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Optimal Manufacturing-Reconditioning Decisions in a Reverse Logistic System under Periodic Mandatory Carbon Regulation

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Abstract: Due to environmental concerns, firms are under increasing pressure to comply with legislations and to take up environmental strategies. This leads researchers and firms to develop new sustainable supply chains, where a new area has emerged for a manufacturing and reconditioning system. The originality of this work consists in simultaneously considering carbon emissions strategies, carbon tax and mandatory emission in a manufacturing-reconditioning system. The proposed system is composed of two parallel machines, a manufacturing stock, a reconditioning stock and a recovery inventory. In order to make the proposed green manufacturing system more realistic, it is assumed that manufactured (new products) and reconditioned products are distinguishable. The quantity of worn products (used products) depends on the sales in the previous periods, and the repair periods of the machines are stochastic and independent. The aim of this work is to determine the optimal capacities of manufacturing and reconditioning stocks that maximize the total profit, as well as the optimal value of worn products under two carbon emissions' limitations. An evolutionary algorithm is developed, along with an efficient improvement method, to find the optimal value of decision variables. Ultimately, numerical results are provided to show the impact of the period of carbon limit and the worn products (returned products) on decision variables.

Keywords: production planning; carbon regulation; reconditioning; green logistics; optimization

1. Introduction

Throughout the past few decades, massive carbon emissions have caused serious global environmental damage, such as thick haze and worsening greenhouse gas effects. The Intergovernmental Panel on Climate Change (IPCC), which is the international body for the assessment of climate change, has pointed out in its fifth assessment report that it is necessary to curb the global greenhouse gas (GHG) emissions by 40%–70% from the 2010 level before 2050, and to curb the global GHG emissions to the level of near zero by the end of the 21st century [1]. The IPCC has defined a complete method to standardize the computation of GHG emissions at the national level. Today, most countries are monitoring GHG emissions by using IPCC guidelines to perform annual inventories assessing the quantity of six main gases (CO_2: carbon dioxide, CH_4: methane, N_2O: nitrous oxide, HFCs: hydrofluorocarbons, PFCs: perfluorocarbon, SF_6: sulfur hexafluoride) [2]. It was found that CO_2 makes up the broad majority of GHG emissions—it represents about three-quarters of total GHG emissions. For instance, in the USA, the emissions from the industry occupies 24% of total emissions. Indeed, GHG emissions from industry primarily come from burning fossil fuels for energy, as well as GHG emissions from certain chemical reactions necessary to produce goods from raw materials [3,4]. To achieve the IPCC targets, the development of climate change mitigation technologies have played a pivotal role [5]. Therefore, the industrial companies have adopted new technologies and strategies to alleviate climate change impact associated with their activities. For example, to reduce the carbon emissions, several companies are devoted to recuperating and remanufacturing worn products instead of producing new ones. Indeed, carbon emissions from producing new parts is higher than that for remanufactured ones.

Nowadays, carbon emission control as well as maintaining sustainable economic development has become an increasing challenge, and many countries have attempted to curb carbon emission compulsively through enacting legislation [6]. Several governments promulgated some carbon emission laws, such as carbon taxes, mandatory carbon emissions capacity, and carbon emission cap and trade [7]. The most known regulations are carbon pricing and emissions trading [8]. Those policies can be classified into two categories: mandatory and non-mandatory. The mandatory policy are strict regulations where governments set a strict emissions cap on a firm for a given period. Non-mandatory policies allow companies to choose between reducing and paying for emissions [9], including carbon tax and emission trade (also known as cap and trade). According to the European Commission, European Union Emission Trading System (EU-ETS) is the first and largest emission trading scheme: 75% of international carbon trading covers more than 11,000 companies in 31 countries. Under this policy, companies are allocated a cap or quota on carbon emissions [10]. Indeed, when a company exceeds the allocated cap, it can purchase extra carbon allowance trough the carbon market trading. Conversely, when its carbon emission is under the cap, it can sell its surplus via trading [11]. Besides, carbon tax is a tax on carbon emissions. Companies under this policy are charged a tax proportional to the amount of carbon emitted [12]. Since the implementation of the Kyoto Protocol in 1997, several countries have enacted a variety of carbon tax schemes that have attracted wide attention in the manufacturing management [13]. According to the International Monetary Fund (IMF), carbon tax is the most effective policy to mitigate carbon emissions. With these environmental regulations, companies are constrained to adopt new production policies in order to curb their carbon emissions. From the beginning of the nineties until today, several published papers in the literature have dealt with production decision, taking into account carbon emissions regulations. Ingham and Ulph [14] have presented the case for using a carbon tax to control carbon emissions, and have illustrated the implications for the UK manufacturing. In addition, they have computed a total abatement cost curve corresponding to different levels of emissions' curbing to see whether there are critical points at which costs rise quickly. Fang et al., [15] have developed a mathematical programming model of a flow shop-scheduling problem that considers peak power load, energy consumption, and associated carbon emission in addition to cycle time. The objective is to determine the optimal scheduling that increases the energy consumption and the carbon emissions. Turki and Rezg [16] have proposed an optimal design for a manufacturing/remanufacturing system that sorts worn products into three quality levels. The authors have determined optimal production decisions regarding new and remanufactured products while considering carbon tax policy. As in a real case, the authors have considered that the carbon emissions from producing remanufactured products is different from those of new ones. Indeed, the benefit of the remanufacturing is that the worn products are recovered and reused. In addition, the carbon emission from producing remanufactured products is lower than that for producing new ones. More recently, Dou et al., [17] have considered a manufacturer who produces new parts in the first period and makes new and remanufactured parts in the second period under carbon tax policy, where the tax price differs over the two periods. The authors have determined optimal manufacturing and remanufactured plans that reduce the carbon emissions when the carbon tax varies. He et al., [18] have considered a supply chain network constrained by a stringent mandatory carbon cap, the purpose of which is to examine how stringent carbon regulations and operational decision modes jointly influence the profitability and emissions control of the system. The authors have shown that only when the mandatory cap is set in intermediate level rather than excessively mild or tight can it be effective to balance system profitability and emission control well. Indeed, the mandatory carbon policy is very efficient to curb the carbon emissions; however, due to its sternness, this policy drives away the investors. Some European countries are periodically applying the mandatory carbon regulation. For example, the French government applies the mandatory carbon policy on transport and manufacturing activities for a defined period when a high pollution rate is revealed. To the best of our knowledge, there is no work in the literature which deals with a periodic mandatory carbon policy. In this paper, we will combine the carbon tax and mandatory carbon regulation. Indeed, we will consider the carbon tax as a permanent policy to reduce the overall emissions, and the mandatory carbon as a periodic regulation when the emissions exceed a tolerated threshold.

