Journal of Optimization and Supply Chain Management

JOSCM

2024, Volume 1, Issue 2, pp. 133-146
ISSN-Print: 3079-1022
ISSN-Online: 3079-1030
https://joscm.refconf.com

Optimizing Maintenance Life for Transport Fleets in A Poultry Meat Supply Chain

Fatemeh Mahdizadeh [a], Amir-Mohammad Golmohammadi [b*] and Hamidreza Abedsoltan [c]

[a] Industrial & Systems Engineering Department, Faculty of Engineering, Kharazmi University, Tehran, Iran
[b] Department of Industrial Engineering, Arak University, Arak, Iran
[c] School of Industrial Engineering, College of Engineering, University of Tehran, Tehran, Iran

Abstract

Modern maintenance scheduling is a complex optimization problem that combines resource constraints, uncertain environments, and critical times. In this research, the maintenance life of logistics tools within an agricultural product supply chain is optimized. Like any other supply chain, an agricultural supply chain is a network of organizations working together in various processes and activities to bring products and services to the market, aiming to meet customer demands. This study focuses on increasing the maintenance life of trucks and reducing transportation costs by optimizing the periodic repair time of trucks in the chicken meat distribution network, specifically from the slaughterhouse in Rasht to retailers in Tehran, Iran. The designed optimization problem was simulated and solved using a gradient-based method and the concept of nonlinear programming in the MATLAB software environment. By using this method, the simulation results indicate a 16% reduction in maintenance costs.

Keywords: Maintenance costs; Optimization; Chicken meat supply chain; Nonlinear programming.

1. Introduction and literature review

Maintenance optimization models typically include mathematical models aimed at finding the optimal balance between maintenance costs and benefits or determining the most appropriate time to perform maintenance. Key parameters often considered in this optimization include the cost of failure, the cost per time unit of failure, corrective and preventive maintenance, and the cost of replacing a repairable system. The foundation of any maintenance optimization model relies on the fundamental deterioration process and component failure behavior. Over the past decades, maintenance optimization models have garnered increasing attention and have now become a well-established research area.

Among the different types of maintenance policies, preventive maintenance (PM) is widely used in many technical systems such as production systems, transportation systems, and critical infrastructure systems (Lolli, Coruzzolo et al., 2022). One of the most common maintenance policies is the Age Replacement Policy (ARP), developed in the early 1960s (Lolli et al., 2022). Under this policy, a unit is always replaced at age T or failure, whichever occurs first (de Jonge, Klingenberg et al., 2015). An aged replacement policy (ARP) makes sense when the cost of replacing the failure is greater than the planned replacement and the failure rate increases dramatically (Fouladirad, Paroissin et al., 2018). Numerous studies have examined the basic form of ARP, and the first one is related to the implementation of the Bayesian approach to determine the optimal replacement strategy (Insua, Ruggeri et al., 2020). In this study, the authors present a fully Bayesian analysis of the optimal replacement problem for block replacement protocol with

*Corresponding author email address: a-golmohammadi@araku.ac.ir
DOI: 10.22034/ISS.2024.7876.1009

minimal repair and simple age replacement protocol. Optimal replacement strategies are obtained by maximizing expected utility with uncertainty analysis. In the following work (Fu, Zhu et al., 2020), the author introduces an ARP for a used unit, considering that the unit is replaced by another of the same age in case of failure or at time T, whichever occurs first. Additionally, optimizing maintenance logistics on offshore platforms with AI is discussed in (Ukato, Sofoluwe et al., 2024). In (Hrušovský, Hemmelmayr et al., 2024), an integrated planning approach for fleet sizing and fleet management of freight railcars is provided. Moreover, the use of Internet of Things (IoT) based predictive maintenance techniques for sustainable transportation fleets is explored in (Kansal & Ediga, 2024). A novel multi-objective optimization approach to guarantee quality of service and energy efficiency in a heterogeneous bus fleet system is presented in (Peña, Tchernykh et al., 2023). In (Zhao, Mizutani et al., 2015) the authors introduce alternative policies for a unit that executes sequential tasks with cycle time. In this article, three planned replacement policies are defined in continuous and discrete times:

- Continuous age replacement – the device is replaced before failure at the scheduled time *T*.
- Discrete age replacement – the device is replaced before failure at the end of the work cycle.
- Age replacement with overtime - the unit before failure is replaced at the first completion of the duty cycle at the scheduled time T.

Considering that maintenance costs (especially breakdown costs) are difficult to determine in practice, other optimal criteria may also influence the maintenance policy. For example, in the work of (Cavalcante, Lopes et al., 2018), the authors consider the cost structure and operational reliability during the definition of the maintenance strategy. The developed approach allows determining the age limit for preventive replacement in an age-based replacement policy when the cost of failure is unknown. The analyzed reliability measure is defined as the time distribution between operational failures (Tusar & Sarker, 2022). where the authors propose a new age-dependent reliability model that includes parameters related to the monitoring and maintenance effectiveness and working conditions of equipment (both environmental and operational). In the presented articles, the authors assume:

- An operating unit is completely replaced whenever it reaches a certain age.
- When the age of the part or device exceeds the critical age for repairs, the unit with a high probability of failure is either minimally repaired or replaced with a new unit with a low probability of failure.

