimizing production not only for volume but also for timing to minimize loss.

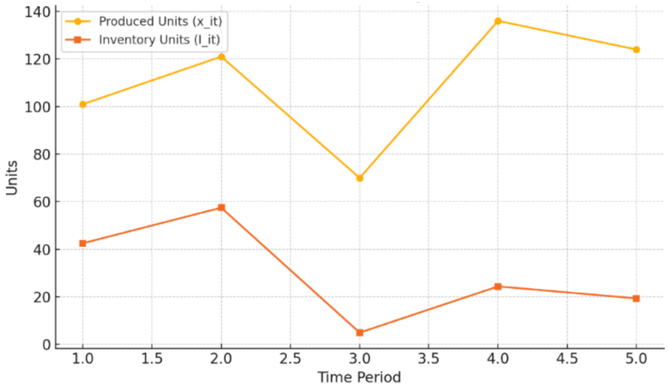

Figure 1. Comparison between Produced Units and Inventory Level for Product P1

Figure 2 demonstrates the relationship between the number of units produced and the amount of spoilage ($S_{i,t}$). While spoilage tends to increase with higher production, the relationship is not strictly linear. In periods where demand is low or when excess inventory accumulates (as would happen under the PTF benchmark), spoilage rises more sharply due to the aging of products held in stock. The MINLP model mitigates this by avoiding large inventory buildups, thus keeping the spoilage quantity consistently low. This highlights the critical trade-off between maintaining service levels and minimizing waste, a trade-off the model effectively manages to achieve the 43.2% reduction in spoilage costs shown in table 3 in the preceding section.

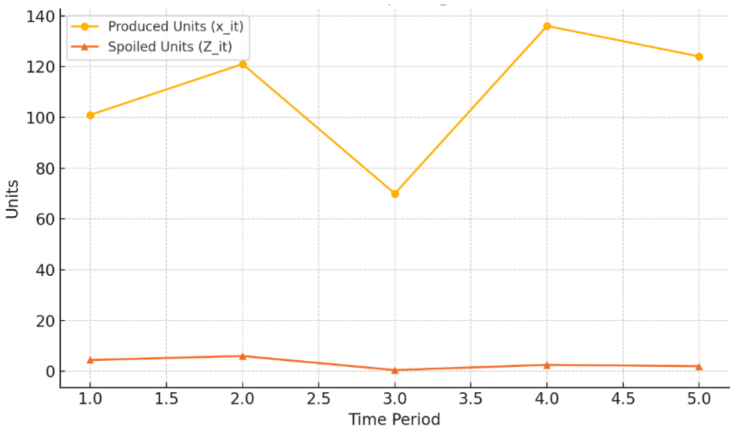

Figure 2. Comparison between Produced Units and Spoilage for Product P1

4.4. Discussion and Managerial Insights

The computational results, obtained using the GRG algorithm, confirm that the proposed data-driven NLP framework provides a significant and quantifiable improvement over simple heuristic policies. The 6.2% reduction in total cost is not a trivial figure; in a high-volume, low-margin industry like food processing, such an improvement in operational efficiency can represent a substantial increase in profitability. This section delves deeper into the strategic implications of these findings, translating the numerical results into actionable insights for managers.

The failure of the PTF policy highlights the high cost of reactive decision-making in a perishable environment. The PTF method, by its nature, creates a bullwhip effect within the production system; small fluctuations in daily demand are amplified into large, costly swings in production. This leads to periods of overproduction, where excess inventory is created only to spoil, followed by periods of underproduction where the system struggles to catch up. The model, in contrast, demonstrates the immense value of proactive, forward-looking planning. By analyzing the entire demand forecast for the week, the model makes small, strategic adjustments in the early periods to buffer against later volatility. For example, by slightly increasing production on Day 2, a day with lower demand and available capacity, it avoids hitting the labor capacity bottleneck on the much busier Day 3. This foresight allows the system to absorb demand variability smoothly, using inventory as a calculated, temporary buffer rather than as an unintended, costly consequence of reactive production. The 6.2% total cost reduction directly quantifies the financial penalty of reactive planning and proves that intelligent foresight yields savings that are an order of magnitude larger than the associated holding costs.