One of the processes to curb carbon emissions in the industrial domain is remanufacturing. Remanufacturing, or refurbing, is considered as a great industrial process, within which worn-out products are restored to new products, providing benefits both environmentally and economically, while at the same time enhancing their image as environmentally responsible, since products are reused instead of being discarded, including curbing carbon emissions [19]. It is supposed that remanufactured products are profitable, at 45%–65% of the price of a new product. Furthermore, they are beneficial under emission regulation [20]. In general, the remanufacturing is a series of industrial processes: disassembly of the worn product on parts, restoring of the reusable parts, replacement of the parts if necessary, and reassembly of the parts [21]. Most of the published papers in the literature have assumed that remanufactured products have the same quality as new ones [22–25]. However, in practice, the quality of new products is mostly higher than for remanufactured ones. In this case, the remanufactured parts are called "reconditioned parts" and are sold with a lower price than new ones. Over the lasts years, the reconditioning production keeps increasing. In recent years, for example, in the automotive sector, reconditioning firms cover 35% of all production firms in the sector. That in the aerospace sector represents 25%. Concerning the sales, for example, in Asia, the sales of reconditioned smartphones represent 23% of the mobile phones market. In France and according to BACK MARKET and REMADE TECHNOLOGY companies, which produce and sell remanufactured products such as smart phones, laptops and home appliances, the market of remanufactured products posted a growth rate of 7% in 2018, unlike that of new ones, which fell by 6.5%. In the literature, few researchers distinguish between new and reconditioned parts. Gaur et al., [26] have conducted a real case of a battery manufacturer based in India. The authors have proposed a supply chain system, which considers that reconditioned batteries have a lower performance specification and more limited warranty relative to the equivalent new product. They have determined an optimal sales and production plan as well as configuration of the proposed supply chain system. Turki and Rezg [27] have determined the optimal storage, manufacturing, and reconditioning planning, while taking into consideration the difference between new and reconditioned parts. Indeed, they considered that the reconditioned and new parts are distinguishable, and the reconditioned parts are sold at lower price in a market different from that existing for new ones. Therefore, in order to conduce a real-world case of a manufacturing-reconditioning system, we will consider two distinguished markets: the first market for selling new parts and the second for reconditioned ones. Indeed, we will propose a reverse supply chain system that recovers the worn parts from the first market, and then reconditions them to then be sold in the second market. Furthermore, to satisfy markets demands, we will consider two machines: the first for producing new products and the second for reconditioning worn parts. Moshtagh and Taleizadeh [28] have considered a manufacturing-reconditioning system with two machines, one for manufacturing and one for reconditioning. The authors have taken into account inventory costs, production and reconditioning costs, ordering cost, and sales revenue. However, the authors have neglected some characteristics of manufacturing systems, such as machine breakdowns and time to repair [29]. In fact, in real-life manufacturing systems, the time to repair is a manufacturing dead time that cannot be neglected as it causes production delays and raises the risk of stock shortage. Therefore, when the time to repair is stochastic, as in practice, certainly, the control of the manufacturing, reconditioning, and parts' stocks becomes much more complicated. In this paper, in order to make our proposed system closer to the real-life case, we will consider that both machines are subject to random breakdowns and repairs. Furthermore, to control manufacturing and reconditioning processes, we will apply hedging point policy [30] that ensures that the number of parts does not exceed a defined stock threshold. Moreover, concerning the return of the worn parts, most works have assumed that the return of worn products is proportional to the demands, while this assumption is not true and causes a suboptimal in production policies. Therefore, in this work, we assume that the quantity of worn products depends on the sales in the previous periods. The configuration of the proposed system is inspired by the real-life firm, which produces new and reconditioned products such as smart phones or laptops. In addition, due to already existing environmental preoccupations and hard economic concurrence, we assume that the proposed system is operating in a competitive environment. Thus, in order to keep the system competitive, we aim to find the optimal stocking strategy and production planning that maximize the total profit. This consists to determine the optimal capacities of manufacturing and reconditioning stocks and the optimal production control, under carbon tax and periodic mandatory regulation, taking into account stochastic machine breakdowns and repairs. To perform the study and the simulation of the proposed system closer to reality, we adapt the discrete flow model [31] that is adopted in several works. The benefit of the discrete flow model is that it is faithful to describe discrete production systems. In addition, the simulation of the discrete flow model is clear and not painful. However, its optimization takes a huge amount of time to search the solutions. The efficient optimization method chosen was inspired from the evolutionary algorithm [32], and we developed an improvement method based on local search to give better solutions.

Compared with the existing works, this paper contributes mainly in two ways: the first is to examine a manufacturing-reconditioning system simultaneously considering the periodic mandatory carbon emission and carbon tax. The second is to develop a new approach to determine the quantity of new and reconditioned products to produce when the government imposes a limit carbon emission in a random period, the optimal levels of the manufactured-reconditioned stock, and the optimal percentage of returned worn products that maximizes the total profit. The present work is important for implementation of a new circular economy and green deal, which is now on top of the agenda for Europe.

After having stated our purpose, this paper is organized as follows: Section 2 introduces the manufacturing-reconditioning system and the mathematical models. Section 3 presents the developed optimization method inspired from the evolutionary algorithm to find the optimal value of decision variables. Section 4 analyzes the computational results. Finally, in Section 5, we conclude our work.

2. Materials and Methods

In this section, we present and explain the proposed system.

In the Table 1 we present parameters and decision variables that are used to formulate the models in this paper:

Table 1. Parameters and decision variables.

t	instant time.
Δt	time period length.
T	total simulation time.
S_A	stock capacity for new products.
$S_A{}^*$	optimal stock capacity for new products.
S_{Ar}	stock capacity for reconditioned products.
$S_{Ar}{}^*$	optimal stock capacity for reconditioned products.
$s_A(t)$	stock level of new products at time t.
$s_{Ar}(t)$	stock level of reconditioned products at time t.
$s_r(t)$	stock level of worn products at time t.
$u_A(t)$	production rate of the machine M_1 at time t.
U_A	maximum production rate of the machine M_1.
$u_{Ar}(t)$	production rate of the machine M_2 at time t.
U_{Ar}	maximum production rate of the machine $M_{2.}$
$d_A(t)$	demand for new products at time t.

Table 1. *Cont.*

$d_{Ar}(t)$	demand for reconditioned products at time t.
$P_A(t)$	quantity of unmet demand for new products at time t.
$P_{Ar}(t)$	quantity of unmet demand for reconditioned products at time t.
$V_A(t)$	quantity of new products sold at time t.
$V_{Ar}(t)$	quantity of reconditioned products sold at time t.
$R(t)$	quantity of worn products that are collected and returned from market 1 at time t.
p	percentage of the returned products (worn products).
p*	optimal percentage of the returned products.
α	lifetime of products.
$\theta(t)$	state of the machine M_1 at time t.
β(t)	state of the machine M_2 at time t.
cv_A	unit selling price for new products.
$\mathrm{cv}_{\mathrm{Ar}}$	unit selling price for reconditioned products.
cu_A	unit production cost of new products.
cu_{Ar}	unit production cost of reconditioned products.
cs_A	unit storage cost for new products.
cs_{Ar}	unit storage cost for reconditioned products.
cr	unit storage cost for returned product.
cp_A	unit lost sales cost for new products.
cp_{Ar}	unit lost sales cost for reconditioned products.
ct	unit carbon emission cost.
q_l	quantity limit of carbon emission.
q_{pm}	carbon emission quantity of new products.
q_{pr}	carbon emission quantity of reconditioned products.
W	length of the mandatory carbon period.
$F(t)$	total profit function.
$F(t)$*	optimal value of total profit.

The aim of our work is to find the optimal stock capacity for new products, S_A*, for reconditioned products, S_{Ar}*, and the percentage of the returned products, p*, that maximizes the total profit, $F(t)$.

2.1. Description of the System

Figure 1 presents the model system, that is composed of two machines denoted M_1 for manufacturing and M_2 for reconditioning, which are subject to random repairs and failures. The machine M_1 produces new products from raw material, and we supposed that it never starves. This assumption defines the general case of the manufacturing system where the raw materials are usually acquired. The machine produces new products at variable rate $u_A(t)$ and they are stored in the stock S_A. The variable $u_A(t)$ represents the decided amount for producing new parts in the period t. In fact, $u_A(t)$ is determined at the period t-Δt according the machine state ($\theta(t)$) and the stock level of new parts $s_A(t)$. The production rate $u_A(t)$ takes a value between 0 and its maximum U_A. The stock S_A satisfies the demand of new products $d_A(t)$ coming from the Market 1. The sold new products will be used for a period α and then will be collected and returned to the manufacturer, then, after, they are stored in the recovery inventory R, to be reconditioned by the machine M_2, and finally are stored in S_{Ar}. The production rate of the reconditioning machine (M_2) is denoted $u_{Ar}(t)$, which represents the decided amount for producing reconditioned parts in the period t. Indeed, $u_{Ar}(t)$ is determined at the period t-Δt according the machine state ($\beta(t)$), the stock level of reconditioned parts $s_{Ar}(t)$ and the stock level of worn products $s_{Ar}(t)$. The production rate $u_{Ar}(t)$ takes a value between 0 and its maximum U_{Ar}. The stock S_{Ar} satisfies the demand of reconditioned products $d_{Ar}(t)$ coming from the Market 2. We supposed that the sold reconditioned products in Market 2 will be destroyed after their end of life. Indeed, in the real case, most reconditioned products are reused one time. In order to study the system under the carbon emission regulations used, we take into consideration the carbon emission emitted by producing the new/reconditioned products. In our model, the carbon emissions represent the quantity of carbon emitted from producing either new or reconditioned products. In other words, we do not consider the carbon footprint, but we directly calculate the carbon quantity generated by the production of new and reconditioned parts.

