Journal of Robotics and Control (JRC)
Volume 4, Issue 6, 2023
ISSN: 2715-5072, DOI: 10.18196/jrc.v4i6.20667

Balancing Inventory Management: Genetic Algorithm Optimization for A Novel Dynamic Lot Sizing Model in Perishable Product Manufacturing

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***Abstract*—In Indonesia, the significant role of perishable products in food wastage has placed the country fourth globally in household food waste. Managing inventory for such products, with their short shelf life and stringent safety standards, emphasizes the need for efficient lot sizing planning. This study introduces a novel Dynamic Lot-Sizing (DLS) model, addressing perishable products and inventory constraints across multiple products, periods, and varying demands. The model aims to optimize production quantity and binary production, minimizing overall system costs. Employing a Genetic Algorithm (GA), this research solves the DLS model under constrained and unconstrained inventory capacities. Real-case data from a bread manufacturing company validates the model, while sensitivity analysis examines perishability's impact on the solution and model performance. The DLS-GA model not only reduces system costs but also effectively considers product perishability, offering optimal production plans.**

Keywords—Dynamic Lot-sizing; Perishable Product; Genetic Algorithm; Production Decisions; Total System Costs.

I. INTRODUCTION

Perishable products, including bread, vegetables, fruit, meat, seafood, and dairy, are an essential and widespread part of our daily lives, contributing to high sales in supermarkets and grocery stores. In Indonesia, the problems associated with perishable products are one of the factors that contribute to a significant amount of food waste and food loss. According to Tiseo [1], Indonesia ranks fourth worldwide for household food waste. The annual economic loss caused by food loss and waste in Indonesia is between IDR 213 and 551 trillion. This represents 4-5% of the country's Gross Domestic Product (GDP) [2]. As a country with significant barriers to food security, minimizing food waste and losses is important. Close collaboration among suppliers, manufacturers, distributors, and retailers is required to address these issues [3]–[9].

Bread and other perishable goods have limited shelf lives [10]–[12]. If mishandled, this could lead to wastage [11]. In addition, the inventory management of bread products varies over time and is affected by critical factors that limit their ability to store large quantities of bread products. These limiting factors are generally related to the perishable nature of bread, which has limited shelf life and storage requirements that must meet strict quality and food safety standards. Therefore, lot sizing planning is essential for managing bread inventory to consider the limitations of the existing inventory.

The concept of inventory lot sizing is critical in this context because it allows companies to determine the optimal number of orders or production lots based on dynamic demand, thereby reducing the risk of excess inventory that can be discarded [13], [14]. By implementing this approach and adjusting for fluctuations in demand, companies can improve their operational efficiency and reduce the waste associated with expired products.

To minimize food waste and the loss of perishable products, lot size planning must consider the perishable rate, return rate, and inventory constraints. Manufacturers can plan production accurately by considering the time it takes to order, produce, and transport a product, ensuring that the product reaches the market or consumer on time and under optimal conditions [15]. This prevents products from reaching the end of their shelf life before reaching consumers.

Determining the optimal lot size for perishable products, such as food and medicine, requires careful consideration of the perishable rate, which is influenced by the expiration date [16]–[20]. These products have a limited shelf life, necessitating careful calculation of the quantity to be produced and stored in a single lot to minimize waste from expired goods before they can be sold [21]–[24]. Researchers have rarely included the impact of perishability from consumers' perspectives in their model [25]. Freshness is one of the key factors affecting consumer purchase decisions [18]. This approach improves inventory management efficiency, reduces food waste, and maintains product quality, while minimizing food loss.

Various mathematical models have been developed to determine the most cost-effective solution with the goal of minimizing overall costs. Nahmias [26] incorporated constraints and assumptions, such as demand rates, production lead times, and shortage costs, which are frequently incorporated into these models, along with the product's fixed expiration date. However, uncertainties that occur in the real world make solving the lot sizing optimization problem more difficult [27].

Several researchers have investigated expiration dates within the inventory model framework. Feng et al. [18] created an inventory model to maximize profits by considering demand as a multivariate function that depends on unit price, displayed stock, product freshness, and expiration date. The authors' primary goal was to determine the optimal selling prices, replenishment cycle times, and final stock levels to maximize the overall profit. Acevedo-Ojeda et al. [23] introduced mixed-integer programming formulations and sensitivity analysis to address multi-level classical lot-sizing problems. They emphasized the integration of perishability and raw material deterioration. Furthermore, Sazvar et al. [28] proposed an innovative mathematical framework for an optimal ordering problem across multiple periods and products by considering expiration dates within a first-expired-first-out (FEFO) system. Sundararajan et al. [29] proposed EOQ model with and without backlogging by considering expiration date under shortage. They proposed a mixed-integer nonlinear inventory model and sensitivity analysis.

Additionally, considering return rates enables manufacturers to predict the likelihood of products being returned from the market owing to defects, rejections, or lack of sales [30]. Return rates can vary widely based on product type, ranging from 3-4% for dairy items and 8% or higher for delicate fresh produce [26]. Variations in both the quantity and quality of returned products play a critical role in effectively managing closed-loop supply chains effectively [31]. Incorporating return rates into lot-sizing strategies allows companies to avoid overproduction, ultimately reducing food waste. These policies enable companies to manage their returns, while maintaining efficient operations.

Moreover, incorporating return rates into lot-sizing strategies allows companies to avoid overproduction, ultimately reducing food waste. These policies enable companies to manage their returns, while maintaining efficient operations. For example, Aazami and Saidi-Mehrabad [32] proposed return, discount, and credit period policies to optimize the production and distribution planning of packed vegetables across a three-level supply chain consisting of factories, distribution centers, and retailers. Additionally, Yang et al. [33] developed a dynamic ordering system with integrated cash and product flows for fresh food retailers by utilizing a heuristic algorithm to incorporate return rates. Koken et al. [34] investigated a Dynamic Lot Sizing (DLS) problem involving product returns and remanufacturing in a hybrid manufacturing system that produces manufactured, remanufactured, and hybrid products to meet separate demands. Furthermore, Parsopoulus et al. [35] proposed a metaheuristic optimization approach called Differential Evolution (DE) to address the DLS problem with product returns and remanufacturing. The simplicity of implementing DE and its effectiveness in solving integer optimization problems make it a promising approach for tackling lot sizing problems of this type.

In addition to considering the return rate, inventory constraints should also be considered when determining the optimal lot sizing [36]–[39]. A limited storage capacity can restrict the maximum inventory level and increase the risk of stock-out. Therefore, inventory constraints must be incorporated into the perishable lot-sizing model.

Al-e-hashem [40] proposed a novel mixed integer programming model to minimize total costs with subject to warehouse capacity. These costs include procurement, inventory holding, ordering, backordering, and expiration costs. Other recent research publications on the maximum lifetime span were conducted by Kaya and Bayer [41]. They proposed a stochastic dynamic programming model to decide when and how much inventory should be ordered and how these products should be priced, considering their freshness over time. The results show that, under certain parameter settings, dynamic pricing can lead to significant savings over static pricing. In addition, dynamic pricing leads to longer replenishment cycles than static pricing, although similar quantities are ordered for each replenishment.

To the best of our knowledge, no previous research has combined three parameters, namely perishable rate, return rate, and inventory constraint, from the case of lot size on perishable products. Therefore, this study proposes a novel DLS model that considers the perishable rate, inventory constraint, and return rate under multiple products and dynamic demand. The objective of this study is to minimize the total system cost, including surveying, raw material, inventory, return, perishable, and setup costs by using Genetic Algorithm (GA) approach to find optimal or near-optimal solution including production quantity and binary production.

The primary contributions of this study are summarized as follows.

1. This research develops a DLS model that takes into account the perishability rate and return rate in multi-product and dynamic demand scenarios. The model is designed to address two cases: one with inventory constraints and the other without inventory constraints. The model is solved using GA.
2. Through a sensitivity analysis, this study investigates the effects of the return rate and perishability rate on lot sizing decisions and total system costs.

II. Mathematical Formulation

This section explores the challenge of determining the optimal production quantity and binary production for inventory management with multiple products and periods while considering perishable products over time. To address this issue, a mathematical lot-sizing model is developed. Before developing the model, the following notations and assumptions are used:

A. Notations and Assumptions

The following notation was used:

Index Set

t	:	Number of periods, $t = 1, 2, 3, \ldots, T$.
p	:	Number of products, $p = 1, 2, 3, \ldots, P$.
i	:	Number of ingredients used for making the

bread, i= 1, 2, 3, …, I.

Parameter

$D_{t,p}$	:	Demand for product type p in period t.
$A_{t,p}$	:	The costs associated with surveying the demand of product type p in period t.
S_t	:	The cost associated with setting up the production process in period t.
$M_{t,p}$	:	The costs associated with total material used for making the bread of product type p in period t.
K_i	:	The cost of each ingredient, i, used to make bread for every 25 kg sack of flour for all products, P.
W_p	:	The weight of the dough is 60 grams for each kind of bread product p.
$H_{t,p}$	:	The costs associated with storing the boxes or crate for product type p in period t.s
$I_{t,p}$	:	The inventory balance for product type p at the end of period t.
C_p	:	Inventory level constraint for product type p.
$BI_{t,p}$	:	Number of boxes or crates containing product type p at the end of period t
$B_{t,p}$	:	The number of bags of flour (per bag contains 25 kg) to make bread for product p in period t.
CB_p	:	The capacity of a box or crate to contain a specific product p.
$RC_{t,p}$	:	Return cost for product type p in period t.
R	:	Number of products returned based on the previous set of periods $T, \sum_{i=1}^{T} R_{t-i}$
$E_{t,p}$	:	The expected product returns resulting from expiration for product type p during time period t.
J_p	:	Estimated duration to store products until they can be shipped to the next period (in hours).
L_p	:	Estimated duration for the product to expire (days).
G_p	:	The perishable rate during inventory.
X_p	:	Deterioration rate of quality.
$O_{t,p}$	:	Original purchasing cost from manufacturer to retailer for product type p in period t.
$PI_{t,p}$	:	The costs associated with perishability due to storing the excessive product type p in period t.

Independent Variables

$Q_{t,p}$	:	Production quantity for product type p in period t.
$Y_{t,p}$	:	1, if there is a number of products produced for product type p in period t, 0, otherwise.

Dependent Variables (binary variables)

$Z_{t,p}$	:	1 if there are inventory products of product type p at the end of period t, 0, otherwise.
V_t	:	A binary variable is used to indicate production activity, where 1 represents positive production of any product type during a given time period, and 0 represents no production activity across all product types in a given time period.
TC	:	Total system costs.

Owing to the complexities of the model, the following assumptions were made.

a. The demand for products is known to be dynamic during the planning period.

b. Shortages are not allowed; demand must be satisfied.

c. No quantity discounts were made.

d. The processing costs for manufacturing the products are fixed over the planning period, except for the return costs, which depend on the fluctuating return rate.

e. No transportation costs are assumed for returning defective/unsold products.

f. If there are products in the inventory in a certain period, they will be used first in the next period.

g. No costs are incurred specifically for each excess unit of bread product in the box or crate inventory. The overall inventory cost of bread in boxes or crates is allocated equally to all bread units in the inventory regardless of whether there are redundant units.

B. Problem Description

A bakery manufacturing company produces a range of perishable products, as illustrated in Fig. 1. In practice, the manufacturer conducts order demand surveys from retailers three days before the shipment of ordered products. This allows the production planning team to incorporate the latest retailer demand information into decisions on how much of each type of bakery product is produced.

The results of the demand survey three days prior to shipment provide sufficiently accurate data and still leave enough preparation time to carry out the manufacturing, packaging, and shipping processes of the bakery products in the specified period.

By surveying the retailer's order demand for different types of bread, the company can adjust its production to meet these needs three days before shipping the products. However, several factors should be considered when producing multiple bread products: (a) *Perishability*: Manufacturers need to consider the perishability of bread products and plan production accordingly to minimize spoilage due to expiration; and (b) *Returns*: Manufacturers may receive returns of bakery products due to expiry or other reasons.

