An environmental decision support system for determining on-site or off-site additive manufacturing of spare parts

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Abstract. Effective spare part management can increase the competitiveness of supply chains, but the intrinsic characteristics of spare parts (e.g., intermittent demands, dependence on suppliers) make their effective management complicated. In recent years, additive manufacturing (AM) has emerged as a possible way to overcome these issues and received significant research attention, especially the topic of supply chain configuration. AM enables the easy production of parts close to the point of use, thus favoring the decentralization of supply chains (i.e., on-site production), but while this topic has been studied extensively from an economic perspective, its environmental implications remain unexplored. The literature is limited merely to mentions of the reduced transportation emissions associated with on-site production strategies, without, for example, a lifecycle perspective in which the production phase is considered. It is common knowledge that different countries adopt different energy mixes, thus generating different carbon dioxide–equivalent emissions during the production phase. A lifecycle perspective therefore casts doubt on whether on-site production strategies are always environmentally preferable over strategies in which spare parts are produced far from the point of use and then shipped (i.e., off-site production or centralized supply chains). In this paper, we aim to resolve this doubt by developing a decision-support system that can assist managers and practitioners in determining the most environmentally friendly AM spare part production strategy, considering both the transportation and production phases.

Keywords: Additive Manufacturing, Decentralized Supply Chain, Spare Parts Production.

1 Introduction

Spare parts are crucial for ensuring the high availability of production systems, and an appropriate spare parts management is needed to ensure that the right spare parts are available at the right time, at the right location, and in the right amount. However, it is not easy to manage spare parts correctly due to their main characteristics: intermittent demand (hard to predict both quantity and frequency), long lead times, high costs if they are not immediately available, and strong dependence on supplier [1, 2].

Researchers and practitioners have recently been investigating additive manufacturing (AM; also known as 3D printing) for the production of spare parts [3, 4], which would limit some of the disadvantages linked to their main characteristics, particularly the long lead times. Indeed, AM enables the production of spare parts both on-demand and close to the point of use [5–7], and in addition to economic benefits (e.g., lower transportation costs, lower holding costs due to lower inventory levels), researchers have reported that it also generates environmental benefits due to production close to the point of use [8, 9].

In the current work, we investigate, for the first time, whether AM and its decentralized use (i.e., close to the point of use, hereinafter called "on-site production") is indeed environmentally beneficial. The existing works in the literature mention the reduced environmental burden of on-site production through reduced transportation emissions, and while they are accurate, a lifecycle perspective should be used to properly evaluate whether an on-site production strategy is environmentally preferable to a strategy in which parts are produced far from the point of use and then shipped (hereinafter called "off-site production"). Just as an example, producing 1 kWh of electricity in China produces more than twenty times more carbon dioxide equivalent (CO_2e) emissions than in Sweden [10], so when considering both the production and transportation phases and the fact that different countries have different energy mixes, it becomes clear that on-site production might not always be the best environmental strategy.

In this work, we develop a decision-support system (DSS) to help managers and practitioners to determine whether to adopt on-site or off-site AM production of spare parts to minimize CO_2e emissions (i.e., the most environmentally friendly production strategy). To develop this DSS, a four-step methodological framework is used, as described in the Methodology section.

The remainder of this paper is structured as follows: Section 2 provides a literature review regarding the impact of AM on spare part supply chains from different perspectives; in Section 3, the methodology used to obtain the DSS is described; in Section 4, the DSS is presented and discussed; and in Section 5, the conclusions are presented, together with managerial implications, limitations, and possible future research.

2 Literature Review

As mentioned, AM offers significant potential benefits for spare part supply chains, and researchers have examined, from different perspectives, when spare parts should be produced using AM. Initially, the focus was on the economic perspective, with the aim of understanding when spare part supply chains using AM technologies are convenient compared to conventional manufacturing (CM) technologies (casting, forging, etc.).

Examples of these works include [5, 6, 11–16], in which AM and CM spare part supply chains are compared by considering different supply chain costs (ranging from inventory holding costs alone to all costs from a lifecycle perspective), different spare part characteristics (e.g., demands, properties, materials), and different constraints (e.g., limited storage capacity).