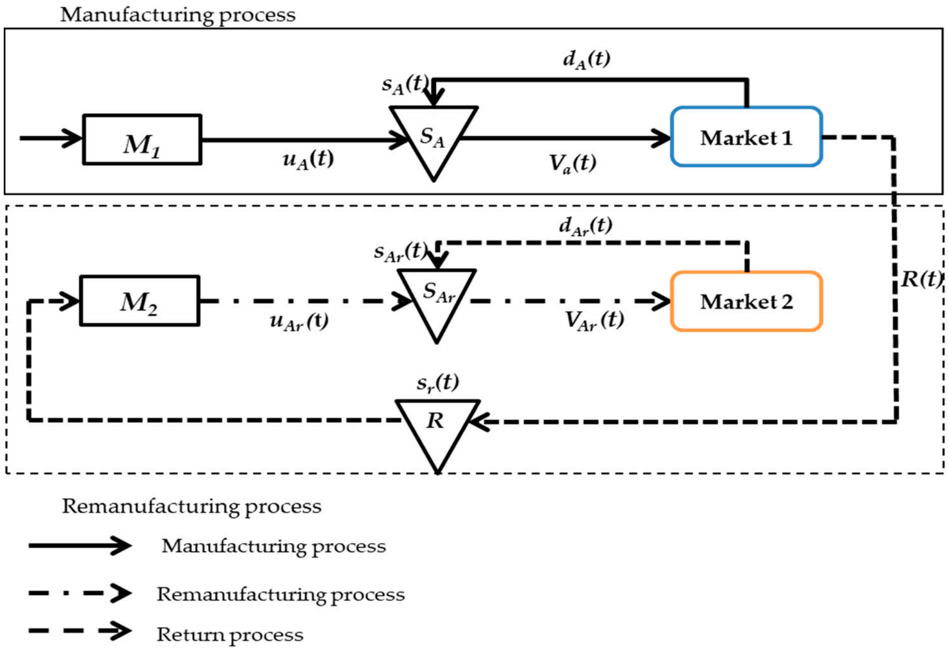

Figure 1. Manufacturing-Reconditioning system.

2.2. Mathematical Model

As assumed before, the machine M_1 is always supplied from raw materials, the state of this machine is either up or down. The machine states are presented in the Equation (1).

$$\theta(t) = \begin{cases} 1 & if\ machine\ M_1\ is\ up \\ 0 & if\ machine\ M_1 is\ down \end{cases} \quad (1)$$

The state of machine M_2 is given by in the Equation (2).

$$\beta(t) = \begin{cases} 1 & machine\ M_2\ is\ up \\ 0 & machine\ M_2\ is\ down \end{cases} \quad (2)$$

We supposed that the machines M_1 and M_2 are subject to a random failure exponentially distributed. When M_1 is up, $u_A(t)$ is between 0 and its maximum U_A and when it is down, $u_A(t) = 0$. It is the same for the machine M_2. The production rates of the machines M_1 and M_2 are given by the Equations (3) and (4).

$$\begin{cases} 0 < u_A(t) \leq U_A & if \theta(t) = 1 \\ u_A(t) = 0 & if \theta(t) = 0 \end{cases} \quad (3)$$

$$\begin{cases} 0 < u_{Ar}(t) \leq U_{Ar} & if \beta(t) = 1 \\ u_{Ar}(t) = 0 & if \beta(t) = 0 \end{cases} \quad (4)$$

The stocks $s_A(t)$ and $s_{Ar}(t)$ at time t are equal to the level of the stock in the previous period plus the number of products produced in the previous period, minus the number of products outgoing from the stock. In order to simplify the calculations, it assumed that $\Delta t = 1$. Thus, the stock levels at time t are given by the Equations (5) and (6).

$$s_A(t) = s_A(t - \Delta t) + u_A(t - \Delta t) - V_A(t) \quad (5)$$

$$s_{Ar}(t) = s_{Ar}(t - \Delta t) + u_{Ar}(t - \Delta t) - V_{Ar}(t) \tag{6}$$

The demands $d_A(t)/d_{Ar}(t)$ are satisfied respectively by the stock level in the previous time $s_A(t - \Delta t)/s_{Ar}(t - \Delta t)$ if stock levels are higher or equal to $d_A(t)/d_{Ar}(t)$), otherwise the number of the sold products is equal to the stock levels at $t - \Delta t$. The numbers of new/reconditioned products sold at time t are expressed by by the Equations (7) and (8).

$$V_A(t) = \begin{cases} d_A(t) & if\ s_A(t - \Delta t) \geq d_A(t) \\ s_A(t - \Delta t) & otherwise \end{cases} \tag{7}$$

$$V_{Ar}(t) = \begin{cases} d_A(t) & if\ s_A(t - \Delta t) \geq d_A(t) \\ s_A(t - \Delta t) & otherwise \end{cases} \tag{8}$$

The numbers of unmet demand $P_A(t)$ and $P_{Ar}(t)$ equal the demand at time t minus the number of sold products at time t. We assume that unmet demands generate a lost cost. This assumption is considered in practice. Indeed, when the customer is not satisfied, a lost cost equivalent to the loss of the business relevance is considered. The Equations (9) and (10) show the number of lost demands at time t:

$$P_A(t) = d_A(t) - V_A(t) \tag{9}$$

$$P_{Ar}(t) = d_{Ar}(t) - V_{Ar}(t) \tag{10}$$

The number of worn products that are returned at time t is proportional to the quantity of satisfied demand after their lifetime. The number of used products equals a percentage of the number of the products sold at $t - \alpha$, where α is the lifetime of the products and p represents the percentage of returned products ($0 < p < 1$). Thus, when $t - \alpha < 0$, there is no return. Therefore, the quantities of returned products are given by the Equation (11).

$$R(t) = \begin{cases} p \cdot V_A(t - \alpha) & if (t - \alpha) \geq 0 \\ 0 & otherwise \end{cases} \tag{11}$$

The Equation (12) represents the level of the recovery inventory at time t, which equals the number of the recovery inventory at $t - \Delta t$ plus the number of worn products that are returned at time t, minus the number of products reconditioned by the machine at $t - \Delta t$.

$$s_r(t) = s_r(t - \Delta t) + R(t) - u_r(t - \Delta t) \tag{12}$$

For the machine M_1, the production rate at time t (see Equation (13)) depends on the machine state $\theta(t)$ and on the stock level of new products at time t. We assumed that the machine is never starved from raw materials. The production rate follows these constraints:

- Equal to the maximum rate production when the state of the machine is up and the stock level capacity is lower than its maximum level.
- Equal to difference between the stock level capacity and its maximum level, when the state of the machine is up and the stock level at time t is between zero and its maximum level.
- Equal to the demand when the state of the machine is up or the stock level at time t has reached its maximum.