These returns need to be managed carefully to avoid wastage. (c) *Inventory*: Manufacturers need to maintain an adequate inventory of bakery products to meet customer demand without overstocking, as excess inventory can lead to product spoilage. In this case, once the bread product leaves the company, the bread expires in four days.

To ensure the careful planning and optimization of production decisions for multiple perishable bread products, this study proposes a DLS model. This model effectively determined the optimal production quantities for each bread type, considering the perishable nature of the products.

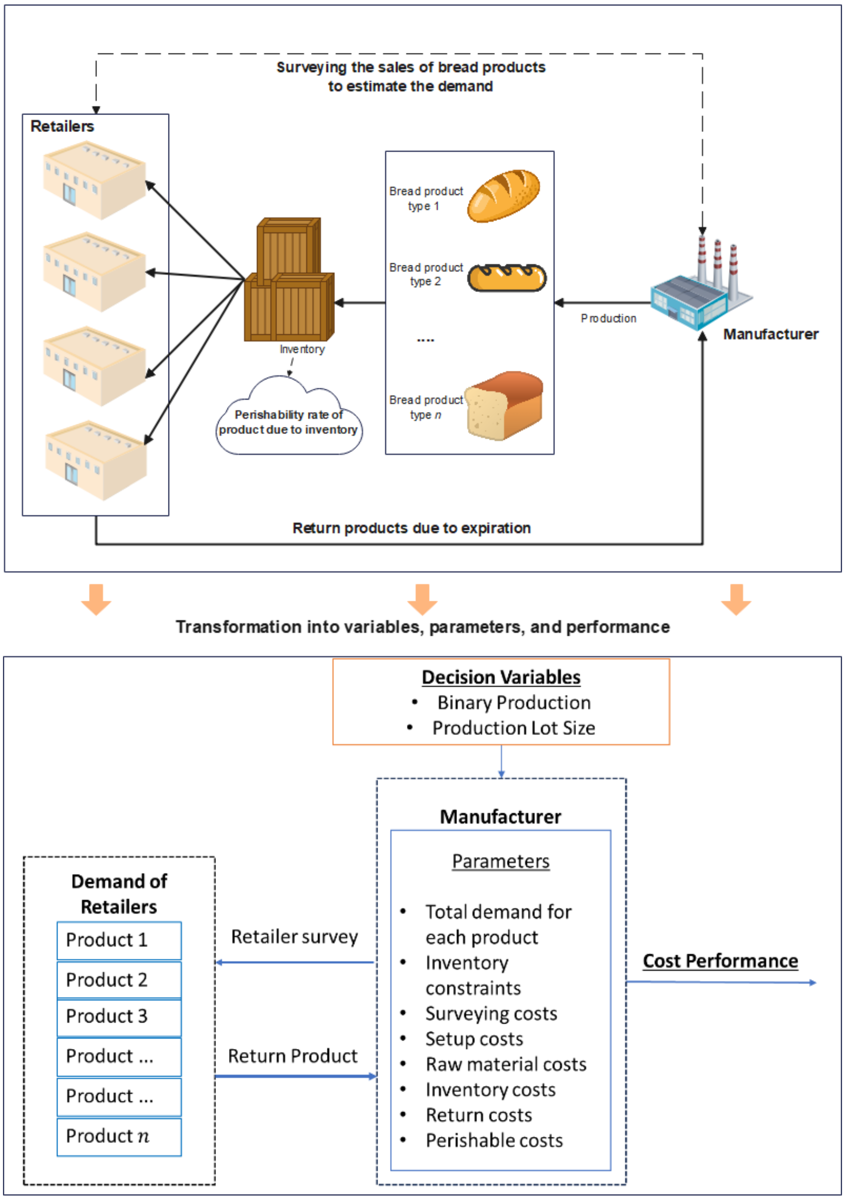


Fig. 1. The manufacturer and retailers production inventory lot sizing system

Furthermore, the model incorporates binary production decisions, allowing the manufacturer to determine whether to produce a particular bread type during each period. This flexibility enables the manufacturer to adapt production schedules based on real-time demand patterns and inventory levels, thereby minimizing the risk of overproduction and spoilage.

The proposed DLS model provides a comprehensive decision-making model for manufacturers of perishable bread products, enabling them to optimize production, minimize costs, and reduce waste. Based on Fig. 1, the described system is transformed into quantifiable variables, parameters, and cost performance to establish the lot-sizing model. Solving this model requires determining the optimal production quantity and binary production decisions. To achieve this, the manufacturer must survey sales and return data from retailers, which is a crucial step when considering dynamic demand fluctuations and the risk of product expiration before they can be sold. Additionally, manufacturers need to factor in storage capacity constraints when managing inventories for these limited shelf-life products. The key parameters considered in the DLS model for perishable products include dynamic demand, setup costs, inventory costs, survey costs, return costs, and perishability costs. Perishability costs arise from product storage over specific periods. Therefore, developing a DLS model for perishable products is essential to determine production quantities and binary production that minimize the total system costs while adhering to constraints, even without inventory capacity constraints.

C. Mathematical Model

This study presents a DLS model for optimizing the production planning of various perishable food products over a limited planning horizon. This integrated approach incorporates the critical constraints related to product returns, perishability, and limited inventory capacity across product types. These dynamic factors significantly influence tactical decisions (production quantities and binary production) aimed at meeting demand while minimizing the total system costs. The mathematical expressions for these costs are as follows.

$$\text{Min } TC = \sum_{t=1}^{T}\sum_{p=1}^{P} A_{t,p}Y_{t,p} + H_{t,p}Z_{t,p}BI_{t,p} + Y_{t,p}M_{t,p} + RC_{t,p}E_{t,p} + PI_{t,p}Z_{t,p}I_{t,p} + \sum_{t=1}^{T} S_tV_t \quad (1)$$

Subject to:

$$I_{t,p} = Q_{t,p} + I_{t-1,p} - D_{t,p} \qquad \forall_t \in T, \ \forall_p \in P. \quad (2)$$

$$I_{t,p} \leq C_p \qquad \forall_t \in T \quad (3)$$

$$Z_{t,p} = \begin{cases} 1, \text{ if } I_{t,p} > 0 \\ 0, \text{Otherwise} \end{cases} \qquad \forall_t \in T, \ \forall_p \in P \quad (4)$$

$$BI_{t,p} = \frac{I_{t,p}}{CB_p} \qquad \forall_t \in T, \ \forall_p \in P \quad (5)$$

$$M_{t,p} = B_{t,p}\sum_{i=1}^{I} K_i \qquad \forall_t \in T, \ \forall_p \in P \quad (6)$$

$$B_{t,p} = \frac{Q_{t,p}W_p}{2.4} \qquad \forall_t \in T, \ \forall_p \in P \quad (7)$$

$$E_{t,p} = \frac{R}{\sum_{t=1}^{T} D_{t,p}} D_{t,p} \qquad \forall_t \in T, \ \forall_p \in P \quad (8)$$

$$X_p = \frac{100\%}{L_p} \qquad \forall_p \in P \quad (9)$$

$$G_p = 100\% - \left(\frac{X_pJ_p}{24}\right) \qquad \forall_p \in P \quad (10)$$

$$PI_{t,p} = (100\% - G_p)O_{t,p} \qquad \forall_t \in T, \ \forall_p \in P \quad (11)$$

$$Y_{t,p} \in \{0,1\} \qquad \forall_t \in T, \quad (12)$$

$$V_t = \begin{cases} 1, \text{if } \sum_{p=1}^{P}\sum_{t=1}^{T} Y_{t,p} > 0 \\ 0, \quad \text{Otherwise} \end{cases} \qquad \forall_t \in T, \ \forall_p \in P \quad (13)$$

$$Q_{t,p}, I_{t,p} \geq 0 \qquad \forall_t \in T, \ \forall_p \in P. \quad (14)$$

The objective functions defined in Eq. (1) minimizes the total system costs, which include expenses related to surveying, inventory, materials, returns, perishability, and setup Constraint (2) derives the inventory balance for each bread product in a given period, whereas constraint (3) imposes an upper bound on inventory by restricting the levels to less than or equal to the designated capacity for each product and period. It should be noted that constraint (3) will be applied to a certain condition for this model. Constraint (4) was set such that no shortage occurred in this model.

Eq. (5) calculates the number of boxes or crates containing the product type p at the end of the period t by considering the inventory balance and capacity of the boxes. In this case, the inventory is calculated based on the number of boxes, because the boxes will take up storage space on the production floor. Eq. (6) formulates the costs associated with the total material used for making bread of product type p in period t. This was done by considering the number of flour bags, as calculated in Eq. (7) and the total cost of each ingredient. Moreover, the constraint in Eq. (8) expresses the estimated product return rate owing to expiration.

The formulations in Eqs. (9), (10), and (11) define the perishable costs of storing a product over a given period. In addition, the constraints in Eq. (12) describes the binary production variable, where a value of 1 indicates that the production of one product type p in period t has occurred and a value of 0 indicates that no production has occurred. Unlike Eq. (12), Eq. (13) sets a binary variable that indicates overall production activity, where a value of 1 represents positive production of any product type within a given time period, whereas a value of 0 represents no production activity across all product types within the same time period. Finally, constraint (12) ensures that the production quantity and inventory level are non-negative.

III. Solution Approach-based Genetic Algorithm

Metaheuristic algorithms have been widely utilized for tackling complex global optimization problems across diverse domains in engineering and science [42]. Common metaheuristic techniques described in the literature include GAs [43], particle swarm optimization [44], firefly optimization [45], and more [46]–[48]. Among these, the GA has emerged as a popular intelligent search method owing to its straightforward implementation logic and robust capacity for exploring high-dimensional search spaces to find globally optimal solutions [49], [50], [59], [51]–[58]. By mimicking the natural selection processes, GAs can efficiently navigate complex search spaces and identify competitive solutions.

GAs have been widely recognized as powerful optimization tools for solving lot sizing problems due to their robustness and ability to handle complex problems [60]–[62]. GAs are heuristic search algorithms that have shown effectiveness in adaptation and optimization problems [63]. They are capable of providing rich expressions of solutions for various problems and are particularly suitable for tuning parameters and array optimization [64]. The adaptability and wide accommodation of genetic algorithms make them well-suited for addressing optimization problems, including lot sizing problems [65]–[71].

One of the key strengths of GA is their ability to avoid premature convergence and filter local optimal solutions, thus leading to more accurate and reliable models [72]. This is particularly important in the context of lot sizing problems, where finding the global optimum is crucial for efficient production planning and goods flow control [73]. Additionally, GAs have been applied to solve single-item lot sizing problems with immediate lost sales in profit maximization models, demonstrating their versatility in addressing different variations of lot sizing problems [74].

Furthermore, GAs have been utilized in various industrial applications, such as in the mining industry for solving optimization problems [75]. They have also been employed in the optimization of milling tools to maximize cutting depth for chatter-free machining, showcasing their effectiveness in addressing practical manufacturing challenges [76].

In summary, genetic algorithms offer a robust and adaptable approach to solving lot sizing problems, providing rich solution expressions, avoiding premature convergence, and demonstrating versatility across different industrial applications.

Therefore, this study employs a GA approach to identify the optimal production quantities and binary production that minimizes the total system costs.

The general workflow involves key steps, including the initialization of a population of chromosome solutions, evaluation of fitness based on an objective function, selection, crossovers, mutations, and repetition over generations to converge on optimal or near-optimal solutions tailored to the problem at hand. When tuned appropriately, the GA provides an adaptive optimization technique suitable for production lot-sizing problems.