Under the PM aging model, each PM is assumed to reduce the operating stress to the time units existing before the PM intervention, where the recovery interval is less than or equal to the PM interval. Optimization criteria are also based on the structure of maintenance costs (De Jonge & Scarf, 2020). A summary of the reviewed research in the field of preventive maintenance is given in Table 1.

An agricultural supply chain (ASC), like any other supply chain, is a network of organizations working together in various processes and activities to bring products and services to the market, with the goal of meeting customer demands. What distinguishes ASC from other supply chains is the importance of factors such as food quality and safety (Sharma, Kamble et al., 2020). Other relevant characteristics of agricultural products include their limited shelf life, demand variability, and prices, which make infrastructure supply chain management more challenging than in other supply chains. A given general production-distribution network with all existing and potential facilities consists of three stages: production stage, distribution stage, and customer stage. The primary challenge in network design lies in selecting the facilities to open in order to establish a production-distribution system that minimizes overall costs while maximizing customer service levels (Ding, Benyoucef et al., 2009).

A solution to the centralized clustering problem with capacity using the clustering search algorithm, which uses the concept of hybrid meta-heuristics, is presented in (Chaves & Lorena, 2010) .In the following study (Musa, Arnaout et al., 2010), a new algorithm is proposed to solve the cross-docking network transportation problem, aiming to minimize the total transportation cost of transporting pallets from suppliers to customers through distribution centers .The effect of poultry slaughterhouse modernization and updating of food safety management systems on microbiological quality and product safety has been studied in (Barreto, Ferreira et al., 2007). The concepts of extended products and extended enterprises to support the activities of dynamic supply networks in the agri-food industry have been presented in (Hunt, Wall et al., 2005).

Table 1. Summary of literature review

	Authors	***PM Method***	***Inventory holding***	***Machine Capacity***	***Reliability***
1	Lolli et.al.(2022)	Age-Based Maintenance	*		*
2	de Jonge et al(2015)	Optimization Under Uncertainty			*
3	Fouladirad et al. (2018)	Parameters Sensitivity			*
4	Insua et al. (2020)	Bayesian Decision Making			*
5	Fu et al. (2020)	Optimum Component Reallocation			*
6	Zhao et al. (2015)	Continuous or Discrete Scheduled Times			*
7	Cavalcante et al. (2018)	Replacement Policy			*
8	Ukato et al. (2024)	AI Based PM			*
9	Hrušovský et al. (2024)	Integrated Planning	*		
10	Kansal & Ediga (2024)	IoT-Enabled PM			*
11	Peña et al. (2024)	Evolutionary Algorithm		*	
	This Research	*Lifetime replacement*	*	*	

In this research, focusing on the chicken meat distribution network, a study has been conducted to optimize the periodical repair time of distribution network trucks from slaughterhouses and cold stores to retailers. This research aims to increase the lifespan of trucks during maintenance periods and reduce transportation costs.

This investigation makes a significant contribution to the field of logistics and supply chain management by focusing on the perishable goods industry, which presents unique challenges in balancing maintenance with minimizing spoilage and ensuring freshness in a time-sensitive supply chain. Unlike many studies that primarily concentrate on theoretical models or abstract simulations, our work applies optimization algorithms to address real-world problems within this sector. The developed model incorporates practical constraints faced by the industry, including transportation routes, fleet size, and maintenance intervals, thus enhancing its applicability and relevance. Furthermore, our research not only aims to optimize truck maintenance but also indirectly supports sustainability and cost-efficiency in supply chain management. By effectively reducing truck downtime and preventing breakdowns, our model contributes to lowering operational costs while ensuring a continuous flow of fresh products, a crucial factor in the highly competitive fresh food market. This comprehensive approach highlights the practical implications of our findings and establishes a valuable framework for further research in optimizing logistics operations for perishable goods.

In Section 2, we develop a mathematical model to optimize truck maintenance using data from Sepid Makian, with the aim of extending service life and minimizing costs through a gradient-based approach. Section 3 presents the simulation and solution of this optimization model, utilizing nonlinear programming techniques in MATLAB to evaluate the method's effectiveness. Finally, in Section 4, we demonstrate that optimizing the maintenance schedule for trucks in the fresh chicken meat supply chain resulted in a 30% increase in the service life of high-cost trucks, along with a 16% reduction in overall maintenance costs.

2. Problem definition and mathematical modeling

Due to the importance of cargo transportation in the commercial transportation system, the suspension system of vehicles carrying heavy loads wears out in a relatively short time. Given the expense and importance of this system in commercial vehicles, the service period of this part of the vehicle was optimized. A mathematical model is needed for the operation of the suspension system in commercial vehicles.

For this purpose, due to the ease of work, a quarter car model (Figure 1) was selected from the suspension system. For modeling, the stiffness and damping coefficient of rubber b_2, k_2, and the mentioned coefficients in the suspension system are considered as b_1, k_1. The distance from the flat ground surface w, the distance from the center of the wheel x_2, and the distance from the roof of the vehicle x_1 are considered.