More recently, researchers have begun to consider the environmental perspective; here, too, the main focus has been on comparing the environmental footprint of AM spare part supply chains with those using CM technologies, such as [17–20], which considered different raw materials (e.g., aluminum alloys, steel alloys, titanium alloys), AM production methods (e.g., selective laser sintering, electron beam melting, multi-jet fusion), transportation vehicles (e.g., trucks ships, trains), and energy mixes (i.e., the amount of CO_2e emissions based on the sources used to generate electricity).

However, these works have mostly been case-specific and have considered either off-site or on-site AM production, but to the best of our knowledge, not both. In this paper, we aim to address this gap by developing a DSS that helps managers and practitioners to determine whether to adopt off-site or on-site AM production of spare parts with the goal of minimizing CO_2e emissions.

3 Methodology

The proposed DSS in the current research is a decision tree derived from a comparison of the CO_2e emissions of different spare part supply chain scenarios (i.e., supply chains characterized by different backorder costs, production costs, production and transportation lead times, energy mixes, etc.). To develop the DSS, we follow a four-step methodology, but before describing these steps in detail, the basic features of the DSS and the assumptions behind it will be described.

As already mentioned, the DSS is intended to help managers and practitioners to determine the most environmentally friendly production strategy (i.e., on-site or off-site) for AM spare parts, and to achieve this, a lifecycle perspective is needed. The lifecycle of a spare part consists of different phases: raw material extraction, production, and transportation and spare part production, transportation, use, and recycling/disposal [21]. In this work, we assume that the decision to produce spare parts on-site or off-site depends only on the production and transportation phases and that these are independent of the others (the environmental footprint of raw material extraction and preparation, for example, is considered the same regardless of the on-site or off-site production strategy).

Other assumptions are as follows:

- We consider a single material—316L stainless steel— because this is one of the most commonly used, but the methodology is independent of the material.
- In the case of an on-site production strategy, we assume that the production is located sufficiently close to the point of use that the transportation phase is negligible.
- For the transportation phase, we consider four different types of transportation vehicles: trucks, trains, airplanes, and cargo ships.

With the main features, control volume, and assumptions of the proposed DSS defined, we will discuss the four-step methodology. In Step 1, a mathematical model to compare the CO_2e emissions of on-site and off-site production is developed. In Step 2, an ANOVA is performed to determine the most relevant input parameters for the mathematical model. In Step 3, those input parameters are used in a parametric analysis, enabling the creation of a dataset consisting of realistic spare part supply chain scenarios (i.e., supply chains with different transportation modes, energy mixes, and distances and spare parts with different mean times to failure, backorder and production costs, and lead times). Finally, in Step 4, the DSS is obtained in the form of a decision tree using a machine learning algorithm (specifically, a decision-tree algorithm) fed and trained with the results of the parametric analysis. Each step is described in detail below.

3.1 Mathematical Model

In each scenario, the on-site and off-site production strategies are evaluated in terms of CO_2e emissions using a mathematical model based on the input parameters shown in Table 1.

Table 1. Input parameters

Parameter	Description	Unit Measure
Input Parameters		
i = 1, 2	Production strategy: on-site $^{(1)}$ or off-site $^{(2)}$	-
T	Review period	[*time*]
h	Holding rate	[*euro / euro * time * unit*]
MTTF	Mean time to failure	[*time* / *unit*]
λ	Failure rate	[*unit* / *time*]
cb_i	Unitary backorder cost	[*€* / *unit*]
cp	Unitary production cost	[*€* / *unit*]
L_i	Lead time of production strategy *i*	[*time*]
Lt	Transportation lead time	[*time*]
Ec	Energy consumption of production	[*kWh* / *kg*]
d	Distance	[*km*]
t	Transportation mode	[gCO_2 / *ton* * *km*]
Em_i	Energy-mix of production strategy *i*	[gCO_2 / *kWh*]
Ps	Part size	[*kg*]
S	Order-up-to level	[*unit*]
Constraints		
S_{max}	Maximum order-up-to level	[*unit*]
Costs		
Ch_i	Holding cost	[*€*]
Cb_i	Backorder cost	[*€*]
C_p	Production cost	[*€*]

Objective Functions		
CO_2e	CO_2e equivalent emission	[gCO_2]
CO_2et	Transportation-based CO_2e equivalent emission	[gCO_2]
CO_2ep	Production-based CO_2e equivalent emission	[gCO_2]