A. *Initial Population*

The GA in this study begins with initialization of the population (PoP), which consists of chromosomes that represent potential solutions to the optimization problem. Each chromosome is defined by a structured representation that includes both the production quantity and the binary production status of a given product (referred to as "product p") during a given time period (referred to as "period t"). The details of this structured chromosomal representation are shown in Fig. 2. Specifically, the population was initialized by randomly generating a set of chromosomes, each consisting of production quantity and binary production for four products over seven discrete periods (7-days). This initialized population provides a starting point for algorithm's exploration. The subsequent steps of GA involve the evolution of the population through selection, crossover, and mutation operators. This iterative process in GA facilitates ongoing chromosome improvement, iteratively refining the optimal production strategy to solve inventory management problems across different products and time periods.

B. *Evaluation*

A key component of GA is the evaluation of the fitness of each chromosome in the population. The fitness value is calculated using the objective function given in Eq. (1) guides the GA towards a more optimal solution. However, some chromosomes generated during initialization or evolution may be infeasible given the model constraints specified in Eq. (4), which is defined as no shortages allowed for the product type p in period t. The literature discusses various methods, such as penalty policies, for handling infeasible solutions [77]. Therefore, in this study, only feasible solutions were generated to solve the model. In this case, infeasible chromosomes were discarded. To accomplish this, the fitness evaluation incorporates a penalty policy in the objective function to account for constraint (4), which is calculated as (15).

$$P_{t,p}^{s} = \begin{cases} 1000000, & \text{if } I_{t,p} < 0 \\ 0, & \text{Otherwise} \end{cases} \tag{15}$$

where $P_{t,p}^{s}$ is a penalty function given by the violating constraint in Eq. (4) for each product p in period t, and is applied to the fitness function, which can be formulated as (16).

$$F_1 = TC + \sum_{t=1}^{T}\sum_{p=1}^{P} P_{t,p}^{s} \tag{16}$$

Therefore, the fitness function in Eq. (16) is used to generate a feasible solution that can minimize the total system cost while allowing no shortages for all specific periods. This is considered a hard constraint, which refers to a constraint that must be strictly satisfied for a feasible solution.

In addition, this study also considers the case of excessive inventory resulting from improper production planning. To address this problem, the fitness function in Eqs. (16) incorporates a new penalty function that discourages bread production from exceeding a predetermined limit as (17).

$$P_{t,p}^{e} = \begin{cases} 1000000, & \text{if } I_{t,p} \geq C_p \\ 0, & \text{Otherwise} \end{cases} \tag{17}$$

where $P_{t,p}^{e}$ is a penalty applied when the end-inventory per product type p in period t exceeds the specified capacity C_p. The new fitness function F_2 for solving the model under the inventory constraint is expressed as (18).

$$F_2 = TC + \sum_{t=1}^{T}\sum_{p=1}^{P} P_{t,p}^{s} + \sum_{t=1}^{T}\sum_{p=1}^{P} P_{t,p}^{e} \tag{18}$$

where Eq. (18) is considered a fitness function that combines the soft constraint. This soft constraint refers to a constraint that can be violated or satisfied to some degree, unlike the hard constraint that must be strictly satisfied.

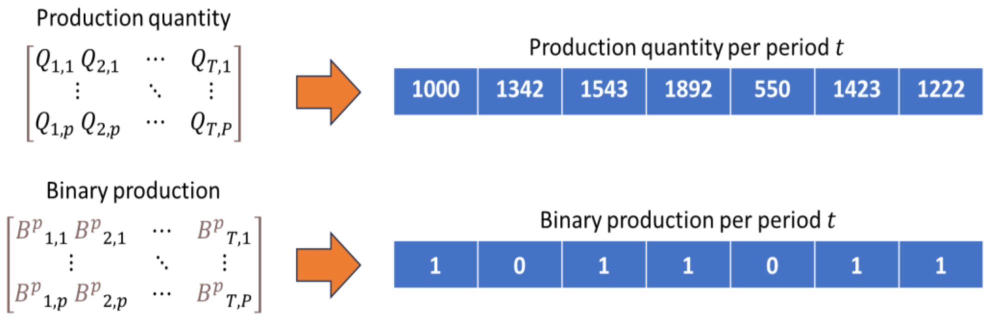


Fig. 2. Example of chromosome for production quantity and binary production

C. Crossover

The crossover phase, which is an integral part of the GA, involves mating selected chromosome pairs to produce offspring solutions. To perform crossover, a pair of parent chromosomes is randomly selected from the current population with a crossover probability, P_c. Several crossover operators exist in the literature, including single-point, two-point, multi-point, and uniform crossover operators [30], [38]. This study implements a two-cut point crossover, which operates by randomly selecting two crossover points. The parent chromosomes are split at these points and the segments after the crossover point are exchanged, recombining the genes to form two new offspring chromosomes. Fig. 3 illustrates this single-point crossover process on sample parent chromosomes representing production quantity vectors with seven periods for a given product; the newly generated offspring chromosomes are then evaluated and inserted into the population, replacing fewer fit individuals. This crossover phase enables beneficial genetic material to be mixed and passed on to future generations, driving the population towards more optimal solutions.

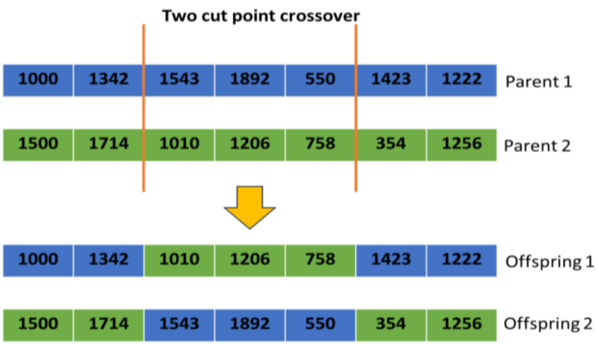


Fig. 3. The representation of two-cut point crossover

D. Mutation

The mutation operator is an important component of the GA as it helps prevent premature convergence and maintains diversity within the population. Mutation introduces genetic diversity by randomly altering the values of the elements within a selected chromosome based on mutation probability P_m. This mutation rate, P_m, refers to the probability that any given chromosome in the population will be mutated. This study implemented mutations through a combination of jump and creep mutations. According to Miner et al. [79], jump mutation involves randomly changing one or more genes to entirely new values, allowing for a more drastic search space exploration. Creep mutations incrementally alter genes by a small amount, enabling minor refinement. Each gene was assigned a separate mutation probability for jump and creep mutations, denoting the likelihood that the gene will undergo that type of mutation. By occasionally introducing random modifications through this dual-mutation approach, new genetic material can be introduced over generations, allowing escape from local optima and continued exploration. An example illustrating the mutation process using the jump and creep method on a sample chromosome is shown in Fig. 4.

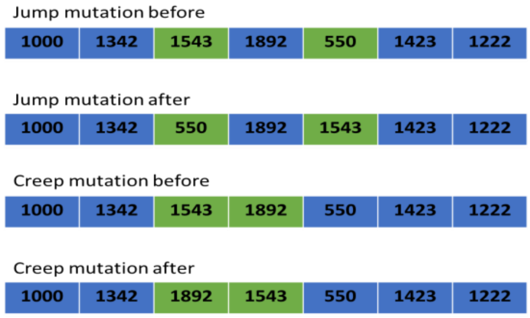
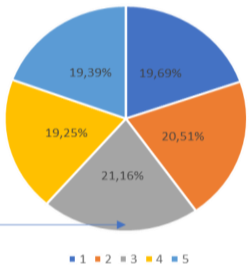


Fig. 4. The representation of mutation process

E. Selection

The chromosome selection step for the next generation plays a key role in guiding the GA towards the optimal solution. Several selection methods are commonly used in GA, including elitist strategy, tournament selection, and roulette wheel selection. In this study, roulette-wheel selection was implemented, in which chromosomes were selected based on their fitness proportion. Subsequently, a random spin of the weighted wheel is used to select the chromosomes. This allows diverse genetic material to persist, while still giving preference to more fit individuals. Chromosomes with higher fitness, such as lower total system costs in a cost minimization problem, are assigned a larger slice of the roulette wheel and, therefore, have a higher chance of being selected. However, chromosomes with lower fitness still have a chance of being selected because they occupy a smaller fraction of the wheel rather than being entirely excluded. A representation of the selection process using the roulette wheel method is shown in Fig. 5.



Individual chromosome	Fitness	1/Fitness	Fitness proportion (%)
1	113754660	8,791E-09	19,69%
2	109171736	9,16E-09	20,51%
3	105837697	9,448E-09	21,16%
4	116347298	8,595E-09	19,25%
5	115506462	8,658E-09	19,39%

Fig. 5. The best fitness selection using roulette wheel method

F. Stopping Criteria

The termination stage is an important component of the GA method. Specific stopping criteria must be established to determine when a satisfactory solution has been reached. Common stopping conditions described in the literature include reaching a certain number of generations (G_n), reaching a threshold fitness value, or observing improvement over the iteration period [80]. This study used a fixed number of generations as the stopping criterion and concluded that the GA had elapsed after 800 generations.

IV. Experimental Results

This section presents a formal analysis of the primary experiments conducted on DLS, utilizing a case study from a bread industry company. This study encompasses dynamic demand for four distinct product types across seven discrete periods (one week), as shown in Table I.

TABLE I. Demand of Bread Product

Period	1	2	3	4	5	6	7
Product- 1	2417	3900	4100	2750	3420	4779	3318
Product- 2	1554	1950	2270	1550	1480	2025	1425
Product- 3	250	400	300	350	350	450	300
Product- 4	1626	1318	1200	1882	1567	1963	934

Moreover, detailed problem parameters were used to test and validate the proposed model, as presented in Table II. Note that Table II only discusses the base value for each product; however, these values remain the same throughout the period.

TABLE II. Data Parameter

Parameters	Product-1	Product-2	Product-3	Product-4
$A_{t,p}$ (IDR)	75000	50000	100000	75000
$H_{t,p}$ (IDR)	132000	144000	168000	86400
K_i (IDR)	574530	574530	574530	574530
S_t (IDR)	2969000	2969000	2969000	2969000
$RC_{t,p}$ (IDR)	1320	1440	1680	2400
R (units)	545	387	248	212
W_p (grams)	60	60	60	60
C_p (units)	200	200	200	108
CB_p (units)	100	100	100	36
L_p (days)	4	4	4	4
J_p (hours)	24	24	24	24
$O_{t,p}$ (IDR)	2200	2400	2800	4000

To conduct an empirical analysis, the proposed DLS model was implemented using spreadsheet modelling (Microsoft Excel) integrated with the XL optimizer ® add-in for GA optimization. The Excel-based model was executed on a personal computer with an Intel(R) Core (TM) i3-1115G4 central processing unit clocked at 3.0 GHz with 8 GB of random-access memory. This configuration allowed for efficient computational experiments to assess the performance of the dynamic optimization model under different parameter settings and demand scenarios. The use of a spreadsheet and GA provides a flexible and accessible platform for representing the lot-sizing problem, as shown in Fig. 6.

This study proposes an experimental methodology that employs a GA to optimize the DLS model for perishable products with and without inventory constraints. To enhance the production planning performance and provide a thorough analysis, the research first examined a wide range of GA parameter combinations, including population PoP sizes ranging from 80 to 180 in increments of 20, crossover rates P_c from 0.7 to 0.95 in increments of 0.05, mutation rates P_m from 0.01 to 0.05 in increments of 0.01, and generation G_n limits of 800. The specific GA parameter values are listed in Table III. By adjusting the parameter settings of the GA, it is possible to thoroughly assess the algorithm's ability to generate optimal lot-sizing decisions. The experimental design offers fresh perspectives on the optimal GA configuration to address actual production planning challenges.

