The "Cascade Degradation Coefficient" Dynamic Pricing Model: From Mathematical Framework to Flower Retail Practice

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Abstract: - This article presents the results of the development of a hybrid mathematical dynamic pricing model, the "Cascade Degradation Coefficient," for the cut flower market. The research methodology is based on the synthesis of dynamic and stochastic modeling frameworks, utilizing piecewise-defined functions to describe cascade degradation, monotonic cosine-based functions to model the visual factor, a modified hyperbolic tangent to account for psychological perception, and multiplicative seasonal modulators. As a result, a multiplicative model integrating four independent factors has been created: temporal, visual, psychological, and seasonal. The conducted verification confirmed the model's physical realizability. The practical significance of the research lies in the creation of a tool for transitioning from intuitive pricing to data-driven optimization, enabling the maximization of profit and minimization of losses from write-offs in flower retail and e-commerce.

Key-Words: - Pricing Model, Cascade Degradation Coefficient, Perishable Goods, Cut Flower Market, Hybrid Mathematical Model, Stochastic Modeling, Data-Driven Optimization, Flower Retail, Perishable Product Pricing, Multiplicative Model.

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1 Introduction

The relevance of this study is determined by the high risks associated with pricing in the flower business. The perishable nature of the product, pronounced demand seasonality, its unpredictability, as well as the extremely complex conditions for storage and sale of the floral assortment, create unique challenges for profitability management. Traditional pricing models prove inadequate for this segment, leading to direct losses from write-offs or loss of potential revenue due to suboptimal pricing during periods of peak demand. The digitalization of retail and the development of models analogous to dark kitchens (local refrigerator warehouses for rapid delivery) [1] open new opportunities for floral e-commerce but require corresponding flexible and precise dynamic pricing tools integrated into assortment management automation systems and omnichannel platforms, [2], [3].

The objective of this work is to develop a hybrid mathematical pricing model for cut flowers, adapted to their specific characteristics and applicable in the context of modern digital commerce.

To achieve this objective, the following tasks were set:

- To review and analyze existing classical mathematical pricing models for perishable goods.
- To substantiate the necessity for developing a new hybrid model synthesizing the accounting of temporal, visual, psychological, and seasonal components.
- To develop the mathematical framework of the "Cascade Degradation Coefficient" (CDC) model.
- To conduct verification of the model for physical realizability and adequacy to industry practice.

The research methodology is based on the application of dynamic and stochastic modeling frameworks. The work utilizes piecewise-defined functions to describe cascade degradation, monotonic cosine-based functions to model the visual factor, modified logistic functions (hyperbolic tangent) to account for psychological perception, as well as multiplicative seasonal modulators. The toolkit includes methods of mathematical analysis to verify function properties (monotonicity, continuity, correctness of derivatives).

The scope of the research covers the segment of cut flowers sold via online marketplaces and other channels of modern digital trade, with a focus on types such as roses. The model assumes the possibility of its parametric configuration for other flower types and storage conditions.

The scientific novelty of the work lies in the synthesis of four independent pricing factors within a unified multiplicative model, allowing for a more adequate description of the price formation processes for a unique perishable product. The practical significance is determined by the fact that the developed model can be integrated into automation systems for assortment and pricing management for flower retail and e-commerce, including platforms operating on the dark store principle. This will enable a transition from intuitive pricing to data-driven optimization, maximizing profit and minimizing losses from write-offs.

2 Materials and Methods

The cut flower market represents a unique segment in the field of price management for perishable goods. Hereafter in the study, by 'product' we will mean a cut flower intended for sale. The key features of the product necessitate the adaptation of classical mathematical pricing models. These features include:

- Multifactorial product degradation, as the cost of flowers is determined not only by time since cutting but also by the visual condition of the flower (petal turgor, leaf freshness, and others).
- Cascade degradation of the product, expressed through a non-linear process of value loss at different stages of the life cycle (e.g., slow degradation in the first days after cutting and a sharp acceleration thereafter).
- Non-linear psychological barriers to consumer willingness to pay, which drop sharply, not gradually, upon the flower reaching a certain "degradation" threshold.
- High event-driven seasonality in the market, where demand for cut flowers (bouquets) is characterized by extreme spikes on pre-holiday days (March 8th, Valentine's Day) and deep troughs following them.