The model allows the comparison of the CO_2e emissions of the two strategies, considering both the production and transportation phases, so that, for each scenario, the strategy that minimizes CO_2e emissions can be selected (Equation (1)):

$$min\, CO_2e \tag{1}$$

where CO_2e is the sum of the CO_2e arising from the production and transportation phases.

$$CO_2e = CO_2ep + CO_2et \tag{2}$$

The production-based CO_2e emissions (CO_2ep) are calculated by multiplying the energy consumption of the production phase (Ec), the order-up-to level (S_i), the CO_2e emissions from the production strategy i (Em_i), and the part size (Ps).

$$CO_2ep = \sum_{i=1}^{2} Ec \cdot S_i \cdot Em_i \cdot Ps \tag{3}$$

The transportation phase is then considered only if the off-site production strategy is adopted. The transportation-based CO_2e emissions (CO_2et) are calculated by multiplying the distance to the production factory (d), the CO_2e emissions resulting from the selected transportation method (t), the order-up-to level (S_i) and the part size (Ps).

$$CO_2et = \sum_{i=2}^{2} d \cdot t \cdot S_i \cdot Ps \tag{4}$$

S_i is representative of the number of spare parts that need to be produced and is calculated through a sub-optimization problem. For this, we assume that spare parts are produced on a make-to-stock basis, as was done in [6]. Such a sub-optimization problem aims to minimize, for each production strategy, the sum of the production, holding, and backorder costs. Therefore, an inventory management model needs to be considered, and we use a periodic review model in which the spare part demand follows a Poisson distribution.

The inventory management model then proceeds by finding different optimal values for S_i through the choice of various sourcing alternatives and review period T. Given the stochastic demand (y) and after identifying T, the optimization problem is as follows:

$$min\, C_{Total} = \min\,(Ch_i + Cb_i + Cp) \tag{5}$$

Equation (5) minimizes the time unit costs; it is rewritten in Equation (6), where Ch_i is the average number of units in stock $\sum_{y=0}^{S-1}(S_i - y) \cdot P_{\lambda,T,y}$ during the coverage time ($T + L_i$) multiplied by the holding cost ($h \cdot c_p$), which is proportional to the unitary production cost (cp), and Cb_i is the average number of units on backorder $\sum_{S+1}^{\infty}(y - S_i) \cdot P_{\lambda,T,y}$ during the coverage time $(T + L_i)$ multiplied by the unitary back-order cost (cb_i).

$$min\, h \cdot cp \cdot \sum_{y=0}^{S-1}(S_i - y) \cdot P_{\lambda,T,y} + cb_i \cdot \sum_{S+1}^{\infty}(y - S_i) \cdot P_{\lambda,T,y} + \lambda \cdot cp \cdot T \tag{6}$$

A backorder takes place each time a demand cannot be met by the stocked units. Cp is the unitary production cost (cp) multiplied by the failure rate (λ), which is obtained from each mean time to failure ($MTTF$) (see Equation 10) and from T, which is the expected number of demands during a period. In this equation, the L_i value in the $(T + L_i)$ coverage time represents the lead time for the on-site and off-site production strategy, although the production lead times are the same for both; however, for off-site production, the lead time is calculated as $L_2 = L_1 + Lt$ to account for delays due to transportation.

$$P_{\lambda,T,y} = \frac{(\lambda \cdot (T + L_i))^y \cdot e^{-(\lambda \cdot (T + L_i)}}{y!} \tag{7}$$

$$0 \leq S_i \leq S_{max} \tag{8}$$

$$S_i \in N \tag{9}$$

$$\lambda = \frac{1}{MTTF} \tag{10}$$

Equation (7) computes the probability that y failures take place during $(T + L_i)$ time using a Poisson distribution with an expected demand of $\lambda \cdot (T + L_i)$. Equation (8) imposes a maximum order-up-to level S_{max}. Equation (9) imposes a discrete S.

3.2 ANOVA

In Step 2, an ANOVA is used to determine which input parameters of the mathematical model influence the choice of production strategy (i.e., on-site or off-site). For this, a preliminary parametric analysis is first performed. As shown in Table 2, the different input parameters have three different values, whose extremes are defined according to the sources also listed in the table. The only exception is t, for which four values have been considered because of the four types of vehicles available as transport options.