TABLE III. Tested GA Parameter Combination

Combination	PoP	P_c	P_m	G_n
1	80	0.75	0.02	800
2	100	0.80	0.05	800
3	120	0.95	0.01	800
4	140	0.7	0.03	800
5	160	0.85	0.04	800
6	180	0.9	0.025	800

In this study, GAs is employed to enhance the efficacy of a dynamic perishable inventory lot-sizing model that features two distinct inventory scenarios: unconstrained and constrained. The GA parameters, including a population size of 160, crossover probability of 0.85, mutation probability of 0.04, and 750 generations, were meticulously chosen after conducting extensive testing of various combinations, as shown in Table III. Five separate trials were executed for each set of parameters, examining the fitness function's performance and consistency of convergence across trials. The combination of PoP = 160, P_c = 0.85, P_m = 0.04, and G_n = 800, as displayed in the fifth row of Table III, demonstrated the lowest average best fitness value and the lowest fitness standard deviation across runs. This suggests that the convergence properties are superior and reliable.

Compared to the other GA settings evaluated in Table III, the chosen parameter set balances sufficient population diversity through crossover and mutation mechanisms with sufficient generations that allow for convergence. A population size of 160 ensured that sufficient unique solutions were evaluated for each generation. Meanwhile, crossover probability allows for efficient recombination between competitive solutions. In addition, a low mutation rate introduces variations without compromising the integrity of the solution. Over 800 generations, configuring the GA search operator at this level seems to encourage exploration and exploitation that reveal quality optima. The effectiveness of these optimized GA parameters was subsequently assessed by applying them to a lot-sizing model with both unconstrained and constrained inventory capacity. The outcomes of incorporating the GA into the two aforementioned model scenarios are detailed below, showcasing how these optimized parameters influence the performance of the models under unconstrained and constrained inventory capacity.

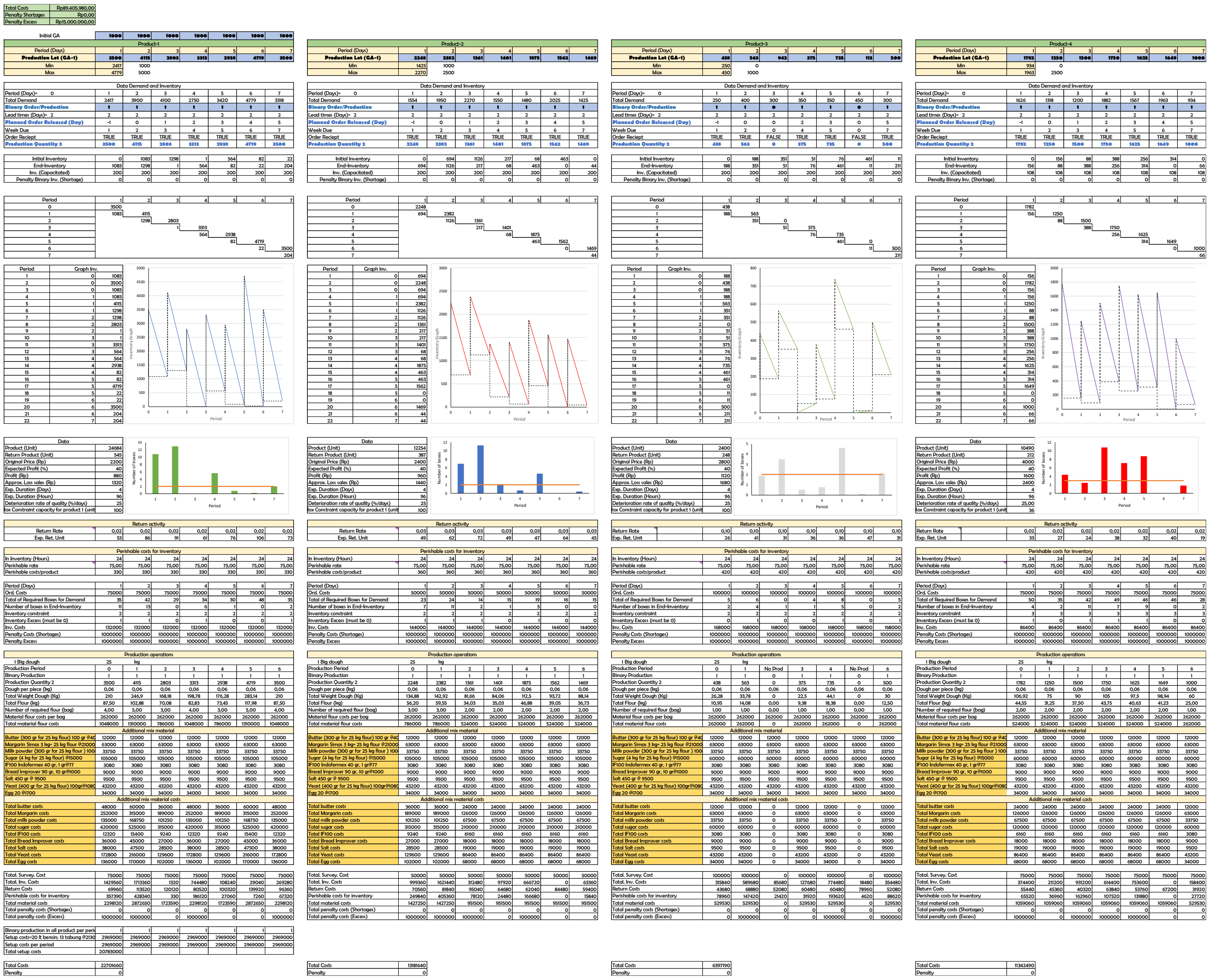


Fig. 6. A representation of spreadsheet DLS model simulation

A. Scenario 1: Unconstrained inventory capacity

The production planning policy optimized by the GA using a population size of 160, crossover probability of 0.85, mutation probability of 0.04, and run for 800 generations to simulate the perishable product DLS model under unconstrained inventory conditions is presented in Table IV, assuming that the constraint in Eq. (3) was not considered in testing this model.

TABLE IV. RESULT OF FIVE-RUN GA IN OPTIMIZING DLS MODEL WITH UNCONSTRAINED INVENTORY CAPACITY

No. Test	Total system cost (IDR)
1	74355170
2	77187120
3	77363320
4	74625650
5	72363750
Average	75179002

This scenario demonstrates the effects of removing the inventory-level constraint, enabling the evaluation of the GA-optimized plan's ability to minimize costs, managing returns from expired products, and managing the impact of perishable products on inventory levels over a longer and variable holding period.

The purpose of Table IV is to present the total system cost after conducting five trials using GA optimization with the selected parameters. Initially, the fitness function is a combination of the initial system cost and a penalty function aimed at preventing inventory shortages and maintaining operational feasibility. The removal of the penalty function is very important due to the GA's exceptional ability to find feasible solutions. Therefore, Table IV displays only the total system cost, excluding the penalty. In particular, the results in Table IV showing the lowest cost of IDR 72,363,750 in Test 5 with an average cost of IDR 75,179,002 are positive results, demonstrating the effectiveness of the GA in reducing costs. The continuous decrease in cost highlights the GA's proficiency in navigating the solution landscape and converging toward a more optimal and cost-effective solution by the fifth test. Fig. 7 illustrates the iterative search process of the GA showing convergence from generation to generation to find the best performing solution shown in the fifth trial.

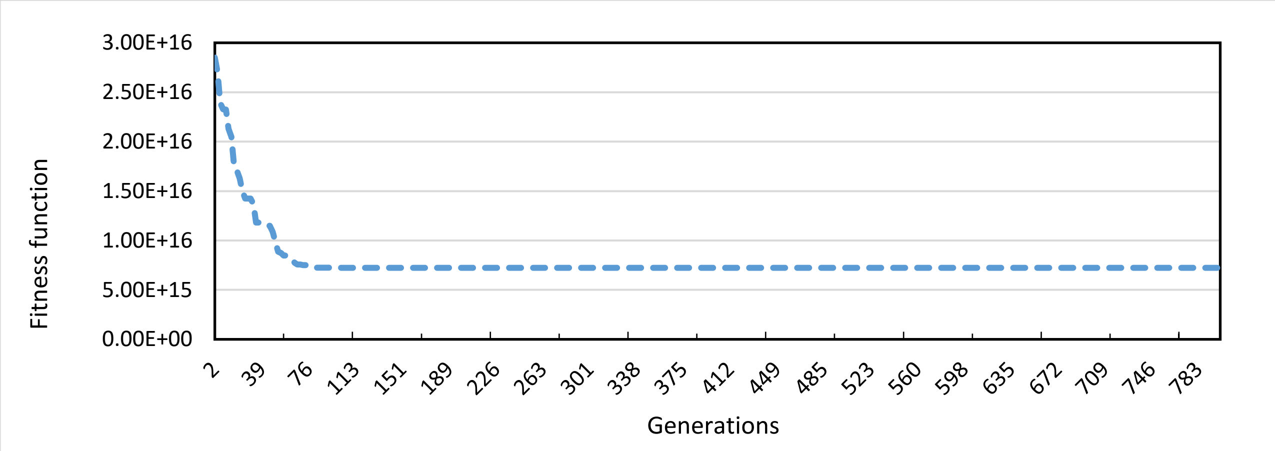


Fig. 7. The search process of GA (test-5) in finding the optimal solution for the DLS model with an unconstrained inventory capacity

B. Scenario 2: Constrained inventory capacity

The implementation of a GA with customized parameters, including a population size of 160, mutation probability of 0.04, crossover probability of 0.85, and generation limit of 800, has proven to be an effective method for finding near-optimal solutions for a perishable product DLS model that considers inventory constraints. The results of the model tests, as presented in Table V, demonstrate the effectiveness of the GA in analyzing the effects of inventory constraints on total system costs. In this scenario, it is assumed that the constraint in Eq. (3) was considered in model testing.

TABLE V. RESULT OF FIVE-RUN GA IN OPTIMIZING DLS MODEL WITH CONSTRAINED INVENTORY CAPACITY

No. Test	Fitness function	Penalty for excessive inventory	Real system costs (IDR)
1	89405980	15000000	74405980
2	90390410	11000000	79390410
3	88739760	13000000	75739760
4	85282590	11000000	74282590
5	86473250	11000000	75473250
Average	88058398	-	75858398

Table V presents the results of five tests designed to minimize the total cost in a system that employs a fitness function that combines the overall system cost with a penalty function, with the aim of addressing inventory shortages and inventory holding limitations. Throughout the tests, an evident upward trend in the fitness function value emerged, indicating continuous improvements in system optimization. Notably, Test 4 achieved the lowest real system cost of IDR 74282590, whereas Test 2 recorded the highest cost of IDR 79,390,410, consistent with the trend of the fitness function. The average fitness function of IDR 88,058,398 reflects satisfactory overall system performance.

Penalty excess is not a representation of an absolute value, but rather a relative indicator that reflects how often and how much the constraints in the lot sizing model are violated. For example, the best result in test 4 with a penalty excess of 11,000,000 shows that there were only violations in 11 out of a total of 28 periods against the inventory capacity constraints of the four defined products. However, when looking at the results in Table IV that consider penalty excess, specifically at the lowest cost value in Test 5 with a penalty excess of 14,000,000, there are 14 out of a total of 28 periods that have violations of the constraint. The fact that the penalty excess value in Test 4 (Table V) is lower than the DLS model without constraints indicates that in the context of inventory constraints, greater effort is made to minimize the number and intensity of constraint violations, confirming the effectiveness of the GA approach with constraint setting in inventory management.

The GA demonstrated its efficiency in discovering feasible solutions that progressively eliminated the penalty for shortages and reduced the penalty for excessive inventories. Most importantly, the penalty for excessive inventory operates as a soft constraint; the less the constraint is breached, the more feasible the system becomes. However, the total system cost remains calculated independently of any penalties, emphasizing the GA's primary focus on minimizing operational expenses. Fig. 8 illustrates the iterative convergence of the GA towards the optimal solution, navigating the balance between inventory constraints and cost minimization within the system.