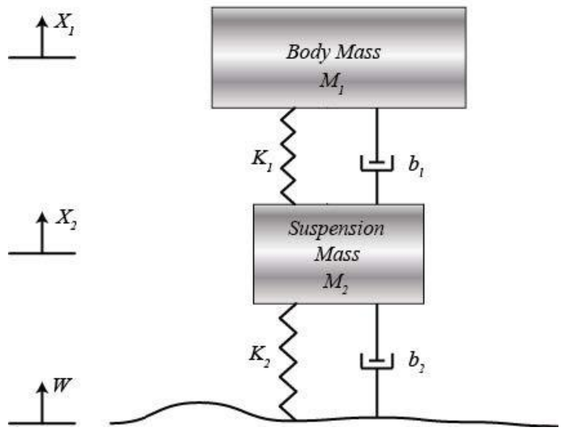

Figure 1. Schematic of the quarter car suspension model

In this model, the masses of the suspension system and the car body, which includes the chassis, are considered separately. Using Figure 1 and writing Newton's second law, we will have:

$$\begin{cases} M_1\ddot{x}_1 = -b_1(\dot{x}_1 - \dot{x}_2) - k_1(x_1 - x_2) \\ M_2\ddot{x}_2 = b_1(\dot{x}_1 - \dot{x}_2) + b_2(\dot{w} - \dot{x}_2) + k_1(x_1 - x_2) + k_2(w - x_2) \end{cases} \tag{1}$$

To better understand how the system moves, the state space of the system's is needed. The vector of state variables is selected as follows:

$$\vec{X} = [(x_1 - x_2) \quad (w - x_2) \quad (\dot{x}_1 - \dot{x}_2) \quad (\dot{w} - \dot{x}_2)]^T \tag{2}$$

In which states $x_1 - x_2$ and $\dot{x}_1 - \dot{x}_2$ denote the movement and velocity of the chassis on wheels respectively. Also states $w - x_2$ and $\dot{w} - \dot{x}_2$ represent the movement and velocity of the wheel respectively. By factoring from relation 2 in formula 1, linear form of Equation 1 is as follows,

$$\dot{\vec{X}} = A\vec{X}, \quad A = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ -\frac{k_1}{M_1} & 0 & -\frac{b_1}{M_1} & 0 \\ \frac{k_1}{M_2} & \frac{b_1}{M_2} & \frac{k_2}{M_2} & \frac{b_2}{M_2} \end{bmatrix} \tag{3}$$

Equation 3 is a linear form of Equation 1, which can be useful for better analysis. Where A is the matrix of coefficients and X is the vector of state variables. Practically, the spring and damper system directly affects the state variable $x_1 - x_2$ and the wheel and tire system affect the state variable $w - x_2$. As it is known, the parameters of matrix A are directly dependent on the coefficients of the spring and damper of the suspension system or tire. These coefficients are not constant during the working cycle of the system and are constantly changing as the system wears out. Therefore, it is clear that the amount of vibration on the main structure of the vehicle, including the driver's cabin and the load-carrying section, is completely dependent on the remaining time until the service and maintenance period. In order to conduct more realistic research, leaf-shaped springs used in heavy transporters were investigated. An example of these springs is shown in Figure 2.

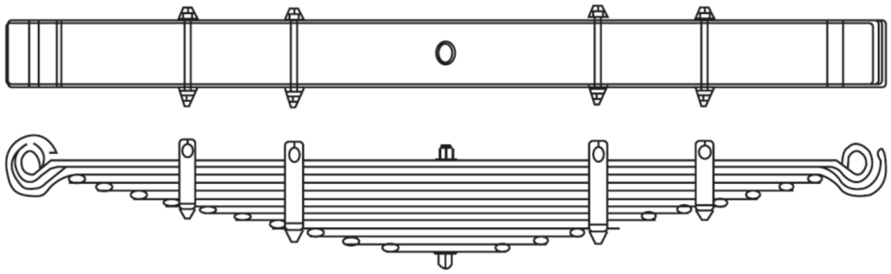

Figure 2. Leaf spring schematic (Arora, Bhushan et al., 2014)

Leaf springs have the ability to carry more load than the springs used in passenger cars. But on the other hand, they provide less comfort for the driver. The relationship between the number of loading cycles of these springs and the failure due to their stress fatigue is shown in Figure 3.