2.1 Review of Classical Pricing Models

Aiming to determine the optimal mathematical pricing model for cut flowers, the authors conducted a review of classical pricing models and assessed their applicability to the cut flower market.

The model [4], [5], based on an exponential decay function:

$$P(t) = P_0 \cdot e^{-\lambda t}, \quad (1)$$

where P_0 is the initial price, λ is the decay rate coefficient, t is time.

The model is effective for describing the basic trend of price decrease. A high decay rate (λ) can roughly approximate the effect of a "collapse" in value closer to the end of the shelf life. This allows concluding the model's applicability as a base for simple and transparent dynamic pricing systems. Its main drawback for the product in question is its dependence solely on time. The model does not account for the visual condition of the flower, which is a critical factor. It cannot model cascade degradation (as it assumes a constant markdown rate) and is useless for forecasting the event-driven seasonality of the cut flower market, as it does not include a demand factor.

The model [6], [7], which demonstrates linear decay:

$$P(t) = P_0 \cdot (1 - \alpha t), \quad (2)$$

where P_0 is the initial price, α is the linear decay coefficient, t is time.

The model is simple to implement and may be applicable during periods of low and stable degradation (e.g., for resilient flower types under ideal storage conditions). However, for the cut flower market, it was deemed by the authors as the least adequate option. Linear decay completely contradicts reality, where value degradation and price drop are non-linear, and the specifics of the psychological barrier relate to a sharp, not smooth, price decrease. Furthermore, like the exponential model [4], it does not account for appearance and demand seasonality.

The model [8] contains a toolkit for stochastic optimization:

$$P^*(t) = arg\ max\ E[\pi(P, D(P), S(t))], \quad (3)$$

where π is profit, $D(P)$ is price-dependent demand, $S(t)$ is inventory remainder, E is the mathematical expectation (The superscript * (asterisk) is used to indicate the optimal value of a variable).

Analysis of the model allowed the authors to conclude that among the considered classical pricing models, this is the most promising and adequate basis for modeling flower prices. Its key advantage is accounting for demand uncertainty ($D(P)$) and inventory levels ($S(t)$). This allows managing event-driven seasonality and linking price to product stock. In practice, this means the ability to dynamically raise prices during periods of peak demand (holidays), aggressively reduce them afterwards to minimize losses, and automatically intensify markdowns with an increase in unsold stock remainder. The only thing the base model does not account for is the qualitative state of the product. For full application in the flower business, it needs modification by introducing into the demand function $D(P)$ not only time t but also a freshness parameter $F(t)$, which describes visual degradation and non-linear thresholds of buyer perception. This transforms it into a hybrid model. $P^*(t, F, S)$.

Thus, none of the classical pricing models in their pure form is ideal for the cut flower market due to ignoring the factor of visual degradation as a key and independent variable influencing demand. The most adequate approach is the development of stochastic models [8] towards hybrid ones, which simultaneously account for time, inventory remainder, demand forecast, and the qualitative state of the product, which is the basis for modern dynamic pricing systems in perishable goods retail.

2.2 Hybrid Models and Approaches for Adaptation

Although a universal model does not exist, the following approaches and their combinations come closest to solving the problem of choosing the optimal mathematical pricing model for the cut flower market.

Condition-Based Pricing models [9], strictly speaking, represent an entire class. The idea is to modify classical models by introducing a "quality (freshness)" parameter $F(t)$. Then the price becomes a function not only of time and stock but also of visual condition: $P^*(t, F, S)$. The quality (freshness) parameter of the flower $F(t)$ can be deterministic. For example, $F(t) = e^{-\gamma t}$, where γ is the visual degradation coefficient (which may be higher than the temporal degradation coefficient λ). Or the parameter can be stochastic – modeled as a random process (e.g., Markovian) to account for the unpredictability of wilting. The authors consider the most promising option to be a measurable operation of the quality parameter $F(t)$, where it is a numerical indicator obtained via computer vision (analysis of the flower image to assess freshness).

As an example, an adaptation of the stochastic model [8] is provided:

$$P^*(t, F, S) = arg\,max\,E[\pi(P, D(P, F), S(t))] \quad (4)$$

where demand D depends not only on price P but also on quality (freshness) F. This is a key change that allows modeling a sharp drop in demand when a threshold value F is reached.