C. Comparison for two scenarios

Fig. 9 presents a comparison between two models in DLS that consider both unlimited and limited inventory capacity. The table details several cost components associated with each model, including survey costs, inventory costs, return costs, perishable inventory costs, material costs, and setup costs. The significant differences in these cost components give an idea of the effect of the inventory capacity setting on the overall cost within the scope of inventory management in the DLS model. Fig. 9 shows that there is a considerable difference between the DLS model with constrained and unconstrained inventory capacity in terms of the mentioned cost components. From this, it can be seen that the model with constrained inventory capacity tends to show a significant increase in inventory compared to the unconstrained model. This increase may reflect the more careful management of inventory allocation when capacity is limited, which is likely to incur additional costs in inventory management.

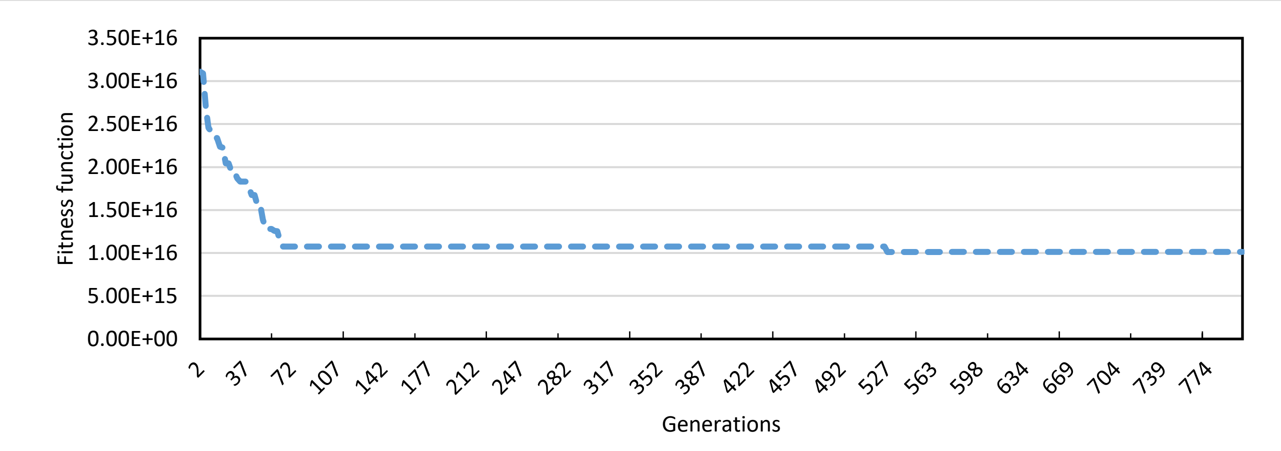


Fig. 8. The search process of GA (test-4) in finding the optimal solution for the DLS model with a constrained inventory capacity

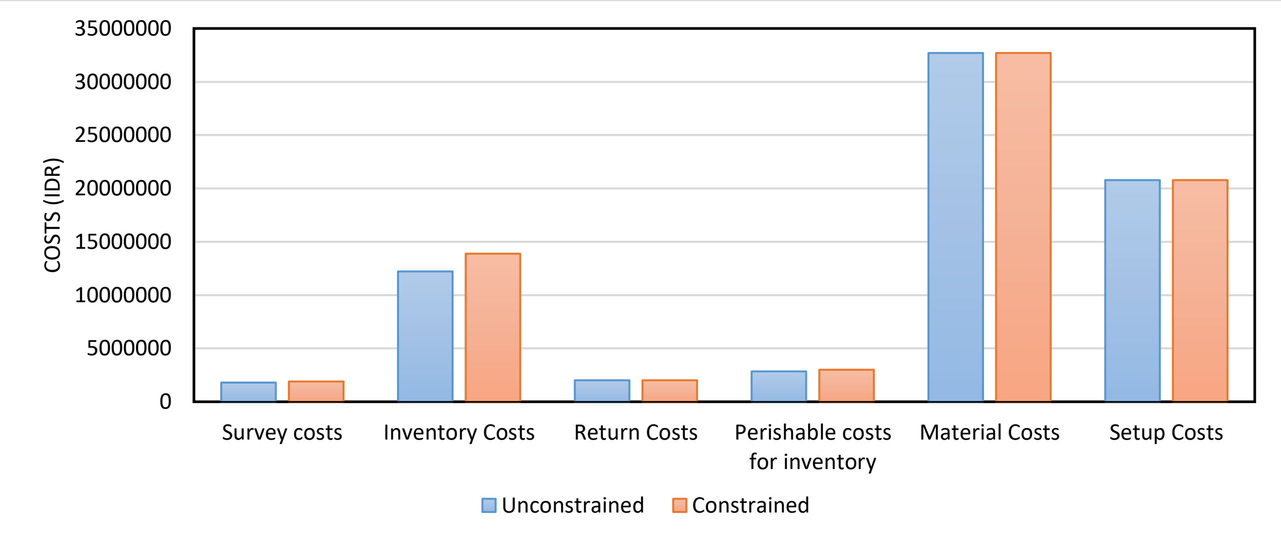


Fig. 9. Result of comparing DLS model for unconstrained and constrained inventory capacity

Limitations in bread production, such as those in the DLS model that place restrictions on inventory capacity, can lead to unique dynamics in total system costs. For example, in Fig. 9, inventory costs tend to vary significantly. In a model with inventory constraints, inventory costs may be higher because production constraints force the manufacturer to store more finished goods in inventory. Because the inventory constraint is a soft constraint, in some periods production is increased to produce more bread. Although violations occurred in certain periods, the number of violations did not exceed the number of violations that occurred in the DLS model without inventory constraints. This may be due to the fact that the production constraints cannot efficiently match supply with demand, forcing the company to hold more inventory and ultimately increasing inventory costs.

Managing perishable goods in a constrained scenario is also more challenging. Perishable costs, indicating losses due to deterioration or spoilage of goods before they are sold, may also be more significant in a constrained model. Production limitations can make it harder to maintain fresh stock, leading to a higher number of unsaleable items.

However, certain cost components remain constant between the two models. For instance, material costs and setup costs may show the same value because the essential characteristics of these costs do not directly depend on the amount of production. Material costs, which are associated with the raw materials used, may remain stable because limited production does not significantly change the need for certain raw materials.

Moreover, setup costs associated with production setup may not fluctuate significantly, as the relationship between production preparation and output is not always proportional. However, in this study, the emphasis is more on the presence of production in any given period. This indicates that whether the number of products produced is limited or abundant, the costs incurred in setting up the production line, organizing equipment, or configuring the workspace have a tendency to stabilize. An interesting aspect is that the effort, time, and resources allocated to the preparation phase are not necessarily determined by the amount of output exclusively but rather relate more to the need to start the production process in each predefined period. This difference in cost patterns explains the interesting dynamics of preparation costs, where their stability is not determined by the size of production, but rather depends on activating the production process rather than the scale of the product produced.

Understanding how production limitations affect cost components provides valuable insights for planning efficient production strategies. This emphasizes the importance of considering not only direct operational costs, but also understanding how production constraints can directly impact other costs, particularly those related to inventory and perishables management.

The comparison between the DLS model with and without constrained inventory capacity reveals differences in production decisions, such as production quantity and binary results, which ultimately affect the final inventory per period and total system costs as shown in Fig. 10 and Fig. 11. Such figures show the impact of production quantity and binary production on the process of survey, production, and inventory. The DLS model optimized using GA in the context of unconstrained inventory capacity is able to provide significant system cost reduction. With the ability of the GA to comprehensively explore the solution space, the resulting production decisions tend to be more efficient. This enables better adjustment to market needs and demand without being burdened by inventory constraints. The impact on inventory, especially in the unconstrained context, is that the right amount of inventory can be held, providing greater flexibility in the face of demand fluctuations.

In this context, determining production quantity and binary production becomes very important. When faced with inventory constraints in DLS, a thoughtful production strategy is necessary. Due to limited inventory capacity, production decisions must account for the balance between market demand and available inventory. Concurrently, it is crucial to ensure product availability meets demand without causing excessive inventory accumulation.

The binary production is a crucial factor in inventory management within the given constraints. It determines whether products are produced each period, and not producing can impact the availability of the product, potentially resulting in loss of market share or dissatisfied customers. Therefore, in DLS with inventory constraints, the decision to produce in binary form is not solely concerned with production efficiency, but also with achieving the appropriate balance between product availability and inventory availability. This underscores the significance of conducting thorough analyses to achieve an ideal balance between market demand, inventory capacity, and production costs.

As shown in Fig. 10 and Fig. 11, both DLS models with and without inventory capacity constraints have the same business process from sales survey to delivery of bread products to retailers. Sales surveys are conducted three days before bread production begins. Whether the model has inventory constraints or not, the information from this survey is crucial to determine the orders received by retailers. This data becomes the basis for determining the amount of production required and when production is carried out to fulfill demand. After the sales survey, 2 days before, the bread production process begins. The number and time of production is predetermined and lasts for 7 periods, equivalent to 1 week. In both models, there are two important aspects to be considered: quantitative production quantities and binary production settings (1=production and 0=otherwise). This aims to address the perishable problem of bread products that only have a shelf life of 4 days after leaving the factory. Production should match the demand identified from the sales survey while taking into consideration the product's durability limitation. While a binary production setup is important to ensure bread is produced according to type, reducing potential production wastage and improving overall efficiency.

On the day before delivery, the packaging process is carried out in both models. This stage is crucial because the bread that has been produced must be prepared for delivery to retailers. This process requires special attention to product quality, proper packaging, and logistical arrangements to ensure that the bread arrives at retailers in the best possible condition in accordance with established quality standards. This is where inventory management and logistics coordination become crucial to ensure the bread reaches the end consumer with optimal quality.

D. Sensitivity Analysis of the DLS Model

Sensitivity analysis is an important approach in systems analysis that aims to measure how sensitive system results or performance are to changes in one or more parameters. Specifically in the context of DLS models without inventory capacity constraints, sensitivity analysis will be a powerful tool to evaluate the extent to which system performance is affected by variations in certain parameters. The focus on crucial parameters such as return rate and perishable rate, which are closely related to expiration date, is an important foundation for making the right decisions regarding inventory management and production decisions.

In performing sensitivity analysis on the DLS model without inventory constraints, the return rate and perishable rate parameters are the main focus. By changing the values of these parameters by ±25% on their baseline values, this analysis aims to understand the extent to which changes in return rate and perishable rate. Note that, the return rate is the function of actual return data, meanwhile perishable rate is the function of the expiration days. Therefore, changes in parameter values that affect the return rate and perishable rate are shown in TABLE VI.