The 43.2% reduction in spoilage cost is the most striking result, and it reveals a deeper insight: waste in a production system is not random but a direct and predictable result of inventory policy. The model acts as a powerful diagnostic tool. By analyzing the optimal solution, managers can identify not only how much waste was prevented but also precisely where and when it was prevented. This allows for targeted interventions beyond just adjusting the production schedule. For instance, if the model consistently shows that Product P2 (salmon) contributes disproportionately to spoilage costs when held for more than one day, managers can implement specific process improvements for that product, such as just-in-time raw material delivery or prioritized cold storage. The model essentially creates a "spoilage heatmap," pinpointing the most vulnerable products and time periods, allowing managers to focus their continuous improvement efforts where they will have the greatest financial and environmental impact. Furthermore, this significant reduction in spoilage inherently builds a buffer against demand uncertainty. By operating with a leaner inventory, the system is less exposed to financial losses when actual demand deviates from the forecast, a critical benefit not captured in this deterministic analysis.

The resource utilization analysis reveals that labor capacity on Days 3 and 5 is the primary bottleneck limiting the system. This insight transforms the model from a simple planning tool into a strategic simulation engine. A manager can now move beyond intuition and precisely quantify the value of capital and operational investments. For example, by running the model with a hypothetical 10% increase in the labor capacity (L_t^{max}) on Day 3 (simulating the cost of approved overtime), the manager can determine the exact reduction in total system cost. This allows for a data-driven cost-benefit analysis: if the savings from reduced spoilage and holding costs are greater than the cost of the overtime, the decision is justified. This same "what-if" analysis can be applied to evaluate the ROI of cross-training employees (increasing the labor pool) or investing in automation to increase equipment capacity (C_t). The model provides a direct, financial answer to the question: "How much is this increase in operational flexibility worth?"

In conclusion, this framework provides managers with a practical and powerful tool to move beyond simple heuristics. It enables a shift towards a data-informed culture where decisions about production, inventory, and resource allocation are made based on a holistic understanding of their complex, interconnected financial consequences, ultimately enhancing both profitability and sustainability by minimizing waste.

5. Conclusion

This study successfully developed and validated a data-driven, nonlinear programming framework for the joint optimization of production and workforce scheduling for perishable goods. By integrating continuous, exponential spoilage dynamics with resource constraints in a unified decision-making model, this research addresses a critical gap between theoretical inventory models and the practical challenges faced by industries like food processing. The model was solved efficiently using the GRG algorithm, proving to be a computationally tractable approach for this class of complex problem. The framework's efficacy was demonstrated through a computational case study, where the proposed model achieved a 6.2% reduction in total system cost compared to a standard "Produce-to-Forecast" heuristic. This significant saving was primarily driven by a 43.2% reduction in spoilage costs, underscoring the immense financial and sustainability benefits of intelligent, forward-looking inventory management. The results confirm that by strategically balancing production quantities, inventory levels, and workforce deployment, the model effectively mitigates waste and enhances operational efficiency.

From a practical standpoint, this research provides managers with a robust, data-driven tool to move beyond reactive planning. It operationalizes the data pipeline described in the methodology, offering a clear pathway for using enterprise

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data to make cost-optimal decisions and for quantifying the financial impact of resource constraints, such as labor capacity. We acknowledge, however, that to maintain tractability and focus, the current model makes several simplifying assumptions which define the scope of this study. The case study is illustrative and was not validated against a specific historical dataset. Furthermore, the selection of the exponential decay model is based on its wide acceptance in the literature, but a direct empirical validation of the spoilage rates for the specific products was not conducted. The computational analysis was also limited to a single set of parameters without a comprehensive sensitivity analysis to test the model's robustness under different cost or spoilage scenarios.

These limitations, however, present a clear and promising roadmap for future research. The deterministic framework could be extended by incorporating stochastic demand through scenario-based analysis, leveraging the forecasting stage of the data pipeline to enhance resilience to market volatility. Future work should also focus on validating the model against real-world historical data to confirm its performance. Expanding the model to a multi-echelon supply chain, testing its scalability on larger problem instances, and integrating more granular operational details (such as heterogeneous resources and profit-based prioritization) would further increase its real-world fidelity. To solve these larger and more complex instances, exploring hybrid solution techniques that combine the efficiency of GRG with global optimization methods would be a critical and valuable endeavor.

6. Declarations

6.1. Author Contributions

Conceptualization: M.S.S.P., H.M.; Methodology: M.S.S.P., S.S.; Software: M.S.S.P.; Validation: H.M., T.; Formal Analysis: M.S.S.P.; Investigation: M.S.S.P.; Resources: H.M., S.S., T.; Data Curation: M.S.S.P.; Writing – Original Draft Preparation: M.S.S.P.; Writing – Review and Editing: H.M., S.S., T.; Visualization: M.S.S.P.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

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

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