Threshold Models [10], [11] are the best solution if the economic implementation priority of the mathematical model is managing the factor of "psychological barriers to consumer willingness to pay." For this, the product's life is divided into several discrete phases (e.g., "fresh," "medium freshness," "wilting"), and each phase is assigned its own pricing function. As a result, instead of one continuous function $P(t)$, a piecewise-defined function is used, as shown in the example:

Phase 1: $(0 < t < T_1): P(t) = P_0$ (premium price).

Phase 2: $(T_1 < t < T_2): P(t) = P_0 \cdot k_1 \cdot e^{-\lambda_1 t}$ (moderate markdown).

Phase 3: $(t > T^2): P(t) = P^0 \cdot k^2 \cdot e^{(-\lambda^2 t)}$, where λ^2 significantly exceeds λ_1 (aggressive, "steep" markdown).

Here, T_1, T_2 are precisely those threshold values of freshness.

Demand-Learning Models [12], [13] have an advantage for managing event-driven seasonality. The price in this case is not set by a deterministic formula in advance but is constantly adapted based on real sales data (the "buy-in" principle). The algorithm in real-time (every day or hour) assesses how quickly the product is selling at the current price. If the sales speed of the flower is below the target, the price is reduced more aggressively. If the product is in high demand, the price reacts with an increase. This allows a flexible response to pre-holiday surges and subsequent slumps.

The analysis of the capabilities and limitations of approaches to applying hybrid mathematical pricing models showed the promise of hybrid modeling, but also revealed the absence of a model that would account for all characteristic features of a perishable product, such as a cut flower. The processes of degradation and consumer perception are non-linear and have threshold division, which requires the creation of fundamentally new mathematical frameworks beyond standard differential equations. At the same time, technology development (computer vision, IoT sensors in refrigerators) allows quantitative measurement of the parameter $F(t)$ in real-time, which was previously impossible. This paves the way for data-driven models, [14]. Given the uniqueness of floral products, a promising solution seems to be not the search for a single ready-made model but the development of a new hybrid model synthesizing the best features of the approaches described above.

2.3 Rationale and Guidelines for Developing a New Model

The success of applying any mathematical framework is determined by clear guidelines for creating an adaptive hybrid model. In the authors' opinion, the most promising model is a stochastic dynamic optimization system where the price. P^* of a flower is found as $arg\,max$ of the mathematical expectation of profit, provided that demand depends on price, time, inventory remainder, and, most importantly, a quantitatively measurable product quality (freshness) parameter.

The stochastic optimization model [8] was taken as a basis, as the most flexible and powerful. The key modification was the introduction of the quality (freshness) parameter $F(t)$ into the demand function:

$D = D(P, F, t, X)$, where X represents other factors (holiday, day of the week).

The form of the function $D(P, F, t, X)$ should be non-linear and have an "S-shaped" or "threshold" nature, dropping sharply when $F(t) < F_{critical}$.

This required formalizing the law of change of $F(t)$ through a differential equation of the form:

$dF/dt = -G(F, t, T, H)$, where T is storage temperature, H is humidity. This allows accounting for logistics and storage conditions.

It also required explicitly introducing a calendar factor into the model – binary variables responsible for pre-holiday days, weekends, etc., which scale the demand function. Thus, the event factor was accounted for.

The model was developed with a focus on its training and validation on real data: historical data on flower sales, remainders, and, if possible, data from sensors or expert assessments of quality (freshness).

3 Results

3.1 The "Cascade Degradation Coefficient" (CDC) Model

The developed model is based on the concept of cascade value degradation – a process of stepwise reduction in product value under the influence of multiple factors with different rates and intensities. The meaning of the expression "cascade degradation" lies in the multi-stage reduction of the consumer value of a perishable product, characterized by different degradation rates at different time intervals.

The final price adjustment coefficient for perishable goods is presented as the product of independent factors: temporal, visual, psychological, and seasonal. All quantitative indicators, as well as transition periods between degradation stages, were obtained experimentally by a professional florist using the rose as an example.