TABLE VI. CHANGING OF RETURN AND PERISHABLE PARAMETER DATA

Changes	Parameter Values	
	Data return per product *p* (units)	**Expire days for perishable rate per product *p***
+50%	954; 678; 434; 371	7; 7; 7; 7
+25%	681; 484; 310; 265	5; 5; 5; 5; 5
0	545; 387; 248; 212	4; 4; 4; 4
-25%	409; 290; 186; 159	3; 3; 3; 3
-50%	273; 194; 124; 106	2; 2; 2; 2

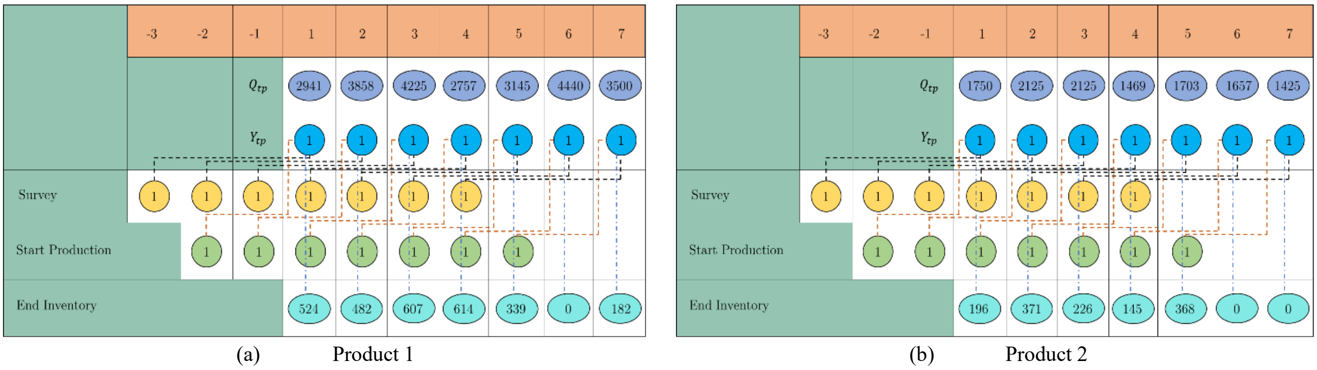


Fig. 10. The impact of the production decision under four products for the DLS model with unconstrained inventory capacity extend to the management of process business in bread making, encompassing both production volume and binary production decisions

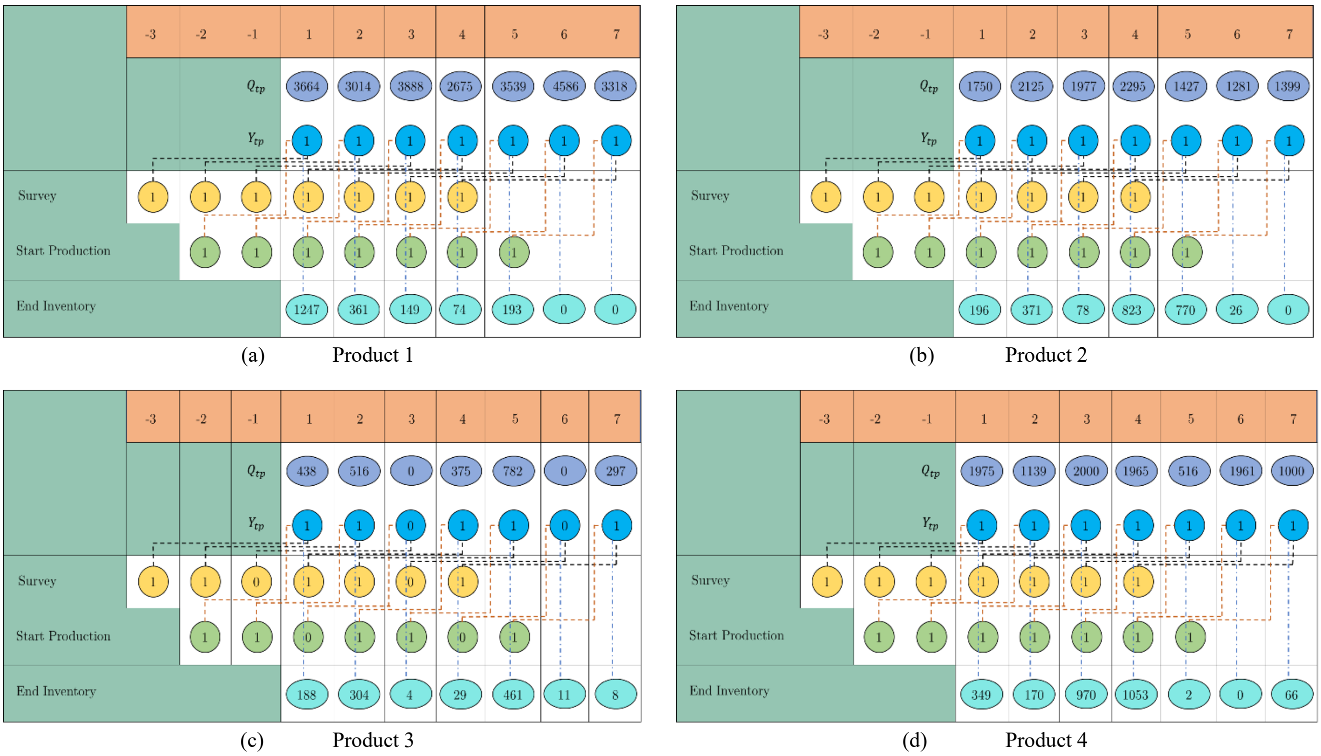


Fig. 11. The impact of the production decision under four products for the DLS model with constrained inventory capacity extend to the management of process business in bread making, encompassing both production volume and binary production decisions

The results of the sensitivity analysis on the return rate and perishable rate in the DLS model without inventory constraints are shown in Table VII and Table VIII. The results of this analysis indicate that changes in return rate and perishable rate can have substantial implications on the total system costs and provide important information for decision makers in devising inventory management strategies that are more adaptive and responsive to market dynamics.

Table VII shows that the return rate is an important parameter to consider when designing a DLS with a perishable product. By understanding the impact of return rate on production quantity, binary production, and total system costs, managers can make better decisions about how to manage their inventory.

The impact of return rate on production quantity is nonlinear. This means that the change in production quantity is not proportional to the change in return rate. For example, a 25% increase in return rate does not result in a 25% decrease in production quantity. However, in practical application, the return rate proves to be a crucial factor that influences the production quantity as the return rate increases, the production quantity decreases. This is because a higher return rate means that more products are being returned, which reduces the need to produce as many new products.

Moreover, the impact of the return rate on binary production is also nonlinear. However, the impact is not as strong as the impact on production quantity. Similarly, binary production, the practice of producing in larger batches, demonstrated a sensitivity to return rate fluctuations. With increasing return rates, binary production declined, reflecting the reduced demand for new products and the efficiency gained from producing in larger quantities.

Lastly, the impact of the return rate on total system costs is relatively linear. This means that the change in total system costs is approximately proportional to the change in return rate. Total system costs, encompassing all expenses associated with production, inventory management, and return handling, exhibited a moderate sensitivity to return rate variations. As return rates increased, total system costs also rose, reflecting the additional costs incurred in processing returned products.

Delving into the sensitivity of DLS models for perishable products, this study explores the impact of varying expiration day (due date) parameters on production quantity, binary production, and total system costs as shown in Table VIII. The expiration day, representing the time beyond which products cannot be sold or consumed, is a crucial factor in perishable product inventory management. Therefore, the perishability rate is the function of the expiration day of the bread product. The analysis systematically altered the expiration day by increments and decrements of 25% from its baseline value, effectively simulating different perishability rates.

The impact of expiration day on production quantity and binary production is nonlinear. This means that the change in production quantity is not proportional to the change in expiration day. On the one hand, what usually happens in practice fulfills the following logic: as the expiration day increases, the production quantity decreases. This is because a longer expiration day means that products have more time to be sold, so there is less need to produce as many new products. Moreover, expiration day has a moderate impact on binary production. As the expiration day increases, the binary production decreases. This is because a longer expiration day means that there is less demand for new products, so it is more efficient to produce in larger batches.

Meanwhile, expiration day has a moderate impact on total system costs. As the expiration day increases, the total system costs increase slightly. This is because a longer expiration day means that there are more products in the system at any given time, which increases the cost of holding inventory.

Overall, analyzing the impact of rate of return and damage rate on production quantity, binary production, and total system cost is a complex task due to the nonlinear and dynamic nature of these variables. Therefore, it is challenging to predict the exact impact of changing these parameters. The interaction between the rate of return, damage rate, and production parameters creates a system with many feedback loops and complicated relationships. Analyzing the impact of the rate of return and perishable rate poses challenges due to various factors.

a. *Nonlinearity of Demand and Production:* Product demand does not always correspond to supply, and the production process often entails fixed costs and batch processing. These nonlinearities create complexities in predicting the effects of alterations in the rate of return and perishable rate on the total cost and production quantity.
b. *Dynamic Nature of Perishability:* Perishable products have a limited shelf life, leading to a decrease in value over time. This dynamic nature adds complexity to the analysis and production decisions should consider the risk of spoilage and associated costs.
c. *The interaction between return rate and perishability: Return rates and perishable rates are not independent variables*; they can influence each other. For instance, an increased return rate could result in more perishable losses due to the extra handling required for returned items. This aspect further complicates the analysis.
d. *Search Behavior of Optimization Algorithms*: To tackle complex optimization problems like dynamic lot sizing, optimization algorithms like GA are commonly utilized. However, GAs demonstrates nonlinear search behavior, which amplifies nonlinearity within the system and complicates the prediction of parameter change impacts.

Ultimately, determining the effects of return rates and perishable rates proves challenging due to the combined influence of nonlinear dependencies, dynamic processes, and complex optimization behavior. Understanding these factors is crucial to developing a durable DLS model that can efficiently handle perishable inventory and enhance system performance.

TABLE VII. THE EFFECT OF CHANGES IN RETURN RATE

p	t	$Q_{t,p}$	$Y_{t,p}$	p	t	$Q_{t,p}$	$Y_{t,p}$	p	t	$Q_{t,p}$	$Y_{t,p}$	p	t	$Q_{t,p}$	$Y_{t,p}$	p	t	$Q_{t,p}$	$Y_{t,p}$
	1	3125	1		1	2423	1		1	2941	1		1	3688	1		1	4063	1
	2	3617	1		2	4386	1		2	3858	1		2	2727	1		2	2258	1
	3	3699	1		3	3973	1		3	4225	1		3	4156	1		3	4250	1
1	4	2879	1	1	4	3373	1	1	4	2757	1	1	4	3600	1	1	4	3500	1
	5	4520	1		5	3203	1		5	3145	1		5	4848	1		5	4251	1
	6	3707	1		6	4008	1		6	4440	1		6	2736	1		6	3125	1
	7	3137	1		7	3318	1		7	3500	1		7	2929	1		7	3501	1
	1	1984	1		1	1750	1		1	1750	1		1	2231	1		1	1750	1
	2	1844	1		2	2125	1		2	2125	1		2	2032	1		2	2383	1
	3	1946	1		3	2125	1		3	2125	1		3	2367	1		3	1708	1
2	4	1750	1	2	4	1394	1	2	4	1469	1	2	4	2268	1	2	4	1630	1
	5	1750	1		5	1543	1		5	1703	1		5	0	0		5	1333	1
	6	1563	1		6	1892	1		6	1657	1		6	1931	1		6	2125	1
	7	1422	1		7	1425	1		7	1425	1		7	1750	1		7	1750	1
	1	500	1		1	750	1		1	360	1		1	250	1		1	650	1
	2	500	1		2	0	0		2	477	1		2	719	1		2	0	0
	3	0	0		3	215	1		3	785	1		3	0	0		3	313	1
3	4	376	1	3	4	785	1	3	4	0	0	3	4	625	1	3	4	625	1
	5	750	1		5	0	0		5	778	1		5	125	1		5	813	1
	6	0	0		6	650	1		6	0	0		6	688	1		6	0	0
	7	274	1		7	0	0		7	0	0		7	0	0		7	0	0
	1	1933	1		1	1627	1		1	1642	1		1	1955	1		1	1750	1
	2	1500	1		2	1317	1		2	1679	1		2	2000	1		2	1594	1
	3	832	1		3	1313	1		3	1522	1		3	1598	1		3	1563	1
4	4	2000	1	4	4	1781	1	4	4	1183	1	4	4	1658	1	4	4	1119	1
	5	1632	1		5	1563	1		5	1567	1		5	1456	1		5	1567	1
	6	1659	1		6	1955	1		6	1963	1		6	1823	1		6	1969	1
	7	1000	1		7	1000	1		7	1000	1		7	0	0		7	1000	1
TC		71942270		TC		68130780		TC		72363750		TC		91618820		TC		75688170	