- Is null when the state of the machine is down.

$$u_A(t) = \begin{cases} U_A & if\ \theta(t) = 1\ and\ s_A(t) + U_A \le S_A \\ S_A - s_A(t) & if\ \theta(t) = 1\ and\ S_A - U_A < s_A(t) < S_A \\ d_A(t) & if\ \theta(t) = 1\ or\ s_A(t) = S_A \\ 0 & if\ \theta(t) = 0 \end{cases} \tag{13}$$

For the reconditioned products, the machine M_2 is supplied by the recovery inventory. Then, when it is empty or very low, the machine starves. The production rate for reconditioned items looks like the previous one, but also depends on the recovery inventory $R(t)$. Indeed, the production rate for reconditioned products at time t is given the Equation (14).

$$u_{Ar}(t) = \begin{cases} U_{Ar} & if\beta(t) = 1\ and\ s_{AR}(t) + U_{Ar} \le S_{Ar}\ and\ s_r(t) \ge U_{Ar} \\ S_{Ar} - s_{AR}(t) & if\beta(t) = 1\ and\ S_{AR} - U_{Ar} \le s_{Ar}(t) < S_{AR}\ and\ s_r(t) \ge S_{AR} - s_{Ar}(t) \\ d_{Ar}(t) & if\beta(t) = 1\ and\ s_{AR}(t) = S_{Ar}\ and\ s_r(t) \ge d_{Ar}(t) \\ s_r(t) & \begin{cases} if\beta(t) = 1\ and\ s_{AR}(t) + U_{Ar} \le S_{Ar}\ and\ s_r(t) < S_{Ar} \\ or\ if\beta(t) = 1\ and\ S_{AR} - U_{Ar} \le s_{Ar}(t) < S_{AR}\ and\ s_r(t) < S_{AR} - s_{Ar}(t) \\ or\ if\beta(t) = 1\ and\ s_{Ar}(t) = S_{AR} and s_r(t) < d_{AR}(t) \end{cases} \\ 0 & if\beta(t) = 0\ and\ s_r(t) = 0 \end{cases} \tag{14}$$

In this section, we describe the methodology used to plan the production for manufactured and reconditioned products, in the period where the government sets a limitation for carbon emission on a random period (periodic mandatory carbon emission). First, we present the time horizon discretization for the studied problem (see Figure 2).

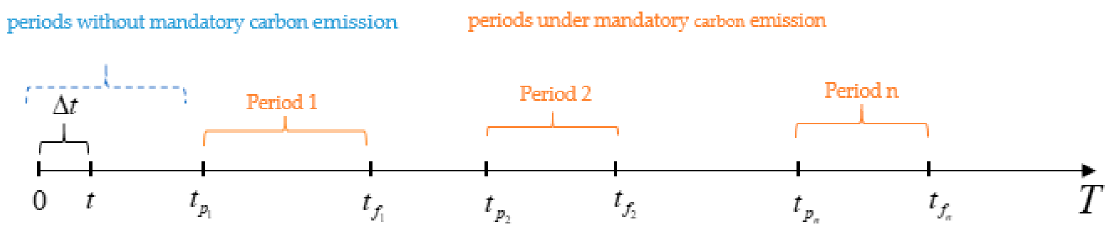

Figure 2. Studied time horizon.

The horizon $[0, T]$ is the finite horizon discretized into periods of time Δt, where Δt is the simulation time step. The occurrence of a period under mandatory carbon emission in the system and the length of the period are generated by truncated normal distribution.

- In order to determine the production quantity for manufacturing and reconditioning products under carbon regulation, we have provided a method to determine the quantity that respects the limited carbon emission and answers to the demand according to the determined production quantity under hedging point policy. We recall q_{pm} and q_{pr} present the carbon emissions of manufacturing and reconditioning respectively, and q_l is the limit quantity of carbon emission to not exceed. We have developed two algorithms (please see Algorithms 1 and 2 that are given in Appendices A and B) that build a function system capable to calculate the proportion of the production rate of the nearest manufactured and reconditioned products under the constraint to not exceed the limit of carbon emissions. The steps are as follows: We calculate the proportion of the production for new and reconditioned products:

$$P_{SC} = \frac{U_A(t)}{U_A(t) + U_{Ar}(t)} \tag{15}$$

$$P_{AC} = \frac{U_{Ar}(t)}{U_A(t) + U_{Ar}(t)} \tag{16}$$

- We search, with two counters i and j running from 1 to the upper bound ($u_A(t)$ and $u_{Ar}(t)$), to respect the constraint of not exceeding the limit of carbon emission:

$$i.q_{pm} + j.q_{pr} <= q_l \tag{17}$$

- We calculate the proportion:

$$P_{m2co} = \frac{i}{i+j} \tag{18}$$

$$P_{R2CO} = \frac{j}{i+j} \tag{19}$$

Then, we developed a function that gives the nearest values corresponding to the sum value P_{m2co} and P_{R2CO} closest to P_{SC} and P_{AC}. The total profit function is determined by the difference between the total revenue and the total costs. The total revenue includes the total cost from the new products $\sum_{t=0}^{T} V_A(t) \cdot cv_A$, and the total cost for reconditioned products $\sum_{t=0}^{T} V_{Ar}(t) \cdot cv_{Ar}$. The total cost includes: the total production costs for new products $\sum_{T=0}^{T} u_A(t) \cdot cu_A$ and the total production costs for reconditioned products $\sum_{T=0}^{T} u_{Ar}(t) \cdot cu_{Ar}$, the total storage cost for new products $\sum_{T=0}^{T} s_A(t) \cdot cs_A$, the total storage cost for reconditioned products $\sum_{T=0}^{T} s_{Ar}(t) \cdot cs_{Ar}$, and the total storage cost for returned products $\sum_{T=0}^{T} s_r(t) \cdot cs_r$. The total return cost for worn products $\sum_{T=0}^{T} R(t) \cdot cr$, the total lost sales for new products $\sum_{T=0}^{T} P_A(t) \cdot cp_A$, and the total lost sales for reconditioned products $\sum_{T=0}^{T} P_{Ar}(t) \cdot cp_{Ar}$. The total amount of carbon emitted from producing new products over the horizon [0, T] is $\sum_{T=0}^{T} u_A(t) \cdot ct \cdot q_{pm}$ and from reconditioned products is $\sum_{T=0}^{T} u_{Ar}(t) \cdot ct \cdot q_{pr}$. We try to maximize the total profit function given by:

$$F(t) = \sum_{t=0}^{t=T} \left[\begin{array}{c} (v_A(t) \cdot cv_A + v_{Ar}(t) \cdot cv_{Ar}) - (s_A(t) \cdot cs_A + s_{Ar}(t) \cdot cs_{Ar} + \\ s_r(t) \cdot cs_r + P_A(t) \cdot cp_A + P_{Ar}(t) \cdot cp_{Ar} + R(t) \cdot cr + u_A(t) \cdot cu_A + \\ u_{Ar}(t) \cdot cu_{Ar} + u_{Ar}(t) \cdot ct \cdot q_{pr} + u_A(t) \cdot ct \cdot q_{pm}) \end{array} \right] \tag{20}$$

3. Optimization Method

The mathematical model presented above is clearly based on simulation. Machines states are simulated, random failures are also simulated according to an exponential distribution law, and time flow is also simulated. From all of this, values of stock levels, number of new and reconditioned products, lost demands, return products quantities, production rates of both machines, limit of carbon emission constraint, production plan, and total profit function are calculated, according to Equations (5) to (20). It is obviously not an integer linear mathematical model, but we have developed an optimization method to cope with the non-linearity and random variables challenges, and managed to obtain a total profit function maximization.

The total profit function was programmed in the language C++ with the free software Dev-C++. The optimization method was also developed in this language. In order to facilitate the method handling, we have put the decision variables in a vector. Each value of the vector can be between a minimum and a maximum value. The optimization process is illustrated in Figure 3.