The formula for calculating the price adjustment coefficient has a multiplicative structure:

$$K(TTL, t, events) = [\psi(TTL) \cdot \Phi(TTL) \cdot \Omega(TTL)] \cdot [1 + \Theta(t, events)], \quad (5)$$

where:

$K(TTL, t, events)$ is the final price adjustment coefficient;

$\psi(TTL)$ is the cascade temporal factor (see formula 6);

$\Phi(TTL)$ is the visual attractiveness factor;

$\Omega(TTL)$ is the psychological perception factor;

$\Theta(t, events)$ is the seasonal-event modulator;

TTL is the normalized Time To Live ∈ [0,1]

$$TTL(t) = (T_{lifetime} - T_{current})/T_{lifetime}, \quad (6)$$

where:

$T_{lifetime}$ is the total flower lifespan (in hours);

$T_{current}$ is the current time (in hours).

3.2 Cascade Temporal Factor $\psi(TTL)$

The cascade factor reflects the unevenness of the value loss process over time. Analysis of empirical data from the flower market showed the presence of three distinct degradation regimes (Table 1).

Table 1. Product Degradation Regimes

TTL Range	Formula ψ(TTL)	Regime	Description
(0.8, 1.0]	1.0	Stability Regime	Product is fresh, maximum value, no signs of degradation.
[0.3, 0.8]	0.185 + 0.815 × (TTL / 0.8)²	Moderate Degradation	Slight quality decrease, product still sells well.
[0.1, 0.3)	0.05 × exp(8.95 × (TTL - 0.1))	Critical Degradation	Rapid decline in consumer value.
[0, 0.1)	0.05	Emergency Sale	Minimal value, the product must be sold urgently.

Source: created by the authors

The stability regime (TTL > 0.8) is optimal for pricing, as the product retains its full consumer value. For the moderate degradation regime (0.3 ≤ TTL ≤ 0.8), the linear relationship reflects a steady loss of appeal. This form of dependency was selected based on an analysis of empirical sales data, which showed that within this TTL range, the perceived price reduction by customers is close to linear. The critical degradation regime (0.1≤TTL<0.3) is executed through an exponential function, which models a sharp drop in demand. For the emergency sale regime (TTL<0.1), the constant corresponds to the product's residual value.

The mathematical justification of the regimes is presented in Figure 1.

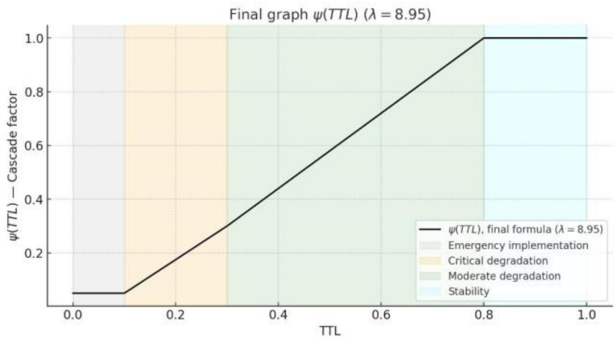

Fig. 1: Graph of the function $\psi(TTL)$
Source: created by the authors

3.3 Visual Attractiveness Factor $\boldsymbol{\Phi(TTL)}$

The visual attractiveness of flowers degrades non-linearly (Figure 2). To model this process, a monotonic cosine-based function is used:

$$\Phi(TTL) = 0.7 + 0.3 \cdot cos(\pi \cdot (1 - TTL)^{1.5}), \quad (7)$$

The base level of 0.7 corresponds to the minimum visual attractiveness. The amplitude of 0.3 ensures a range of [0.4, 1.0]. The exponent of 1.5 models accelerated loss of attractiveness. The authors determined the properties of the function $\Phi(TTL)$ through expert means:

$\Phi(1) = 0.7 + 0.3 \cdot cos(0) = 1.0$ (maximum attractiveness);

$\Phi(0) = 0.7 + 0.3 \cdot cos(\pi) = 0.4$ (minimum attractiveness);

$d\Phi/dTTL > 0$ для $TTL \in [0,1]$ (monotonic increase).

The non-linear exponent (1.5, i.e., 3/2) is a key parameter that "warps" the cosine argument and ensures accelerated loss of attractiveness as TTL decreases. The exponent of 1.5 makes the decline sharper at the initial stage and smoother towards the end, which, the model assumes, better reflects the real process of visual product degradation.