Table 2. Input parameters' values and sources

Parameter	Admissible Values	Unit measure	Source used to define the admissible values
T	4; 8; 12	[*weeks*]	[6]
$MTTF$	26; 91; 156	[*weeks* / *unit*]	[6]
c_b	1000; 26000; 51000	[*€* / *unit*]	[6]
c_p	150; 700; 1400	[*€* / *unit*]	[6]
L_1	0.1; 0.2; 0.4	[*time*]	[6]
L_2	1; 2; 4	[*time*]	[6]
Ec	20; 100; 180	[*kWh* / *kg*]	[22]

d	200; 7600; 15000	[*km*]	Authors' experience
t	14.4; 18.9; 90; 1080	[gCO_2 / *ton* * *km*]	[22]
Em_i	50; 350; 650	[gCO_2 / *kWh*]	[10]
Ps	0.8; 4; 8	[*kg*]	[6]
h	0.0058	[*euro / euro * weeks * unit*]	[6]

A total of 78,732 scenarios are thus created. It is worth noting that h is considered fixed and equal to the cost per unit and week and that cp and L_1 depend on the Ps; the lowest value of cp and L_1 are encountered when the part size is small (0.8 kg) and the highest when it is large (8 kg), and the same holds for the middle value [6]. The mathematical model developed in Step 1 then determines the AM production strategy that minimizes CO_2e emissions for each scenario. An ANOVA is then performed, using Minitab software, in which the input parameters to the model are input factors to the ANOVA and the optimal production strategies determined by the model are the responses.

3.3 Parametric Analysis

After performing the ANOVA, the parameters with negligible effect on determining the most environmentally friendly production strategy are excluded. Those that significantly affect the results are used in Step 3 and are varied to create an extensive dataset, which is needed to feed and train the decision-tree algorithm to develop the DSS.

The data used to perform this parametric analysis is obtained as follows. First, the possible values of the input parameters are determined according to the results of the ANOVA (see Table 3). The values of the input parameters with negligible effect are treated as constants and equal to the intermediate values reported in Table 1, while additional values are considered for the input parameters with non-negligible impacts on the production strategy decision. Specifically, the extreme values remain the same as in Table 2 and more intermediate values are added (Table 3). In this way, a data set consisting of 2,268 scenarios is obtained. Finally, the mathematical model developed in Section 3.1 is applied to the data for each scenario and the optimal production strategies and CO_2e emissions determined for each.

Table 3. Input parameters' values to create extensive dataset

Parameter	Admissible Values
T	8
MTTF	91
c_b	26000
c_p	700
L_1	0.2
L_2	2
Ec	20; 40; 60; 80; 100; 120; 140; 160; 180
d	200; 2050; 3900; 5750; 7600; 9450; 11300; 13150; 15000

t	14.4; 18.9; 90; 1080
Em_i	50; 150; 250; 350; 450; 550; 650
Ps	4
h	0.0058

3.4 Decision Tree

Finally, in step 4, a DSS in the form of a decision tree is developed using a decision-tree algorithm, which is a classification method that predicts an item's class based on specific parameters. The results obtained by applying the mathematical model to each of the scenarios created by the parametric analysis performed in Step 3 are then used as a dataset to feed and train the decision tree, as follows.

Starting from a root node, the dataset is iteratively divided into binary branches based on the Gini Diversity Index (gdi), where k is the class label and $p(k)$ is the probability of choosing the data point with class k. The gdi (see Equation (10)) measures the probability of misclassification of a given data point in a dataset when randomly selected. Thus, $gdi = 0$ means that all data points in the dataset belong to a particular class, while $gdi = 1$ implies that the data points are randomly distributed among the different classes. At each tree node, an attribute and its breakpoint are selected to create two branches to minimize Equation (11). Thus, the branches that provide the maximum purity are determined. In Equation (11), n is the number of data points in the original node, n_{left} is the number of data points in the new node in the left branch, n_{right} is the number of data points in the new node in the right branch, gdi_{left} is the Gini diversity index in the new node in the left branch, and, gdi_{right} is the Gini diversity index in the new node in the right branch [6].

$$gdi = 1 - \sum_{k=1}^{K} p(k)^2 \tag{11}$$

$$\min \left(\frac{n_{left}}{n} gdi_{left} + \frac{n_{right}}{n} gdi_{right}\right) \tag{12}$$