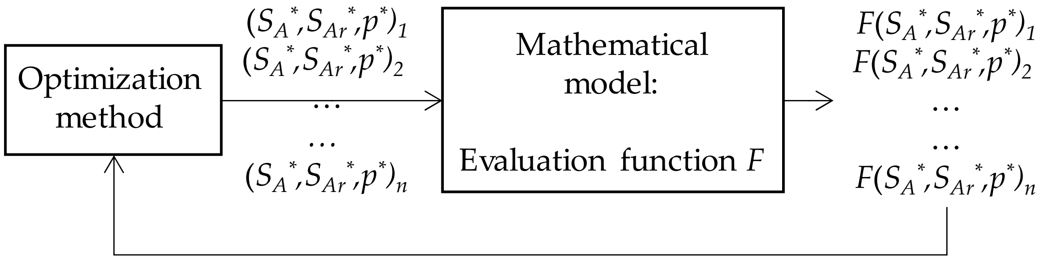

Figure 3. Optimization process of the decision variables (S_A*, S_{Ar}*, p*)

The model is stochastic by construction. Therefore, we calculate the average of three simulations to obtain a more precise value of the objective function, in order to be able to have the best surface possible to perform optimization. The simulation time horizon is fixed to 10^7 time units. The optimization method is inspired from evolutionary algorithms and returns the optimal values of the vector which maximizes the total profit function. The quality of the results obtained by this method depends on the number of tests. The larger the number of tests, the better the results. However, the simulation time can also increase too much. Thus, we developed an improvement method based on local search that can give better solutions by testing the function the least amount possible. The steps are the following:

Initialization: random individuals are created, with each vector of values respecting the boundaries of each of its parameters.

Evaluation: In addition to the pre-determined constraints on variables, the following constraint is written: $S_A > S_{Ar}$. This equation imposes that the storage of new products should be higher than that of reconditioned ones in order to ensure the return of worn products. Consequently, unadapted individuals are rejected.

Selection: We retain the best adapted individuals, those who give satisfying total profit function results.

Mutation: Among the best adapted individuals, we try some neighborhood tests, thanks to a deviation of some values of the vector describing an individual, to see if its characteristics are better adapted.

Evaluation: If a new generated individual meets the constraints, it is evaluated with its total profit value.

Replacement: If the new total profit function is better than the previous, it is retained.

In the end, the final solution is represented by the following vector (S_A, S_{Ar}, p).

The second part of the proposed optimization method is composed of local improvement procedures, which are very useful to perform a better optimization [32]. We developed three main procedures. The first one changes the value of a parameter, chosen at random, in one sense or in the other, here again chosen at random (positive or negative). It can go up until the appropriate bound, but the variation is also at random (it may not "hit" the bound). The set of parameters is then inside each variable bounds, by construction, but the constraints may be violated anyway. Then, after a constraint checking, its objective function is evaluated. If it improves the current solution, it is kept, and if not, the counter of tested solutions is incremented. We allow to test up to 100 valid neighborhoods.

The second neighborhood iteratively repeats the procedure described below, until there is no improvement between two successive iterations. Positive and negative alterations are tested on each of the chromosomes of an individual. If any best improves the objective function, it is kept. Since this neighborhood is iterative, it is only launched once.

The third neighborhood we have implemented is also iterative. For each couple of values of the decision variables vector, we test an alteration of each possible direction's combinations. Since the vector we have to optimize is composed of 3 values (S_A*, S_{Ar}*, p*), at each time this neighborhood method is called, it evaluates ($c_3^2 \times 4 = 12$) combinations of values around a current vector. A Pseudo-code algorithm of this iterative neighborhood is given in Appendix C (Algorithm 3). The optimization method we have developed combines both the necessity to consider a stochastic function, with the uncertainty and weakness associated, and the need of efficiency with a relatively long computing, time-consuming objective function. As well as the objective function, this method is also stochastic, and its results cannot be considered as optimal. Nevertheless, they allow a quick convergence towards the optimal region by testing an infinitesimal part of the solution space, thanks to the power of the neighborhoods developed. Moreover, in a stochastic solution space, all but convex, and where quasi-optimal solutions have values in a relatively narrow range, the method we have proposed, designed, and developed, optimizes correctly. This allows us first to work on this exhaustive model and to exploit its richness to come to interesting scientific results. This also proves the relevance of this method to treat optimization problems with high computing, time-consuming objective functions.

4. Numerical Results

This section conducts experimental computations to illustrate the proposed model and explore different results to investigate the impact of interesting parameters on the optimal values of the decision variables. In the beginning of this section, we introduce numerical data, then we present four subsections. In the first, we investigate the impact of the returned products percentage, p, on the optimal stock capacity for new products, S_A*, and reconditioned products, S_{Ar}*. This study analyzes the impact of the quantity of returned worn products on the manufacturing, reconditioning, and stocking decisions. In the second, we examine the influence of the period of mandatory carbon regulation (W) on the optimal stock capacity for new products, S_A*, reconditioned products, S_{Ar}*, and the percentage of the returned products, p*. This study allows a firm leader to determine the optimal production and stocking planning when the mandatory carbon period changes. In the third, we analyze the influence of the limited quantity of carbon emission imposed by the government on optimal values S_A*, S_{Ar}*, and p*. This study proposes the optimal stocking management when the government imposes a quantity limit of carbon emissions. In the fourth, we analyze the impact of the carbon emission cost imposed by the government on optimal values S_A*, S_{Ar}*, and p*.

The used input data are:

- The time simulation, $T = 10^7$ periods
- The life cycle of new product, $\alpha = 100$ periods The carbon emission quantity for producing new products, $q_{pm} = 100$ carbon units
- The carbon emission quantity for producing reconditioned products, $q_{pr} = 10$ carbon units
- The quantity limit of carbon emission, $q_l = 1000$ carbon units
- The unit carbon emission cost, $ct = 0.01$ monetary unit (for example, dollars or euros)
- The maximum production rate, $U_A = 2500$ products/period
- The maximum production rate, $U_{Ar} = 2300$ products/period
- The unit selling price for new products, $cv_A = 400$ monetary units
- The unit selling price for reconditioned products, $cv_{Ar} = 180$ monetary units
- The unit storage cost for new products, $cs_A = 0.0005$ monetary units
- The unit storage cost for reconditioned products, $cs_{Ar} = 0.0005$ monetary units
- The unit lost sales cost for new products, $cp_A = 1200$ monetary unit
- The unit lost sales cost for reconditioned products, $cp_{Ar} = 875$ monetary units
- The unit production cost of new products, $cu_A = 50$ monetary unit

- The unit production cost of reconditioned products, cu_{Ar} = 20 monetary unit
- The unit storage cost for returned product cr = 0.0003 monetary unit.

The demand $d_A(t)$ is generated by truncated normal distribution, in which the average = 15 and the standard deviation = 7. For $d_{Ar}(t)$, the average = 7 and the standard deviation = 4. The generation of time to repair and time between failures are exponentially distributed. The occurrence of the period of carbon emission limit and length of the period denoted (W) are generated by truncated normal distribution. For length of the period W, the lower truncated is 40 and the upper truncated is 60, with the average = 50 and standard deviation = 10, and for the occurrence of the period, the upper truncated is 4100 and the lower truncated is 3900, and the standard deviation = 100.

4.1. Impact of the p on S_A*, S_{Ar}*, and F(T)

In this subsection, the we investigate the impact of the returned products percentage, p, on the optimal stock capacity for new products, S_A*, reconditioned products, S_{Ar}*, and the total profit, $F(T)$. Thus, we vary the value of p, and by using the optimization algorithm, we determine the corresponding S_A*, S_{Ar}*, and $F(T)$. The simulations' results are illustrated in Table 2. In order to improve the visualization of the obtained results in the analyzed part, we add two Figures, Figures 4 and 5, to the presented Table.