In formula (7) for $\Phi(TTL)$, cosine is used: $\Phi(TTL) = 0.7 + 0.3 \cdot cos(\pi \cdot (1 - TTL)^{1.5})$. Let's verify the range. At $TTL = 1$ we get $cos(0) = 1$, $\Phi = 1.0$; at $TTL = 0$ we get $cos(\pi) = -1$, $\Phi = 0.4$. The range [0.4, 1.0] is maintained. Monotonicity is also maintained, since $(1 - TTL)^{1.5}$ monotonically decreases, the cosine argument monotonically decreases from π to 0, and the cosine on this interval monotonically increases from -1 to 1.

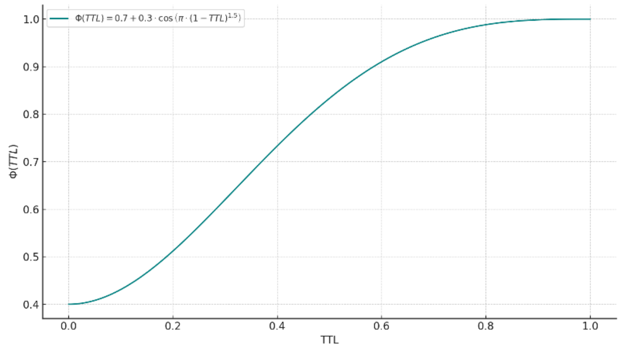

Fig. 2: Graph of the function $\Phi(TTL)$
Source: created by the authors

3.4 Psychological Perception Factor $\boldsymbol{\Omega(TTL)}$

The psychological factor models the change in consumer behavior upon reaching a critical threshold of perception of "staleness." To ensure physical realizability and smooth transition, a modified formula is used:

$$\Omega(TTL) = 1 - 0.4 \cdot [1 + tanh(8 \cdot (\theta_{barrier} - TTL))]/2, \quad (8)$$

where $\theta_{barrier}$ is the psychological barrier (calibrated for each flower type, assumed to be 0.6), $tanh(x)$ is the hyperbolic tangent.

Analysis of the function's behavior for $\theta_{barrier} = 0.6$ is presented in Figure 3. The authors determined the properties of the function through expert means:

For $TTL > 0.6$: $\Omega(TTL) \approx 1.0$ (absence of psychological resistance);

For $TTL < 0.6$: $\Omega(TTL)$ smoothly decreases according to the modified $tanh$ -function;

At $TTL = 0.6$: $\Omega(TTL) = 0.8$ (smooth transition instead of a break).

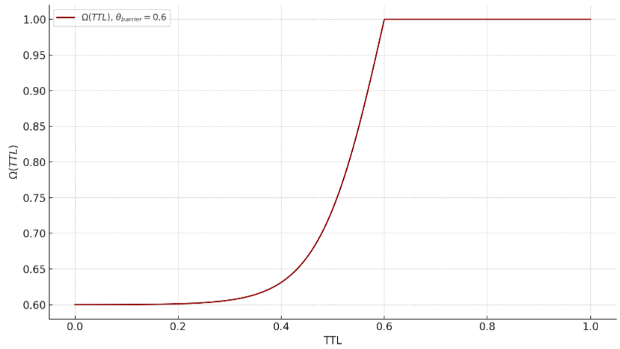

Fig. 3: Graph of the function $\Omega(TTL)$
Source: created by the authors

In formula (8) for $\Omega(TTL)$, a modified hyperbolic tangent is used: $\Omega(TTL) = 1 - 0.4 \cdot [1 + tanh(8 \cdot (\theta_{barrier} - TTL))]/2$. Let's verify the range. For $\theta_{barrier} = 0.6$: at $TTL = 0.6$ we get $tanh(0) = 0, \Omega = 1 - 0.4 \cdot 0.5 = 0.8$; as $TTL \to \infty$ we get $tanh(-\infty) = -1$, $\Omega = 1 - 0.4 \cdot 0 = 1$; as $TTL \to -\infty$ we get $tanh(\infty) = 1, \Omega = 1 - 0.4 \cdot 1 = 0.6$. But since $TTL \in [0,1]$, at $TTL = 1$ we get $tanh(8 \cdot (0.6 - 1)) = tanh(-3.2) \approx -0.996$, $\Omega \approx 1 - 0.4 \cdot 0.002 = 0.9992$; at $TTL = 0$ we get $tanh(8 \cdot 0.6) = tanh(4.8) \approx 0.999$, $\Omega \approx 1 - 0.4 \cdot 0.9995 = 0.6002$. That is, the range is approximately [0.6, 1.0] with a smooth transition around $TTL = 0.6$.