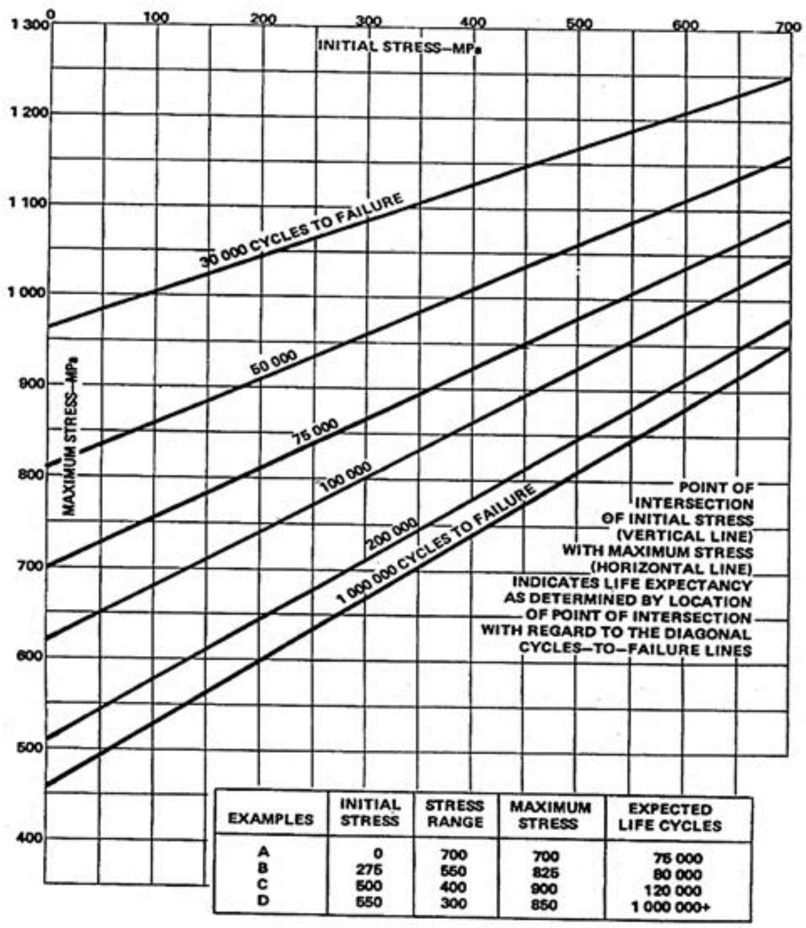

Figure 3. Estimation of fatigue life cycles of steel leaf springs (Kumar & Vijayarangan, 2007)

As shown in this figure, the higher the initial stress is applied to the springs (corresponding to the truck loading tonnage), the shorter their fatigue life. On the other hand, it is not possible to reduce the truck loading tonnage from a certain limit (due to the high cost of fuel and periodic services). For this reason, the fatigue life of the vehicle's springs is greatly reduced in long-haul routes with high tonnage loading. This indicates the necessity of performing an optimization for the problem defined in this article.

2.1. Mathematical modeling of the problem

This paper introduces a novel application problem concerning the optimization of vehicle fleet maintenance scheduling based on the information shared by the Sepid Makian group from one of its slaughterhouses in Rasht, Iran. All information is provided based on real information obtained from the aforementioned company. The problem is outlined as follows:

1- There is a chicken slaughterhouse with two separate cold stores CS_1 and CS_2.

2- CS_1 is located next to the slaughterhouse and CS_2 is located on the road between retailers and CS_1.

3- There are two types of trucks with the quality of A (High Quality) and B (Low Quality).

4- There are m=15 trucks of type B and n=10 trucks of A type.

5- The maintenance cost of the A trucks is higher than the B ones.

6- The reliability of the A truck is more than the B one but a freshly repaired B truck is better than a depreciated A truck.

7- All trucks transport chicken to cold stores or to retail customers, every day,

8- When the A truck is at a certain time of the maintenance interval, it is better to transfer it to the line between the two cold stores and replace it with a B, newly repaired truck.

9- The B trucks are usually responsible for transportation between CS_1 and CS_2, which is a shorter route as shown in Fig. 4 (Route R_1).

10- The A trucks are usually loaded from both cold stores and delivered to the retail customers (Routes R_2 and R_3).

The main problem is to optimize and find this specific time for A trucks. (For example, the operating period of a new car is 100 days until repair, on the 80th day, it is transferred to the cycle between cold storage, and instead of 20 days, it works on this route for 40 days, and during this period, a B, newly repaired truck replaces it). In this case, the maintenance interval of A trucks increases by 20 days. In addition, it is possible to use the newly repaired trucks on the R_3 route and transfer them to the R_2 route after a certain period of time (for example, 50 days). Furthermore, it is better that newly repaired B type trucks are not used on the R_3 route and if necessary, they are transferred to the R_2 route.