Table 2. Optimal decision variables in function of p.

p	S_A*	S_{Ar}*	$F(T)$
10%	1026	5	2.0804929×10^{8}
20%	1019	167	1.57228×10^{10}
30%	1032	188	2.9439×10^{10}
40%	1025	253	4.5063×10^{10}
50%	**1029**	**411**	$\mathbf{6.0738 \times 10^{10}}$
60%	1021	468	4.07471×10^{10}
70%	1028	517	2.06977×10^{10}
80%	1033	532	$-1.8739222 \times 10^{10}$

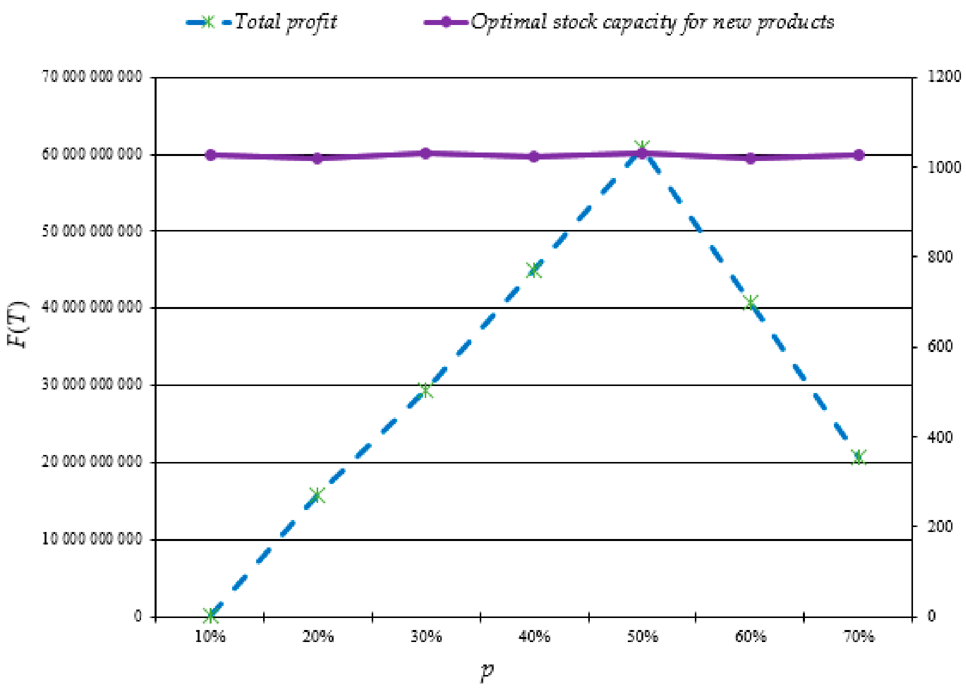

Figure 4. S_A* and $F(T)$ in function of p.

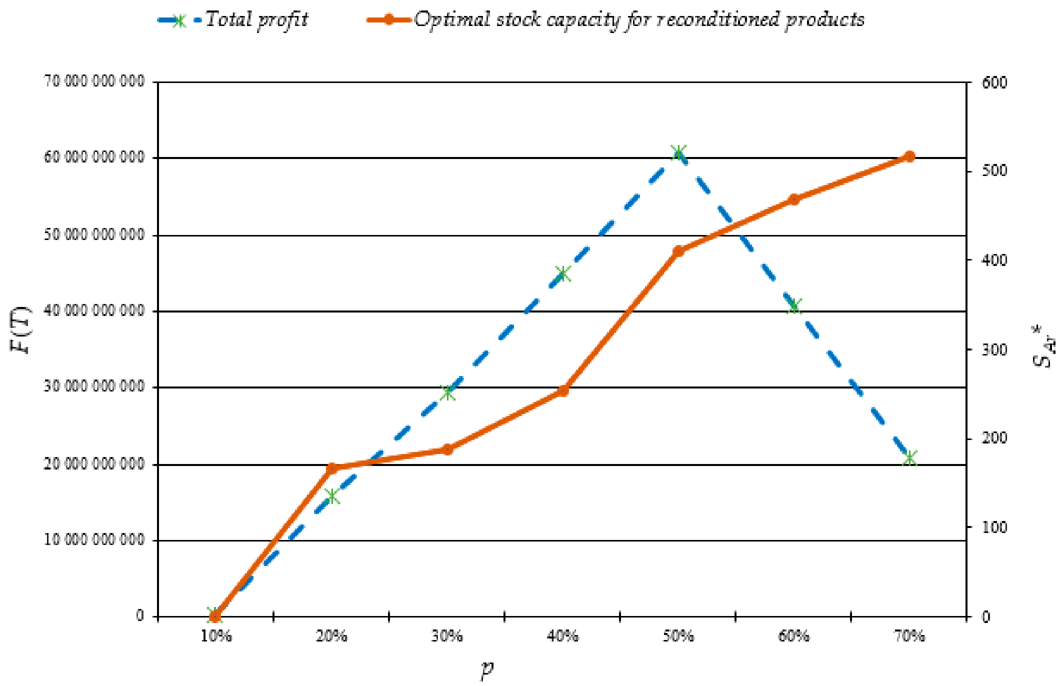

Figure 5. S_{Ar}* and $F(T)$ in function of p.

As shown in Table 2, the total profit is, at the first time, proportional to the percentage of returned products. Then, as the percentage of returned products increases, the profit again decreases and leads to losses. Indeed, it is observed that we have an optimum when p is equal to 50%. This is explained by the fact that when p increases, the number of worn products returned, $R(t)$, increases and replenishes the recovery inventory. Thus, when p is below 50%, the value of profit function increases, which is normal, and the quantity of returned products increases and replenishes the recovery inventory, then the reconditioned products are satisfied. Nevertheless, when p it is above 50%, many of the returned products will be stored in the recovery inventory, which leads to overstocking and generates a high storage cost, and thus explains the losses. The optimal manufacturing stock, S_A*, remains constant, which means that it does not depend on p (see Figure 4). In fact, the production of new parts is independent from the production of reconditioned parts. The optimal reconditioning stock, S_{Ar}*, increases when p increases (see Figure 5), and this is explained by the need of the worn parts for supplying the demand of reconditioned parts in Market 2. If more worn parts are returned to the production system, more reconditioned parts will be available in the stock, S_{Ar}, to satisfy the demand, $d_{Ar}(t)$. This study allows a firm leader to manage, in an optimal way, the manufacturing, reconditioning, and stocking when the quantity of returned worn products varies. Furthermore, when the leader has the option to set the quantity of the returned worn products, he can improve the system management by proposing the optimal quantity of the returned worn products that maximize the profit. Therefore, in the next studies, we add p to the decision variables.

4.2. Impact of the W on S_A*, S_{Ar}*, p*, *and* $F(T)$

In this subsection, we investigate the impact of the length of the mandatory carbon period, W, on the optimal stock capacity for new products, S_A*, reconditioned products, S_{Ar}*, returned products percentage, p, and total profit, $F(T)$. Thus, we vary the value of W, and by using the optimization algorithm, we determine the corresponding S_A*, S_{Ar}*, p*, and $F(T)$. The simulations' results are illustrated in Table 3. In order to improve the visualization of the obtained results in the analyzed part, we add the Figure 6 to the presented Table.

Table 3. Impact of length of the mandatory carbon period W on S_A*, S_{Ar}*, p*, and $F(T)$.

W	Lower	Upper	*Standard Deviation*	S_A*	S_{Ar}*	p*	$F(T)$
50	**25**	**75**	**25**	**1029**	**411**	**50%**	$\mathbf{6.0735 \times 10^{10}}$
100	50	150	50	1241	617	50%	6.07324×10^{10}
500	250	750	250	1641	747	50%	5.11676×10^{10}
750	375	1025	375	2394	783	50%	4.57892×10^{10}