3.5 Seasonal-Event Modulator $\boldsymbol{\Theta(t, events)}$

The seasonal factor accounts for event-driven demand spikes:

$$\Theta(t, events) = B_i \cdot max[0, 1 - |t - e_i|/d_i], \tag{9}$$

where:

t is the current day;

e_i is the event day;

B_i is the peak intensity;

d_i is the decay duration;

$max(0, \dots)$ is the lower bound constraint to prevent the coefficient from becoming negative.

The graph of the seasonal-event modulator $\Theta(t)$ shows a spread of values. For the effective operation of the modulator, historical data loaded from a dictionary is necessary. Formula (9) defines a triangular (linear) event impact profile, which serves as a simple and effective approximation of the real bell-shaped demand surge.

For example, the event of March 8th – a holiday for which, according to accumulated historical data, is associated with the highest demand for the product – is taken. The operation of the modulator $\Theta(t)$ shows that the peak is reached on day 67, with an intensity of 2.0; linear decay ±2 days: activity decreases towards day 65 and 69 (Figure 4).

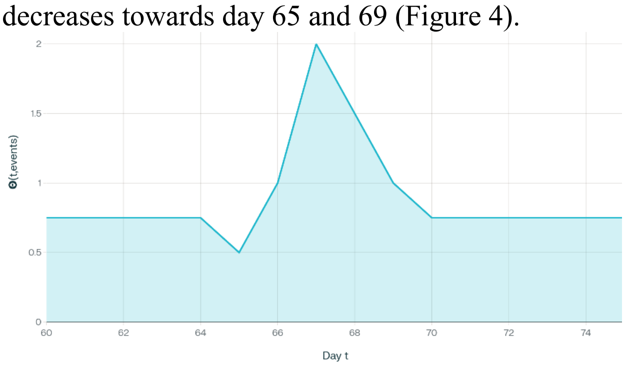

Fig. 4: Graph of the function $\Theta(t, events)$ considering the March 8th event

Source: created by the authors

For clarity, Figure 4 presents a smoothed profile typical of the aggregated influence of multiple pre-holiday demand factors (increasing hype, purchase planning, and demand tapering off before a surge). In the practical system implementation, the piecewise-linear model according to formula (9) is used for computational simplicity. However, parameters B_i and d_i can be calibrated against historical data so that the integral effect on price corresponds to the observed bell-shaped demand curves.

3.6 Verification of the Coefficient K Ranges

Verification of the range for the final price adjustment coefficient K (formula 5) demonstrates that the model covers the spectrum of real market situations – from forced discounting of dead stock to premium pricing at peak demand.

The minimum value models the worst-case scenario for the seller – a product with a practically expired shelf life ($TTL \to 0$) during a period of no seasonal demand ($\Theta = 0$): $K_{min} \approx \psi_{min} \cdot \Phi_{min} \cdot \Omega_{min} \cdot (1 + 0) \approx 0.05 \cdot 0.4 \cdot 0.6 \cdot 1 = 0.0122$. A flower that has completely lost its marketable appearance (accounted for by factors Φ_{min}=0.4 and Ω_{min}=0.6) and entered the "emergency sale" regime (ψ_{min}=0.05) can be discounted down to 1.2% of its original cost, which corresponds to the practice of symbolic pricing or write-off. The model correctly reflects this possibility.

The maximum value models the ideal scenario – an absolutely fresh product ($TTL = 1$, therefore $\psi = \Phi = \Omega = 1.0$) at the peak of surging demand, for example, on March 7th-8th (Θ =2.0): $K_{max} \approx \psi_{max} \cdot \Phi_{max} \cdot \Omega_{max} \cdot (1 + 2.0) \approx 1.0 \cdot 1.0 \cdot 1.0 \cdot 3.0 = 3.0$.