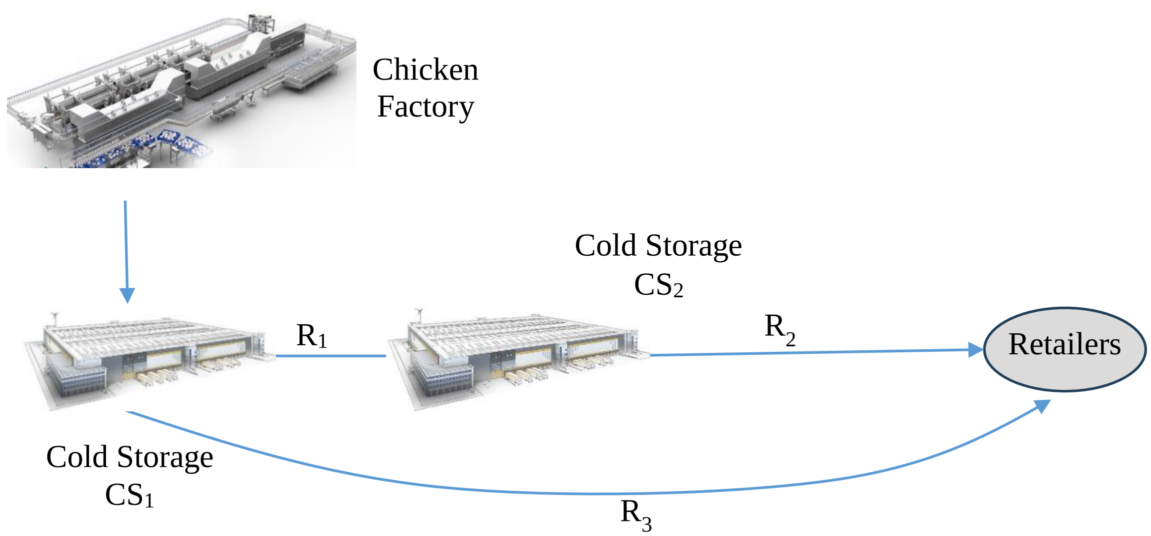

Figure 4. Schematic of the investigated supply chain

The indices and parameters used in this problem are as follows,

Sets:

m	:	Index set of B type truck	m=1, 2, …, 15.
n	:	Index set of A type trucks	n=1, 2, …, 10.
i	:	The index of Cold storages	i=1,2.
J	:	Index set of Routes	j=1,2,3.

Parameters:

CS_i	:	Cold Storage i
R_j	:	Route j
L_j	:	Load cycles in route j
T_{jn}	:	Travel time of truck A_n under route j
T_{jm}	:	Travel time of truck B_m under route j
T_S	:	Service time of trucks
u	:	Production rate
I_i	:	Inventory of the cold storage i
φ_{ij}	:	Output of i^{th} cold storage in j^{th} route
C_i	:	Capacity of the cold storage i
CA	:	Capacity of A type trucks
CB	:	Capacity of B type trucks

Decision Variable:

T_{2n}	:	Travel time of truck A_n under route 2
T_{3n}	:	Travel time of truck A_n under route 2
T_{2m}	:	Travel time of truck B_m under route 3

At the same time, the following assumptions are made:

1- The number of loading cycles of truck leaf springs is considered as one million cycles.

2- Assumed that 1000, 600, and 400 load cycles are applied to the truck springs in the R_3, R_2, and R_1 routes, respectively.

3- In normal situations, such as when a truck does not move between routes R_1, R_2, and R_3, it is transferred to the maintenance department at its specified time (nearly one million working cycles of the springs).

4- $C_1=2\times C_2$.

5- The production of the factory is a fixed number u and equal to 3e4.

6- By using the movement of trucks in three cargo transportation routes, the amount of I inventory in each cold store should be maintained at a certain level and the changes (derivative) of the inventory must be zero.

7- CA=1.5×CB.

8- The optimization variables in this problem are T_{3n} (travel time on the R_3 route for the n^{th} A trucks), T_{2n} (travel time on the R_2 route for the n^{th} A trucks), and T_{2m} (travel time on the R_2 route for the m^{th} B trucks).

9- Cost function of this research, is the periodic maintenance time for cargo trucks. Due to the higher maintenance cost of newer trucks (type A with number n), the cost function coefficient for it was considered to be twice that of type B trucks (with number m).

In this problem, the cost function selected for optimization is as follows:

$$\begin{aligned}
&\text{Optimization Problem}: J = min(\,g), \quad g = \frac{1}{2g_A + g_B} \\
&For\ \ Truck\ \ A: g_A = \sum_{n=1}^{10} (T_{2n} + T_{3n} + \frac{10^6 - T_{2n}L_2 - T_{3n}L_3}{L_1}) \\
&For\ \ Truck\ \ B: g_B = \sum_{m=1}^{15} (T_{2m} + \frac{10^6 - T_{2m}L_2}{L_1})
\end{aligned} \tag{4}$$

Which means the maximum of the periodic maintenance time for cargo trucks. This optimization problem is solved in the presence of the following dynamic constraint:

As shown in Fig. 5 capacity–inventory constraints can be written as follows,

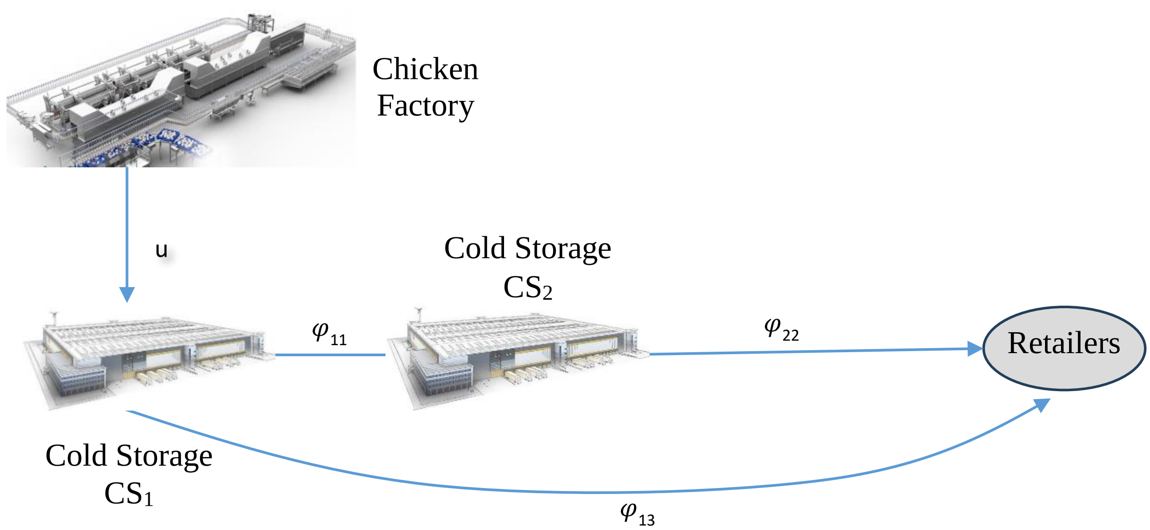

Figure 5. Schematic of two-echelon serial SC realization for a capacity–inventory management model

The dynamics equation of the SC as the set of coupled ordinary differential equations are (Taboada, Davizón et al., 2022):

$$\begin{cases} \dot{I}_1 = u - (\varphi_{11} + \varphi_{13})\dfrac{I_1}{C_1} \\ \dot{I}_1 = \varphi_{11}\dfrac{I_1}{C_1} - \varphi_{22}\dfrac{I_2}{C_2} \end{cases} \tag{5}$$

By using the movement of trucks in three cargo transportation routes, the amount of I inventory in each cold store should be maintained at a certain level. In practice, the control parameter in relation 5 is φ. Now, if relationship 5 wants to fulfill this demand (with appropriate initial inventory in cold stores), the changes (derivative) of the inventory must be zero. This means:

$$\begin{cases} u - \varphi_{22} - \varphi_{13} = 0 \\ \varphi_{11} - \varphi_{22} = 0 \end{cases} \tag{6}$$

Eq. 6 is an important condition for solving optimization problem defined in eq. 4. in which we have:

$$\begin{cases} \varphi_{11} = CA \sum_{n=1}^{10} (\frac{10^6 - T_{2n}L_2 - T_{3n}L_3}{L_1}) + CB \sum_{m=1}^{15} (\frac{10^6 - T_{2m}L_2}{L_1}) \\ \varphi_{22} = CA \sum_{n=1}^{10} (T_{2n}) + CB \sum_{m=1}^{15} (T_{2m}) \\ \varphi_{13} = CA \sum_{n=1}^{10} (T_{3n}) \end{cases} \tag{7}$$

It is important to state that: A trucks have one and a half times the capacity of B trucks. By placing 7 in eq. 6, we have:

$$\begin{aligned} Ceq_1 &=: u - \sum_{m=1}^{15} (T_{2m}) - 1.5 \sum_{n=1}^{10} (T_{3n} + T_{2n}) = 0 \\ Ceq_2 &=: \sum_{m=1}^{15} (\frac{10^6 - T_{2m}L_2}{L_1} - T_{2m}) + 1.5 \sum_{n=1}^{10} (\frac{10^6 - T_{2n}L_2 - T_{3n}L_3}{L_1} - T_{2n}) = 0 \end{aligned} \tag{8}$$

In addition, in order to maintain the defined values for each type A truck, a condition is defined as follows:

$$C_n =: T_{2n}L_2 + T_{3n}L_3 - 10^6 \leq 0 \tag{9}$$

Finally, the range constraint of the design variables is as follows:

$$\begin{aligned} 400 &\leq T_{2m} \leq 800 \\ 500 &\leq T_{2n} \leq 1000 \\ 500 &\leq T_{3n} \leq 1000 \end{aligned} \tag{10}$$

3. Simulation

With the aim of measuring the efficiency of the method introduced in this research, the designed optimization problem is simulated and solved using a gradient-based method and the concept of nonlinear programming in the MATLAB software environment. Considering the number of available trucks and the production rate of the factory, the problem presented does not have a global optimal answer. However, a local minimum can be found for the considered cost function. To find a comprehensive answer, the optimization problem is solved under different initial conditions. The results are as follows:

$$\text{Initial Guess} = [400I_{1\times m}, 500I_{1\times n}, 500I_{1\times n}]; \tag{11}$$

Table 2. Solution of the optimization problem in the first initial conditions for B trucks

Number	T_{2m}	T_S ***of B trucks***
1	656	2172
2	656	2172
3	647	2177
4	795	2103
5	608	2196
6	630	2185
7	400	2300
8	550	2225
9	794	2103
10	598	2201
11	680	2160
12	717	2141
13	794	2102
14	800	2100
15	691	2155