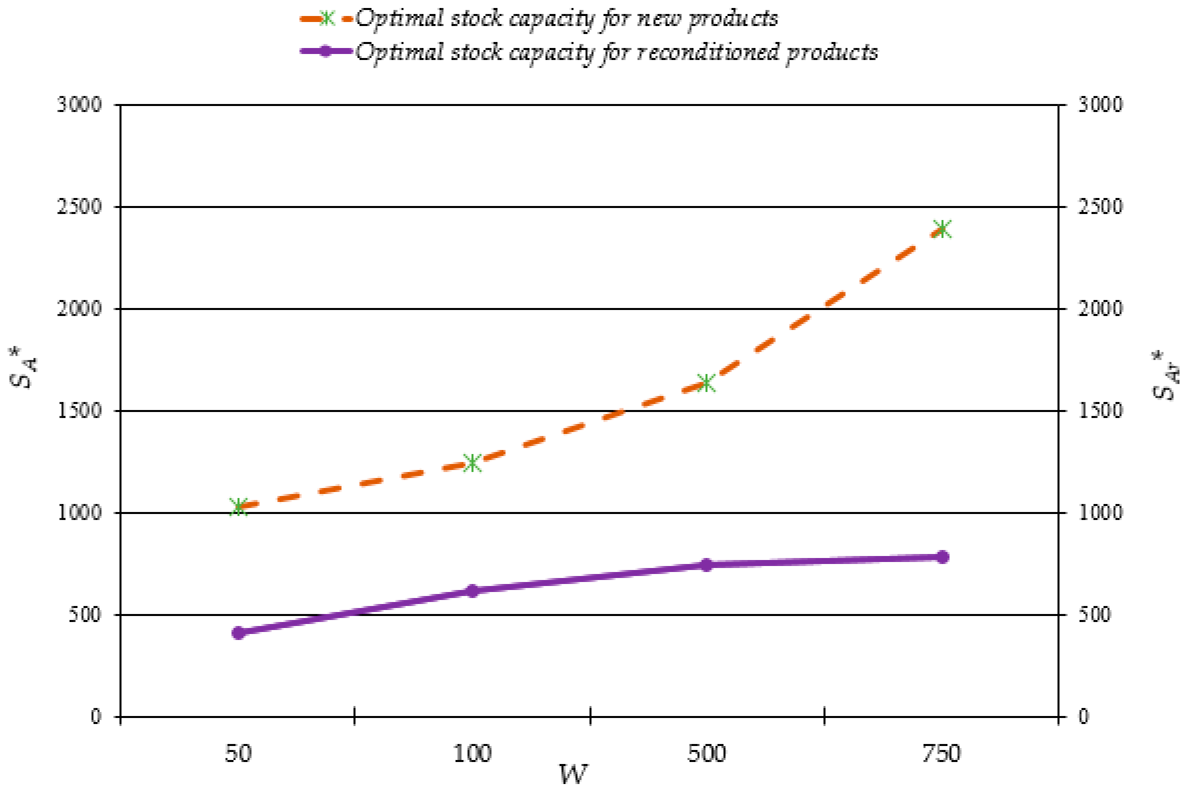

Figure 6. S_{Ar}* and S_A* in function of W.

As it is shown in Table 3, the larger the mandatory carbon period is, the more the total profit decreases, which is explained by lower production in a large period. Also, the optimal of the length of the period of carbon is given (the bold line). Indeed, when the mandatory carbon period is low, the limitation for producing either for new or reconditioned products is low, thus the production is less limited, and the number of satisfying products increases, and then the lost sales costs decreases (see Figure 6). Consequently, to hold the produced products, the optimal storage capacities for both types of products increase. Thus, the demands will be satisfied more, and of course, the profit increases. This study allows a company manager to propose optimal decisions on the manufacturing, reconditioning, stocking, and quantity of returned worn products when a mandatory carbon period is imposed. Indeed, the government imposes a mandatory carbon period when the pollution reaches a level that is considered harmful to humans. In this period, the manager has to respect a fixed limit of carbon emissions. Consequently, the production is limited, and the manager has to find the optimal planning of production, stocking, and returning of worn products.

4.3. Impact of the q_l on S_A*, S_{Ar}*, p*, and $F(T)$

In this subsection, the we investigate the impact of the limited quantity of carbon emission, q_l, on the optimal stock capacity for new products, S_A*, reconditioned products, S_{Ar}*, returned products percentage, p, and the total profit, $F(T)$. Thus, we vary the value of q_l, and by using the optimization algorithm, we determine the corresponding S_A*, S_{Ar}*, p*, and $F(T)$. The simulations' results are illustrated in Table 4. In order to improve the visualization of the obtained results in the analyzed part, we add the Figure 7 to the presented Table.

Table 4. Impact of the limited quantity of carbon emission, q_l, on S_A*, S_{Ar}*, p*, and $F(T)$.

q_l	S_A*	S_{Ar}*	p*	$F(T)$
100	1578	517	50%	6.06718×10^{10}
250	1401	483	50%	6.06987×10^{10}
500	1292	458	50%	6.07126×10^{10}
750	1173	431	50%	6.07297×10^{10}
1000	**1029**	**411**	**50%**	$\mathbf{6.07350 \times 10^{10}}$

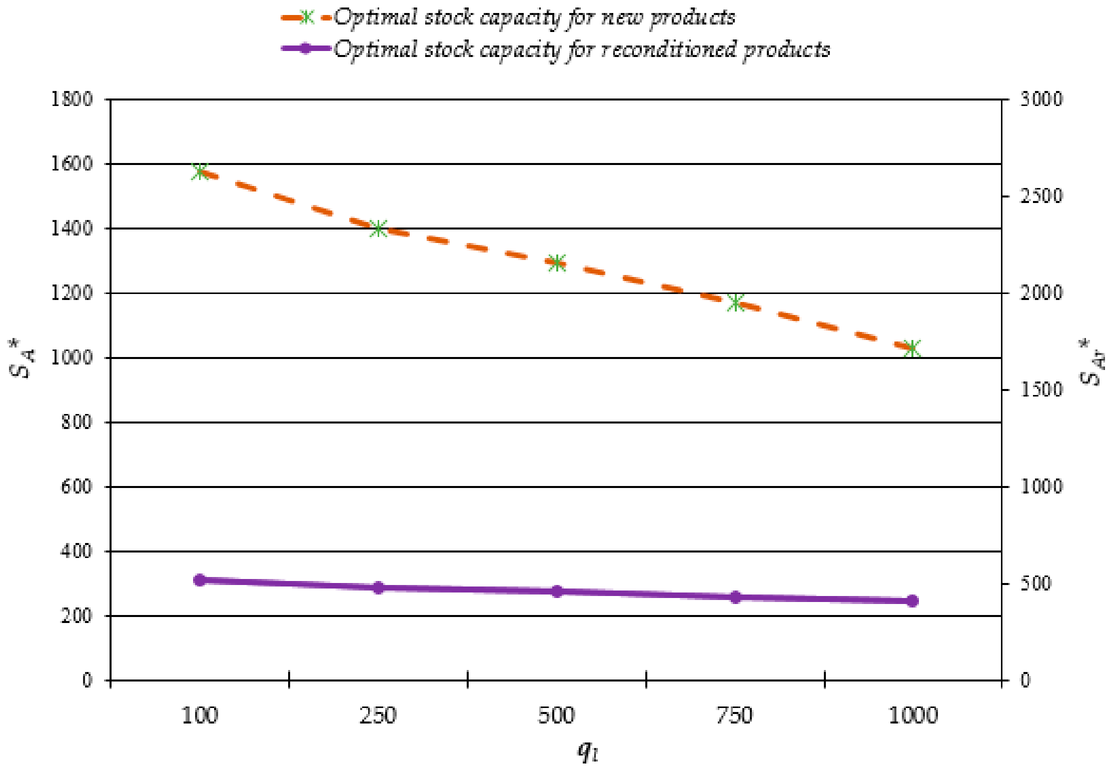

Figure 7. S_{Ar}* and S_A* in function of q_l.

As it observed, when the limited quantity of carbon increases, the profit slightly increases, but both S_A* and S_{Ar}* decrease (see Figure 7). In fact, when the limited quantity of carbon emission is high, the production either for the new or reconditioned products are less limited, and then both types of products are more available, thus, both demands $d_A(t)$ and $d_{Ar}(t)$ are better satisfied. Moreover, when both types of products are available, the stocking decreases as the demands are satisfied. However, when the limited quantity of carbon emission is low, the production either for the new or reconditioned products are very limited. Thus, both types of products are less available and then it shall increase the storing to satisfy the demands. This study allows a firm manager to propose optimal decisions on the manufacturing, reconditioning, stocking, and quantity of returned worn products when the government imposes a limited quantity of carbon emission.