TABLE VIII. THE EFFECT OF CHANGES IN THE EXPIRATION DATE OF PERISHABILITY RATE

p	t	$Q_{t,p}$	$Y_{t,p}$	p	t	$Q_{t,p}$	$Y_{t,p}$	p	t	$Q_{t,p}$	$Y_{t,p}$	p	t	$Q_{t,p}$	$Y_{t,p}$	p	t	$Q_{t,p}$	$Y_{t,p}$
	1	3881	1		1	3524	1		1	2941	1		1	3149	1		1	4848	1
	2	3379	1		2	3269	1		2	3858	1		2	3641	1		2	2532	1
	3	4438	1		3	4250	1		3	4225	1		3	4098	1		3	5000	1
1	4	4966	1	1	4	2877	1	1	4	2757	1	1	4	2281	1	1	4	4692	1
	5	0	0		5	3869	1		5	3145	1		5	4438	1		5	0	0
	6	4702	1		6	3577	1		6	4440	1		6	4719	1		6	4878	1
	7	3500	1		7	3318	1		7	3500	1		7	2375	1		7	2734	1
	1	1672	1		1	2417	1		1	1750	1		1	1688	1		1	1557	1
	2	1869	1		2	2043	1		2	2125	1		2	2194	1		2	2220	1
	3	2233	1		3	2219	1		3	2125	1		3	1896	1		3	2328	1
2	4	1750	1	2	4	2125	1	2	4	1469	1	2	4	2092	1	2	4	1256	1
	5	1938	1		5	0	0		5	1703	1		5	1305	1		5	2067	1
	6	1376	1		6	2031	1		6	1657	1		6	1750	1		6	1426	1
	7	1750	1		7	1422	1		7	1425	1		7	1329	1		7	1400	1
	1	750	1		1	750	1		1	360	1		1	500	1		1	500	1
	2	0	0		2	0	0		2	477	1		2	500	1		2	563	1
	3	200	1		3	906	1		3	785	1		3	516	1		3	0	0
3	4	688	1	3	4	0	0	3	4	0	0	3	4	884	1	3	4	563	1
	5	281	1		5	0	0		5	778	1		5	0	0		5	782	1
	6	484	1		6	750	1		6	0	0		6	0	0		6	0	0
	7	0	0		7	0	0		7	0	0		7	0	0		7	0	0
	1	1750	1		1	1750	1		1	1642	1		1	1750	1		1	1626	1
	2	1993	1		2	1428	1		2	1679	1		2	1813	1		2	1330	1
	3	1500	1		3	1672	1		3	1522	1		3	1875	1		3	1408	1
4	4	1750	1	4	4	1994	1	4	4	1183	1	4	4	1406	1	4	4	1662	1
	5	625	1		5	1719	1		5	1567	1		5	1344	1		5	1598	1
	6	1938	1		6	993	1		6	1963	1		6	1430	1		6	1932	1
	7	1000	1		7	934	1		7	1000	1		7	872	1		7	1000	1
TC		80769364,29		TC		82234372		TC		72363750		TC		85098660		TC		86544520	

Note : p = Number of products, $p = 1, 2, 3, \dots, P$.
$Q_{t,p}$ = Production quantity for product type p in period t.
$Y_{t,p}$ = 1, if there is a number of products produced for product type p in period t, 0, otherwise.
TC = Total system costs.

V. CONCLUSION

This research is an important step in improving DLS model that consider the perishable nature of products, a crucial aspect in inventory management. DLS, which is flexible in managing multiple products and multiple periods, provides a solid foundation in managing inventory in complex production environments. This paper proposes a model that is able to adapt to two different situations, namely unconstrained inventory and constrained inventory capacity, providing a solution that suits the specific needs of the company.

This research highlights the vital role of GA in approximating the optimal solution to the DLS model, especially in managing production decisions such as production quantity and binary production. In both situations, the GA was able to produce efficient solutions, tailored to the company's needs, while significantly reducing the total system cost. The use of GA in testing the model with real data from a bread manufacturer is a crucial step in validating and improving the DLS model. GA, as a broad computational method, is able to thoroughly explore the solution space in optimization problems such as DLS.

Sensitivity analysis of return rate and perishable rate provides an in-depth understanding of the impact of changing these key parameters on model performance and solution. The findings provide a solid foundation for decision makers in inventory management, enabling adaptation of optimal strategies in the face of fluctuations in key parameters.

The adoption of carbon emission parameters in DLS reflects an important step towards green manufacturing. Future studies can explore the integration of environmental aspects into the DLS model by considering carbon impacts in the supply chain, making a major contribution to sustainable production decision-making.

ACKNOWLEDGMENT

This study was supported by Directorate of Research, Technology, and Community Service Ministry of Education, Culture, Research and Technology, Indonesia under the Grant No. 022/PKDN/LPPM UAD/VI/2023.

REFERENCES

[1] I. Tiseo, "Annual household food waste produced in selected countries worldwide as of 2020," *Statista*, 2023.

[2] M. Arkyasa, "Indonesian Annual Food Waste Losses Reportedly Reach Rp 551 Trillion," *tempo.co*, Jakarta, p. 1, 2022. Available: https://en.tempo.co/read/1630680/indonesian-annual-food-waste-losses-reportedly-reach-rp551-trillion.

[3] R. A. C. Leuveano, F. A. Bin Jafar, C. Saleh, and M. R. Bin Muhamad, "Incorporating Transportation Cost into Joint Economic Lot Size For Single Vendor-Buyer," *J. Softw.*, vol. 9, no. 5, pp. 1313–1323, 2014.

[4] R. A. C. Leuveano, M. N. Ab Rahman, W. M. F. W. Mahmood, and C. Saleh, "Integrated vendor-buyer lot-sizing model with transportation and quality improvement consideration under just-in-time problem," *Mathematics*, vol. 7, no. 10, 2019.

[5] M. N. Ab Rahman *et al.*, "Incorporating logistic costs into a single vendor–buyer JELS model," *Appl. Math. Model.*, vol. 40, no. 23–24, pp. 10809–10819, 2016.

[6] K. Biel and C. H. Glock, "Systematic literature review of decision support models for energy-efficient production planning," *Comput. Ind. Eng.*, vol. 101, pp. 243–259, 2016.

[7] R. A. C. Leuveano, M. N. Ab. Rahman, B. Md Deros, and W. M. F. Wan Mahmood, "A Framework for Developing Green Coordinated Decision Model In Supply Chain," *Int. J. Eng. Technol.*, vol. 8, no. 1.2, pp. 157–163, 2019.

[8] R. A. C. Leuveano, F. A. Bin Jafar, and M. R. Bin Muhamad, "Incorporating transportation costs into integrated inventory model for single supplier and single purchaser," *Adv. Sci. Lett.*, vol. 20, no. 1, pp. 290–293, 2014.

[9] D. Zissis, G. K. D. Saharidis, E. Aktas, and G. Ioannou, "Emission reduction via supply chain coordination," *Transp. Res. Part D Transp. Environ.*, vol. 62, pp. 36–46, 2018.

[10] A. Dymchenko, M. Geršl, and T. Gregor, "Trends in bread waste utilisation," *Trends Food Sci. Technol.*, vol. 132, pp. 93–102, 2023.

[11] S. Østergaard and O. J. Hanssen, "Wasting of fresh-packed bread by consumers-influence of shopping behavior, storing, handling, and consumer preferences," *Sustain.*, vol. 10, no. 7, pp. 1–16, 2018.

[12] P. Brancoli, K. Rousta, and K. Bolton, "Life cycle assessment of supermarket food waste," *Resour. Conserv. Recycl.*, vol. 118, pp. 39–46, 2017.

[13] H. Irwan, M. N. Abd Rahman, Z. Ebrahim, and R. A. A. Chairdino, "A Review of Integration Model of Lot-Sizing-Scheduling Problem," *Malaysian Constr. Res. J.*, vol. 17, no. 3, pp. 160–174, 2023.

[14] C. H. Glock, E. H. Grosse, and J. M. Ries, "The lot sizing problem: A tertiary study," *Int. J. Prod. Econ.*, vol. 155, pp. 39–51, 2014.

[15] K. Altendorfer, *Capacity and inventory planning for make-to-order production systems*. Lecture notes in economics and mathematical systems). Switzerland: Springer, 2014.

[16] M. Yu and A. Nagurney, "Competitive food supply chain networks with application to fresh produce," *Eur. J. Oper. Res.*, vol. 224, no. 2, pp. 273–282, 2013.

[17] J. Noble, K. John, and B. Paul, "Inventory management of perishable products with fixed shelf life for a single echelon system," *Mater. Today Proc.*, vol. 72, pp. 2863–2868, 2023.

[18] L. Feng, Y. L. Chan, and L. E. Cárdenas-Barrón, "Pricing and lot-sizing polices for perishable goods when the demand depends on selling price, displayed stocks, and expiration date," *Int. J. Prod. Econ.*, vol. 185, pp. 11–20, 2017.

[19] G. A. Chua, R. Mokhlesi, and A. Sainathan, "Optimal Discounting and Replenishment Policies for Perishable Products," *Int. J. Prod. Econ.*, vol. 186, pp. 8–20, 2017.

[20] V. N. Hsu, "Dynamic economic lot size model with perishable inventory," *Manage. Sci.*, vol. 46, no. 8, pp. 1159–1169, 2000.

[21] Q. Duan and T. W. Liao, "A new age-based replenishment policy for supply chain inventory optimization of highly perishable products," *Int. J. Prod. Econ.*, vol. 145, no. 2, pp. 658–671, 2013.

[22] Z. Alipour, F. Jolai, E. Monabbati, and N. Zaerpour, "General lot-sizing and scheduling for perishable food products," *RAIRO - Oper. Res.*, vol. 54, no. 3, pp. 913–931, 2020.

[23] A. Acevedo-Ojeda, I. Contreras, and M. Chen, "Two-level lot-sizing with raw-material perishability and deterioration," *J. Oper. Res. Soc.*, vol. 71, no. 3, pp. 417–432, 2020.

[24] S. Transchel and O. Hansen, "Supply planning and inventory control of perishable products under lead-time uncertainty and service level constraints," in *Procedia Manufacturing*, 2019, vol. 39, pp. 1666–1672, 2019.

[25] S. Chen, R. Berretta, A. Clark, and P. Moscato, *Lot Sizing and Scheduling for Perishable Food Products: A Review*. Elsevier, 2019.

[26] S. Nahmias, *Perishable Inventory System*. Springer Science & Business Media, 2011.

[27] J. Blackburn and G. Scudder, "Supply chain strategies for perishable products: the case of fresh produce," *Prod. Oper. Manag.*, vol. 18, no. 2, pp. 129–137, 2009.

[28] Z. Sazvar, S. M. J. Mirzapour Al-e-hashem, K. Govindan, and B. Bahli, "A novel mathematical model for a multi-period, multi-product optimal ordering problem considering expiry dates in a FEFO system," *Transp. Res. Part E Logist. Transp. Rev.*, vol. 93, pp. 232–261, 2016.

[29] R. Sundararajan, M. Palanivel, and S. Vaithyasubramanian, "On the EOQ Models with Advertisement-Price-Dependent Demand and Quantity Discount with Expiration Date Under Shortage," *Oper. Res. Forum*, vol. 4, no. 69, 2023.

[30] M. Moeany, A. A. Taleizadeh, and F. Jolai, "Bundle pricing, reservation, and refund policies in a two-level supply chain," *Sci. Iran.*, vol. 29, no. 5 E, pp. 2740–2755, 2022.

[31] S. Khalafi, A. Hafezalkotob, D. Mohammaditabar, and M. K. Sayadi, "Multi objective Fuzzy programming of remanufactured green perishable products using supply contracts," *Int. J. Manag. Sci. Eng. Manag.*, vol. 15, no. 4, pp. 274–287, 2020.

[32] A. Aazami and M. Saidi-Mehrabad, "A production and distribution planning of perishable products with a fixed lifetime under vertical competition in the seller-buyer systems: A real-world application," *J. Manuf. Syst.*, vol. 58, pp. 223–247, 2021.

[33] H. Yang, M. Gao, Q. Xiao, and M. Goh, "Ordering and pricing decisions for perishable goods retailer with zero-inventory and capital constraints," *Int. Trans. Oper. Res.*, vol. 29, no. 5, pp. 3107–3130, 2022.