Table 3. Solution of the optimization problem in the first initial conditions for A trucks

Number	T_{2n}	T_{3n}	T_S ***of A trucks***
1	833	500	1333
2	833	500	1333
3	833	500	1333
4	833	500	1333
5	833	500	1333
6	833	500	1333
7	833	500	1333
8	803	518	1321
9	833	500	1333
10	833	500	1333

In this case, the states of optimality and the constraints of the problem are as follows,

$$[J \quad \max(C)] = [1.6911 \times 10^{-5} \quad -1.1794];$$
$$[\mathrm{Ceq}_1 \quad \mathrm{Ceq}_2] = [-10.888 \times 10^{-5} \quad -27.22 \times 10^{-5}]; \tag{12}$$

As it is can be seen, the cost function of the problem is sufficiently close to zero. Also, the limitations considered for the problem have been fully observed. For a different initial guess:

$$\text{Initial Guess} = [800I_{1\times m}, 1000I_{1\times n}, 1000I_{1\times n}]; \tag{13}$$

Table 4. Solution of the optimization problem in the second initial conditions for B trucks

Number	***T_{2m}***	***T_S of B trucks***
1	688	2156
2	800	2100
3	800	2100
4	800	2100
5	732	2134
6	778	2111
7	800	2100
8	800	2100
9	632	2184
10	800	2100
11	778	2111
12	754	2123
13	800	2100
14	743	2129
15	779	2111

Table 5. Solution of the optimization problem in the second initial conditions for A trucks

Number	***T_{2n}***	***T_{3n}***	***T_S of A trucks***
1	624	569	1335
2	576	583	1255
3	724	566	1290
4	638	617	1255
5	626	625	1250
6	596	643	1238
7	500	700	1200
8	620	559	1351
9	782	531	1313
10	533	680	1213

In this case, the states of optimality and the constraints of the problem are as follows:

$$[J \quad \max(C)] = [1.7495 \times 10^{-5} \quad -0.017623];$$
$$[\text{Ceq}_1 \quad \text{Ceq}_2] = [-4.9484 \times 10^{-5} \quad -12.371 \times 10^{-5}]; \tag{14}$$

As it is can be seen, the cost function of the problem is sufficiently close to zero. Also, the limitations considered for the problem have been fully observed. Finally, for a different initial guess:

$$\text{Initial Guess} = [600I_{1\times m}, 800I_{1\times n}, 800I_{1\times n}] \tag{15}$$

Table 6. Solution of the optimization problem in the third initial conditions for B trucks

Number	T_{2m}	T_S *of B trucks*
1	710	2145
2	710	2145
3	710	2145
4	710	2145
5	710	2145
6	710	2145
7	710	2145
8	710	2145
9	710	2145
10	710	2145
11	710	2145
12	710	2145
13	710	2145
14	710	2145
15	710	2145

Table 7. Solution of the optimization problem in the third initial conditions for A trucks

Number	T_{2n}	T_{3n}	T_S *of A trucks*
1	725	565	1290
2	725	565	1290
3	725	565	1290
4	725	565	1290
5	725	565	1290
6	725	565	1290
7	725	565	1290
8	725	565	1290
9	725	565	1290
10	725	565	1290

In this case, the states of optimality and the constraints of the problem are as follows,

$[J \quad \max(C)] = [1.7249 \times 10^{-5} \quad -0.15996]$;

$$[\mathrm{Ceq}_1 \quad \mathrm{Ceq}_2] = [0 \quad 3.638 \times 10^{-12}]; \tag{16}$$

As it is can be seen, the cost function of the problem is sufficiently close to zero. Also, the limitations considered for the problem have been fully observed.

To better understand the results obtained from the simulations, remember this point: if A trucks travels only on route R_3, its service time will be 1000, and if car B travels only on route R_1, its service time will be 2500. Practically, in this research, we will able to increase the service time for trucks whose maintenance costs are higher. This increase will reduce service time for trucks with lower maintenance costs.

As shown in the considered cost function, due to the higher importance of A trucks Compared to B, the longer the service life of A's trucks, the lower the cost function will be. Conversely, due to the similarity of trucks within the same category, the optimization algorithm does not differentiate between them; instead, it assumes that the optimal response obtained for a specific truck is applicable to other trucks in that category.

The Sepid Makian Company, which was founded in 1980 in the Guilan province of Iran, has been designated as the validation case for this study. The implementation of the findings presented in this article within the company has yielded significant results, achieving a noteworthy reduction of up to 20% in maintenance costs. Furthermore, this positive outcome has not only satisfied the employer but also demonstrates the practical applicability and effectiveness of the proposed methodologies in real-world settings. The success of this case study serves as a testament to the potential benefits that can be realized through the integration of research findings into operational practices in the industry.