This means increasing the price to 300% of the base level, i.e., a 200% markup, which fully corresponds to the realities of the floral business on pre-holiday days. Thus, the final coefficient K varies within a physically realizable range of [0.012, 3.0], consistent with industry practice. It should be noted that the simultaneous achievement of absolute minima by all factors is unlikely, so real operational. K_{min} values will typically lie within the range of [0.02, 0.05], which enhances the model's forecast reliability.

It is important to note that the presented ranges were experimentally identified for the chosen flower, the rose. In practice, the values ψ_{min}, Φ_{min}, Ω_{min} may not be reached simultaneously, and the actual K_min may be slightly higher. The point of this remark regarding the non-simultaneous achievement of minima is proposed to be interpreted as a sign of modeling maturity. The authors understand that in real life, the worst-case scenario where all factors are simultaneously at their absolute minimum is improbable. For example, a flower may be almost completely wilted ($\Phi \rightarrow 0.4$), but the buyer may not experience strong psychological rejection at that moment ($\Omega > 0.6$), or vice versa.

4 Discussion

As noted in the introduction, the developed multiplicative CDC model is a deterministic component designed for integration into a stochastic dynamic optimization framework, similar to the model [8]. The coefficient $K(TTL, t, events)$, calculated by formula (5), directly modifies the demand function $D(P, F, S, t)$ in equation (4). The following integration is proposed:

$$P*(t, F, S) = arg\,max\, E[\pi(P, D(P, F, S, t) \cdot K(TTL, t, events), S(t))], \tag{10}$$

Thus, the deterministic coefficient K, reflecting complex degradation and seasonality, scales the expected demand at each time point t for a given inventory level $S(t)$ and freshness F. This creates a bridge between the analytical degradation model and stochastic price optimization that accounts for demand uncertainty.

The constants and exponents in the factors $\Phi(TTL)$ and $\Omega(TTL)$ (base level 0.7 and amplitude 0.3, exponent 1.5, barrier $\theta_{barrier}$=0.6, coefficient 8 for the hyperbolic tangent) were obtained through an iterative calibration process based on two sources:

1. Expert assessments from experienced florists, who quantitatively evaluated the perceived attractiveness and the "write-off" threshold for roses at different stages of their life cycle.
2. Analysis of historical data on price dynamics and sales velocity depending on the visual condition of the flowers (based on photo reports) and the time remaining until the end of their shelf life.

The exponent of 1.5 in $\Phi(TTL)$ was chosen to approximate the nonlinear, accelerating decline in visual attractiveness that experts described as "almost unnoticeable on the first day, followed by rapid wilting." The parameters in $\Omega(TTL)$ ensure a smooth yet perceptible transition around TTL =0.6, which corresponds to the point beyond which, according to survey data, the buyer's willingness to purchase drops sharply.

5 Conclusion

The "Cascade Degradation Coefficient" (CDC) model developed within this research represents a complete mathematical framework for solving the problem of dynamic pricing in the cut flower market. Its key scientific value is the synthesis of four independent factors determining the consumer value of a perishable product: temporal cascade degradation, non-linear loss of visual attractiveness, psychological perception of quality, and event-driven seasonality.

The model's uniqueness is confirmed by its structure: the combination of a piecewise-defined function for cascade degradation, a monotonic cosine-based function, a modified hyperbolic tangent function for smoothly accounting for the psychological barrier, and a multiplicative seasonal modulator ensures adequate modeling of real processes. Mathematical analysis demonstrates the model's correctness: partial derivatives of the functions are defined, monotonicity is observed, continuity at regime boundaries is ensured, and the final price adjustment coefficient varies within a physically realizable range of [0.012, 3.0], which corresponds to industry practice (from markdowns to 1.2% to markups of 200%).

The practical significance of the model lies in its adaptability. It provides a specific tool for flower business owners and retailers, enabling a transition from intuitive price setting to an optimized data-driven strategy that maximizes profit and minimizes losses from product write-offs.

The prospect of further research is the parametric calibration of the model for specific flower types and logistics conditions, as well as its integration with computer vision systems for the automatic assessment of the quality (freshness) factor F(t) in real-time.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

Mamedova N.A.– conducting the research process, editing the article, verifying data; applying formal methods for analyzing and synthesizing research data, providing computing resources, and obtaining financial support for the project. Golota O.Y. – creation of a research model, metadata creation, accumulation of research data, preparation and creation of a draft manuscript.

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Conflict of Interest

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