[34] P. Koken, V. Arasanipalai Raghavan, and S. W. Yoon, "A genetic algorithm based heuristic for dynamic lot sizing problem with returns and hybrid products," *Comput. Ind. Eng.*, vol. 119, pp. 453–464, 2018.

[35] K. E. Parsopoulos, I. Konstantaras, and K. Skouri, "Metaheuristic optimization for the Single-Item Dynamic Lot Sizing problem with returns and remanufacturing," *Comput. Ind. Eng.*, vol. 83, pp. 307–315, 2015.

[36] A. Liu, Q. Zhu, L. Xu, Q. Lu, and Y. Fan, "Sustainable supply chain management for perishable products in emerging markets: An integrated location-inventory-routing model," *Transp. Res. Part E Logist. Transp. Rev.*, vol. 150, p. 102319, 2021.

[37] J. Fan and J. Ou, "On dynamic lot sizing with bounded inventory for a perishable product," *Omega (United Kingdom)*, vol. 119, p. 102895, 2023.

[38] F. Jing and Y. Mu, "Dynamic lot-sizing model under perishability, substitution, and limited storage capacity," *Comput. Oper. Res.*, vol. 122, p. 104978, 2020.

[39] F. Z. Sargut and G. Işık, "Dynamic economic lot size model with perishable inventory and capacity constraints," *Appl. Math. Model.*, vol. 48, pp. 806–820, 2017.

[40] S. M. J. Al-E-Hashem, Z. Sazvar, A. Baboli, Y. Rekik, and M. Akbari Jokar, "A capacitated multi-product dynamic lot-sizing problem by considering expiration dates; A new approach," in *IFAC Proceedings Volumes (IFAC-PapersOnline)*, 2013, pp. 152–157, 2013.

[41] O. Kaya and H. Bayer, "Pricing and lot-sizing decisions for perishable products when demand changes by freshness," *J. Ind. Manag. Optim.*, vol. 17, no. 6, pp. 3113–3129, 2021.

[42] W. Aribowo, M. Rohman, F. Baskoro, R. Harimurti, Y. Yamasari, and W. Yustanti, "Novel hybrid prairie dog optimization algorithm-marine predator algorithm for tuning parameters power system stabilizer," *J. Robot. Control*, vol. 4, no. 5, pp. 686–695, 2023.

[43] H. M. Asih, R. A. C. Leuveano, A. Rahman, and M. Faishal, "Traveling Salesman Problem With Prioritization for Perishable Products in Yogyakarta, Indonesia," *J. Adv. Manuf. Technol.*, vol. 16, no. 3, pp. 15–27, 2022.

[44] A. Rahman and H. M. Asih, "Optimizing shipping routes to minimize cost using particle swarm optimization," *Int. J. Ind. Optim.*, vol. 1, no. 1, p. 53, 2020.

[45] A. Moghaddas and S. M. H. Hosseini, "Short-term scheduling of hybrid thermal, pumped-storage, and wind plants using firefly optimization algorithm," *Int. J. Ind. Optim.*, vol. 3, no. 2, pp. 80–97, 2022.

[46] S. U. Seçkiner and Ş. Yilkici Yüzügüldü, "A new health-based metaheuristic algorithm: cholesterol algorithm," *Int. J. Ind. Optim.*, vol. 4, no. 2, pp. 115–130, 2023.

[47] Z. Ursani and A. A. Ursani, "Augmented tour construction heuristics for the travelling salesman problem," *Int. J. Ind. Optim.*, vol. 4, no. 2, pp. 131–144, 2023.

[48] T. Nguyen, H.-N. Dinh, V.-T. Nguyen, B. S. Do, T. T. Nguyen, and B.-L. Do, "Ecpoc: an evolutionary computation-based proof ofcriteriaconsensus protocol," *Int. J. Ind. Optim.*, vol. 3, no. 2, pp. 98–109, 2022.

[49] R. Perez-Rodriguez, "An estimation of distribution algorithm for combinatorial optimization problems," *Int. J. Ind. Optim.*, vol. 3, no. 1, pp. 47–67, 2022.

[50] M. N. Khasanah and H. M. Asih, "Developing Simulation Optimization Model to Minimize Total Inventory Cost under Uncertain Demand," in *Proceedings of the Second Asia Pacific International Conference on Industrial Engineering and Operations Management*, pp. 1998–2007, 2021.

[51] A. Hassan, C. Saleh, B. Md Deros, M. N. Ab Rahman, R. A. C. Leuveano, and A. Adiyoga, "Parameter Optimization of VMI System in a Manufacturer and Multi Retailer Using Genetic Algorithm," *Adv. Mater. Res.*, vol. 1115, pp. 622–626, 2015.

[52] M. N. A. Rahman, R. A. C. Leuveano, F. A. Bin Jafar, C. Saleh, and B. M. Deros, "Total cost reduction using a genetic algorithm for multi-vendor and single manufacturer," *Int. J. Math. Model. Methods Appl. Sci.*, vol. 9, pp. 566–575, 2015.

[53] H. M. Asih, K. E. Chong, and M. Faishal, "Capacity planning and product allocations under testing time uncertainty in electronic industry," *J. Adv. Manuf. Technol.*, vol. 12, no. 1, pp. 103–115, 2018.

[54] H. M. Asih and K. E. Chong, "Throughput and Tester Utilization Improvement in the Hard Disk Drive Assembly Line Using Hybrid Simulation Approach," *Adv. Sci. Lett.*, vol. 20, no. 2, pp. 455–459, 2014.

[55] K. E. Chong and H. M. Asih, "An Integrated Robust Optimization Model of Capacity Planning under Demand Uncertainty in Electronic Industry," *Int. J. Mech. Mechatronics Eng.*, vol. 15, no. 3, pp. 88–96, 2015.

[56] H. M. Asih and K. E. Chong, "An Integrated of Robust Optimization and TOPSIS model for Capacity Planning under Demand Uncertainty," in *1st International Conference on Industrial Engineering*, 2015.

[57] X. Yang, Z. Chen, X. Huang, R. Li, S. Xu, and C. Yang, "Robust capacity optimization methods for integrated energy systems considering demand response and thermal comfort," *Energy*, vol. 221, p. 119727, 2021.

[58] N. Harale, S. Thomassey, and X. Zeng, "Dynamic small-series fashion order allocation and supplier selection: a ga-topsis-based model," *Int. J. Ind. Optim.*, vol. 4, no. 2, pp. 82–102, 2023.

[59] A. C. Leuveano, F. A. Bin Jafar, and M. R. Bin Muhamad, "Development of genetic algorithm on multi-vendor integrated procurement-production system under shared transportation and just-in-time delivery system," *Proceeding 2012 Int. Conf. Uncertain. Reason. Knowl. Eng. URKE 2012*, pp. 78–81, 2012.

[60] Y. Lou, L. Zhang, and L. Diao, "The scheduling policy on agent software evolution," in *PIC 2014 - Proceedings of 2014 IEEE International Conference on Progress in Informatics and Computing*, pp. 149–152, 2014.

[61] R. Alayi, H. Harasii, and H. Pourderogar, "Modeling and optimization maximum power point tracking using GA for PV system," *J. Robot. Control*, vol. 2, no. 1, pp. 35–41, 2021.

[62] N. S. Abu, W. M. Bukhari, M. H. Adli, and A. Ma'arif, "Optimization of an Autonomous Mobile Robot Path Planning Based on Improved Genetic Algorithms," *J. Robot. Control*, vol. 4, no. 4, pp. 557–571, 2023.

[63] Z. Yuan and L. BingFen, "The Empirical Study of the Schema Theory of Genetic Algorithm Based on 3-satisfiability Problem," pp. 448–453, 2015.

[64] N. Koide, K. Okuhara, Y. Ichifuji, and N. Sonehara, "Automatic Generation of Robust Agents Using Knowledge," in *Proceedings of the 44th ISCIE International Symposium on Stochastic Systems Theory and Its Applications*, pp. 148–151, 2013.

[65] I. Slama, O. Ben-Ammar, A. Dolgui, and F. Masmoudi, "Genetic algorithm and Monte Carlo simulation for a stochastic capacitated disassembly lot-sizing problem under random lead times," *Comput. Ind. Eng.*, vol. 159, 2021.

[66] B. Le Badezet, F. Larroche, O. Bellenguez, and G. Massonnet, "A Genetic Algorithm for a Capacitated Lot-Sizing Problem with Lost Sales, Overtimes and Safety Stock Constraints," *Commun. Comput. Inf. Sci.*, vol. 1541, pp. 170–181, 2022.

[67] M. Liu, H. Tang, F. Chu, F. Zheng, and C. Chu, "Joint optimization of lot-sizing and pricing with backlogging," *Comput. Ind. Eng.*, vol. 167, 2022.

[68] M. Darwish. *Lot-Sizing And Scheduling Optimization using Genetic Algorithm*. University of Skovde, 2018.

[69] M. Vahdani, Z. Sazvar, and K. Govindan, "An integrated economic disposal and lot-sizing problem for perishable inventories with batch production and corrupt stock-dependent holding cost," *Ann. Oper. Res.*,

vol. 315, no. 2, pp. 2135–2167, 2022.

[70] H. M. Asih, R. Achmad, C. Leuveano, and D. A. Dharmawan, "Optimizing lot sizing model for perishable bread products using genetic algorithm," *J. Sist. dan Manaj. Ind.*, vol. 7, no. 2, pp. 139–154, 2023.

[71] D. Bertsimas, E. Litvinov, X. A. Sun, J. Zhao, and T. Zheng, "Adaptive Robust Optimization for the Security Constrained Unit Commitment Problem," *IEEE Trans. Power Syst.*, vol. 28, no. 1, pp. 52–63, 2013.

[72] C.-J. Wen, X. Liu, and X. Cheng, "Parameter Evaluation of 3-parameter Weibull Distribution based on Adaptive Genetic Algorithm," in *2nd International Conference on Machinery, Electronics and Control Simulation (MECS 2017)*, vol. 138, pp. 426–431, 2017.

[73] N. Brahimi, S. Dauzere-Peres, N. M. Najid, and A. Nordli, "Single item lot sizing problems," *Eur. J. Oper. Res.*, vol. 168, no. 1, pp. 1–16, 2006.

[74] Z. Chen and R. Q. Zhang, "A capital flow-constrained lot-sizing problem with trade credit," *Sci. Iran.*, vol. 25, no. 5E, pp. 2775–2787, 2018.

[75] G. Besiashvili, M. Khachidze, and D. Chokhonelidze, "Application of Adaptive genetic algorithm in mining industry," *2012 4th Int. Conf. 'Problems Cybern. Informatics', PCI 2012 - Proc.*, pp. 1–3, 2012.

[76] A. Mokhtari, M. M. Jalili, and A. Mazidi, "Optimization of different parameters related to milling tools to maximize the allowable cutting depth for chatter-free machining," *Proc. Inst. Mech. Eng. Part B J. Eng. Manuf.*, vol. 235, no. 1–2, pp. 230–241, 2021.

[77] S. Panda, S. Saha, and M. Basu, "Optimal pricing and lot-sizing for perishable inventory with price and time dependent ramp-type demand," *Int. J. Syst. Sci.*, vol. 44, no. 1, pp. 127–138, 2013.

[78] S. H. R. Pasandideh, S. T. A. Niaki, and M. Hemmati Far, "Optimization of vendor managed inventory of multiproduct EPQ model with multiple constraints using genetic algorithm," *Int. J. Adv. Manuf. Technol.*, vol. 71, no. 1–4, pp. 365–376, 2014.

[79] W. H. Miner, P. M. Valanju, S. P. Hirshman, A. Brooks, and N. Pomphrey, "Use of a genetic algorithm for compact stellarator coil design," *Nucl. Fusion*, vol. 41, no. 9, pp. 1185–1195, 2001.

[80] K. M. Abdul Kadhar and S. Baskar, "A stopping criterion for decomposition-based multi-objective evolutionary algorithms," *Soft Comput.*, vol. 22, no. 1, pp. 253–272, 2018.