4. Conclusion

This research focuses on the supply chain of fresh chicken meat, optimizing the maintenance life of trucks within the transport fleet. This optimization, achieved through a preventive method, continuously reduces the workload on trucks that have longer maintenance periods. By using the method used in this research, we are able to increase the working life of trucks with higher repair costs by 30%. Of course, this is accompanied by a decrease in the working life of older trucks (with lower maintenance costs). Finally, the result of this optimization has been associated with a 16% reduction in the cost of maintenance and repair of the transport fleet. The following suggestions are put forth: 1. Expanding the Examination of Initial Conditions: It is recommended to analyze a more extensive range of initial conditions through the application of evolutionary algorithms. This approach would facilitate the identification of the most optimal solutions and increase the overall effectiveness of the model. 2. Scaling the Developed Model for Diverse Retailers: Further research should aim at extending the developed model to accommodate a larger number of retailers, each situated in varying geographical locations. This enhancement would allow for a more comprehensive understanding of the model's applicability across different market scenarios and logistics challenges. 3. Increasing the Variety of Transport Fleets: Another critical area for future work involves expanding the diversity and number of transport fleets considered in the study. By incorporating various fleet configurations, the model could yield insights into how differing transport capabilities impact overall efficiency and service levels. 4. Incorporating Driver Competency Factors: Lastly, it is pertinent to enrich the model by including additional factors that account for the skill level and experience of the drivers. Recognizing the influence of driver competency on operational performance could lead to more nuanced and effective logistics strategies. By pursuing these avenues of research, future studies could significantly contribute to the field, enabling a deeper understanding of the complexities inherent in logistics and transportation management.

References

Arora, V. K., et al. (2014). Fatigue life assessment of 65Si7 leaf springs: a comparative study. *International scholarly research notices*, *2014*.

Barreto, S., et al. (2007). Using clustering analysis in a capacitated location-routing problem. *European Journal of Operational Research*, *179*(3), 968-977.

Cavalcante, C. A., et al. (2018). A general inspection and opportunistic replacement policy for one-component systems of variable quality. *European Journal of Operational Research*, *266*(3), 911-919.

Chaves, A. A., & Lorena, L. A. N. (2010). Clustering search algorithm for the capacitated centered clustering problem. *Computers & Operations Research*, *37*(3), 552-558.

de Jonge, B., et al. (2015). Optimum maintenance strategy under uncertainty in the lifetime distribution. *Reliability engineering & system safety*, *133*, 59-67.

De Jonge, B., & Scarf, P. A. (2020). A review on maintenance optimization. *European Journal of Operational Research*, *285*(3), 805-824.

Ding, H., et al. (2009). Stochastic multi-objective production-distribution network design using simulation-based optimization. *International Journal of Production Research*, *47*(2), 479-505.

Fouladirad, M., et al. (2018). Sensitivity of optimal replacement policies to lifetime parameter estimates. *European Journal of Operational Research*, *266*(3), 963-975.

Fu, Y., et al. (2020). Optimum component reallocation and system replacement maintenance for a used system with increasing minimal repair cost. *Reliability engineering & system safety*, *204*, 107137.

Hrušovský, M., et al. (2024). Integrated planning approach for fleet sizing and fleet management of freight railcars. *Flexible Services and Manufacturing Journal*, 1-35.

Hunt, I., et al. (2005). Applying the concepts of extended products and extended enterprises to support the activities of dynamic supply networks in the agri-food industry. *Journal of food engineering*, *70*(3), 393-402.

Insua, D. R., et al. (2020). Advances in Bayesian decision making in reliability. *European Journal of Operational Research*, *282*(1), 1-18.

Kansal, L., & Ediga, P. (2024). IoT-Enabled predictive maintenance for sustainable transportation fleets. MATEC Web of Conferences,

Kumar, M. S., & Vijayarangan, S. (2007). Static analysis and fatigue life prediction of steel and composite leaf spring for light passenger vehicles.

Lolli, F., et al. (2022). Age-based preventive maintenance with multiple printing options. *International Journal of Production Economics*, *243*, 108339.

Musa, R., et al. (2010). Ant colony optimization algorithm to solve for the transportation problem of cross-docking network. *Computers & Industrial Engineering*, *59*(1), 85-92.

Peña, D., et al. (2023). A novel multi-objective optimization approach to guarantee quality of service and energy efficiency in a heterogeneous bus fleet system. *Engineering Optimization*, *55*(6), 981-997.

Sharma, R., et al. (2020). A systematic literature review on machine learning applications for sustainable agriculture supply chain performance. *Computers & Operations Research*, *119*, 104926.

Taboada, H., et al. (2022). Mathematical Modeling and Optimal Control for a Class of Dynamic Supply Chain: A Systems Theory Approach. *Applied Sciences*, *12*(11), 5347.

Tusar, M. I. H., & Sarker, B. R. (2022). Maintenance cost minimization models for offshore wind farms: A systematic and critical review. *International Journal of Energy Research*, *46*(4), 3739-3765.

Ukato, A., et al. (2024). Optimizing maintenance logistics on offshore platforms with AI: Current strategies and future innovations. *World Journal of Advanced Research and Reviews*, *22*(1), 1920-1929.

Zhao, X., et al. (2015). Which is better for replacement policies with continuous or discrete scheduled times? *European Journal of Operational Research*, *242*(2), 477-486.