The elements obtained at the end of the decision tree, after the last branching, are called leaves. The number of leaf branchings corresponds to the number of depth levels of the tree. To develop a user-friendly DSS, the decision tree is trimmed by determining the maximum depth level (D_{max}) using a sensitivity analysis; this also helps to prevent the problem of overfitting while creating the tree. For pruning, a sensitivity analysis of the total accuracy (A) of the decision tree is performed by imposing various values for D_{max} and calculating the overall A by dividing the number of correct predictions by the total number of predictions.

$$A = \frac{\#\, correct\ predictions_{tree}}{\#\, predictions_{tree}} \tag{13}$$

Finally, the effectiveness of the decision tree is evaluated against three key performance indicators (KPI) related to the tree's leaves. The first is the accuracy of a leaf (a), which is calculated by dividing the number of correct predictions by the total number of predictions in the leaf. The second KPI is the ratio of items reaching each sheet (p), which is calculated by dividing the total number of predictions in that leaf by the total number of predictions in the tree. The third KPI is the average percentage CO_2e emission increase (c) that occurs when an incorrect estimation is made, which is the arithmetic average of the extra CO_2e emission incurred by each wrong estimate.

$$a = \frac{\#\, correct\ predictions_{leaf}}{\#\, predictions_{leaf}} \tag{14}$$

$$p = \frac{\#\, predictions_{leaf}}{\#\, predictions_{tree}} \tag{15}$$

$$c = \frac{\left(\left|\sum_{k=1}^{\#\, wrong\ predictions_{leaf}} \frac{cost\ of\ wrong\ prediction - cost\ of\ correct\ predicton_k}{cost\ of\ correct\ predicton_k}\right| * 100\right)}{\#\, wrong\ predictions_{leaf}} \tag{16}$$

4 Results and Discussion

A DSS in the form of a decision tree was developed to help with determining whether on-site or off-site AM production of spare parts should be adopted to minimize CO_2e emissions. After developing the mathematical model to compare the CO_2e emissions of on-site and off-site production strategies, an ANOVA was performed, whose results are presented in Fig. 1. These results show that five of the ten input parameters (T, Cb_i, $MTTF$, Ps, and L_2) have a negligible effect on determining the most environmentally friendly production strategy, with the mean effect curves created from the ANOVA results being almost horizontal. In contrast, the other input parameters (Ec, Em_i, d, and t) have a non-negligible influence on the decision-making process.

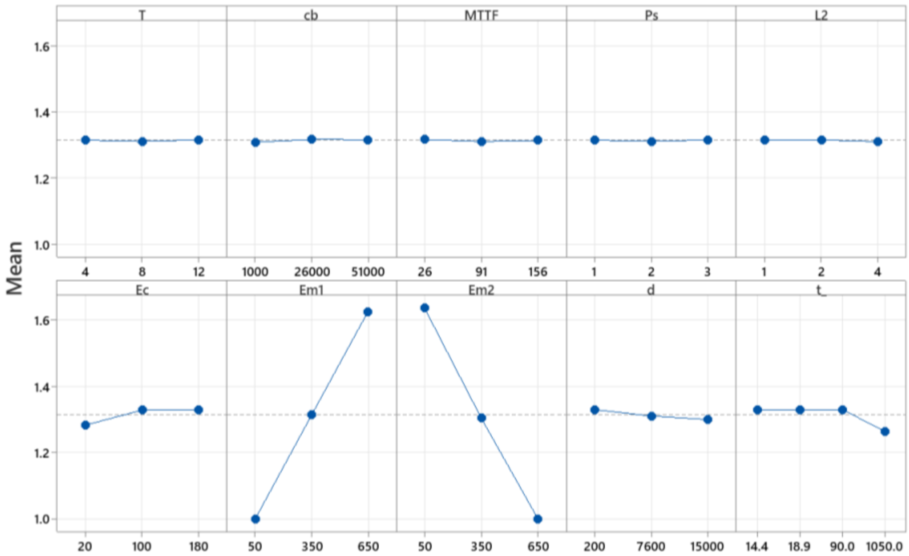

Fig. 1. Results of the ANOVA (Main effects plots)

From the parametric analysis, 15,876 scenarios were created (see Section 3.3). Applying the mathematical model to each scenario determined whether on-site or off-site AM production of spare parts would minimize CO_2e emissions, creating the dataset used to feed and train the decision-tree algorithm. The resulting DSS is presented in Fig. 2.

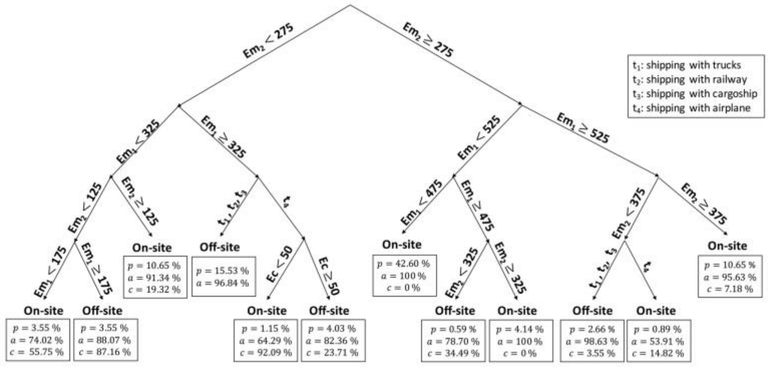

Fig. 2. Decision tree with a maximum depth of 4 levels

As can be seen, not all of the five input parameters are used in the decision tree, which indicates that they are not equally important; as could have been anticipated from the main effect plot, input parameter d (distance) is missing. Examining the decision tree in detail according to the DSS, for seven of the twelve leaves, the most environmentally friendly strategy is on-site production, which is consistent with the existing literature. However, in the five remaining scenarios (26.36%), off-site production is the most environmentally friendly strategy because of variations in the factors affecting CO_2e emissions. More specifically, the on-site production strategy is preferable if the energy mix of off-site production is greater than or equal to the energy mix of on-site production or if transportation is done by air.

Fig. 2 shows the KPI values of each leaf of the decision tree, in which the accuracy rates of some leaves show very high prediction reliability ($a \geq 90\%$), while other leaves showed that the predictions may not be sufficiently reliable ($a < 80\%$). However, the potential rise in CO_2e emissions (c) if the estimation is wrong, which managers and practitioners must consider, is often less than 20%. Although incorrect predictions would negatively affect the environmental friendliness of a company, the low c values of the leaves mean that managers and practitioners can rely on the predictions offered by the decision tree.

5 Conclusion

Choosing on-site or off-site AM production of spare parts can significantly impact companies in terms of economic and environmental sustainability. Although the effects of AM on supply chain management issues have previously been studied, the focus has generally been on economic concerns, and CO_2e emission rates produced by on-site or off-site strategies have been neglected. This study therefore aimed to fill this gap in the literature by developing a DSS to determine the conditions under which on-site and off-site production are optimal for spare parts in terms of producing lower CO_2e emissions. The DSS developed is decision tree–based and was chosen for its user-friendliness and speed of use. To develop the DSS, the following procedure was used:

i. Develop a mathematical model to determine, from an environmental viewpoint, whether to adopt on-site or off-site AM production for spare parts.
ii. Examine the effects of input parameters on the decision using ANOVA and determine the relevant non-negligible input parameters.
iii. Perform a parametric analysis by considering the non-negligible input parameters and apply the mathematical model to determine whether to adopt an on-site or off-site AM production for each scenario resulting from the parametric analysis.
iv. Feed and train the decision-tree algorithm using the dataset developed through the parametric analysis to develop a DSS.

Some leaves in the decision tree have very high accuracy rates, while others are lower, but even with the lower rates, the average additional CO_2e emission increase is not very large. The DSS therefore does a good job of determining whether to adopt on-site or off-site AM production for spare parts. Nevertheless, future studies are needed to reduce possible errors in the decision-making processes by using other machine learning algorithms, such as artificial neural networks, random forests.

The DSS also has the following implications for managers:

– If the energy mix of off-site production is greater than or equal to the energy mix of on-site production, on-site production is always the most environmentally friendly production strategy.
– If airplanes are used as transport for off-site production, for such production strategy to be convenient the energy mix of on-site production must be greater than energy mix of off-site production by at least 1.5 times, and energy consumption must be greater than 50 kWh/kg.

Future research could add an economic perspective and analysis to the current study, developing a multi-objective mathematical model to obtain the optimal production strategies with establishing an appropriate trade-off between environmentally friendliness and cost-efficiency.

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