4.4. Impact of the ct on S_A*, S_{Ar}*, p*, and $F(T)$

In this subsection, we investigate the impact of the cost of carbon emission, ct, on the optimal stock capacity for new products, S_A*, reconditioned products, S_{Ar}*, returned products percentage,

p, and the total profit, $F(T)$. Thus, we vary the value of ct, and by using the optimization algorithm, we determine the corresponding S_A*, S_{Ar}*, p*, and $F(T)$. To study the influence of the cost of carbon emission, we changed the parameters' values for cs_A = 0.00002, cs_{Ar} = 0.00002, and cr = 0.0000001 monetary units. The simulations' results are illustrated in Table 5. In order to improve the visualization of the obtained results in the analyzed part, we add the Figure 8 to the presented Table.

Table 5. Impact of the cost of carbon emission on S_A*, S_{Ar}*, p*, and $F(T)$.

ct	S_A*	S_{Ar}*	p*	F(T)
0.01	**1135**	**434**	**50%**	$\mathbf{6.15698 \times 10^{10}}$
1	922	471	50%	4.65295×10^{10}
4	883	502	50%	9.42485×10^{8}

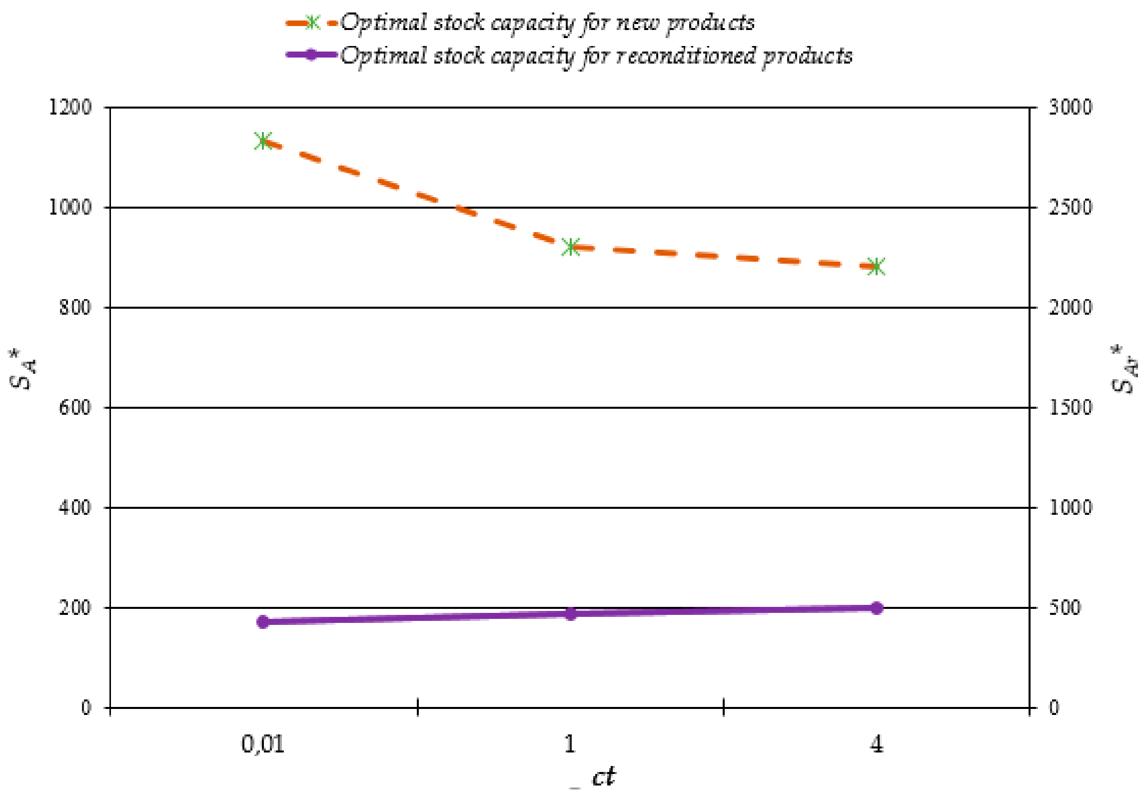

Figure 8. S_{Ar}* and S_A* in function of ct.

The first observation in Table 5 is that the total profit obviously decreases when the cost of carbon increases. Indeed, when the cost of carbon emission increases, the system produces less new parts in order to decrease the cost of emissions, and then, optimal stock, S_A*, decreases (see Figure 8). On the other hand, in order to decrease the cost of emissions, the system produces more reconditioned parts instead of new ones. That explain the increase of optimal stock, S_{Ar}*, when the cost of carbon emission increases (see Figure 8). This study allows a firm manager to propose optimal decisions on the manufacturing, reconditioning, stocking, and quantity of returned worn products when the government increases the carbon emission cost.

5. Conclusions

This paper has proposed a new design of a manufacturing and reconditioning system, taking into account two carbon regulations: carbon tax and periodic mandatory emission. New and reconditioned products are distinguished and sold in different markets. Our work provides, in the framework of this system, a new and quick strategy to quantify the production of parts under the periods of carbon limitation. To make this green manufacturing more realistic, we have considered the failure and repair of the machines, and the amount of returned products (worn products) depends on the previous sales. The demands are stochastic. To simulate the proposed system and to faithfully describe the system behavior, we have developed a mathematical model based on a discrete flow model. Then, an optimization method based on an evolutionary algorithm was developed, to determine the optimal quantity of the returned worn products, and the stock capacity for new and reconditioned products. Four numerical results were obtained by using the optimization algorithm, which help a firm manager to make decisions on the production and storing of new and reconditioned parts. The results have provided optimal strategies of production, storing, and recovery of worn parts in function of the mandatory carbon period length, emission limit, and carbon cost.

In future research, we will consider the mentioned limitations and the carbon emissions exceeded by transportation from stores to markets.

6. Discussion

This work concerned the consideration of a periodic mandatory carbon policy that is combined with carbon tax. A new approach was developed to determine the quantity of new and reconditioned products to produce when the government imposes a limited carbon emission in a random period, the optimal levels of the manufactured-reconditioned stock, and the optimal percentage of returned worn products that maximizes the total profit. Furthermore, the proposed approach combined different options that make the study more realistic, such as: distinction between new and reconditioned parts, the dependence of worn products on the sales in the previous periods, and the variability of the machines repair periods. An efficient optimization method based on evolutionary algorithms was developed that returns the optimal values of the vector, which maximizes the total profit function. The studies provided in this work allow a company manager to propose optimal decisions on the manufacturing, reconditioning, stocking, and quantity of returned worn products when a mandatory carbon period is imposed or when the government increases the carbon emission cost. This work is not exempt from limitations. First, it is considered that the reconditioning process is assured by one machine, but in practice, usually it consists of several machines that are subject to random failures. Second, only one type of product was considered, whereas in practice, almost all companies are producing multiple products. Therefore, in our future research, we will extend the model by assuming that the manufacturing process as well as the reconditioning process consists of several activities carried out at several workplaces. Also, we will consider a multi-product system of production and reconditioning.

Author Contributions: S.T. is the responsible for conducting this research. S.T. proposed the main paper contribution. S.S. developed the mathematical model. C.S. developed the optimization method and algorithms. N.S. supervised this work and contributed to revise this paper. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Algorithm 1: Function near.

Near ($M[n]$, x, $S[n]$, y)
$M[n]$, x, $S[n]$, y
Int i, result; **Double** D;
$D = |TT\ [0] - x| + |SS\ [0] - y|$
$Result = 0$;
For ($i = 1$; $i <$ n; i++){
    If ($|TT[i] - x| + |SS[i] - y|$; $<= D$)
        $D = |TT[i] - x| + |SS[i] - y|$
        $Result = i$;
    End if
End for
Return *Result*

Appendix B

Algorithm 2: Production planning under mandatory carbon emission.

Production plan ($u_A(t)$, $u_{Ar}(t)$)
$k = 0$;
If ($u_A(t)$! 0 and $u_{Ar}(t)! = 0$)
    $P_{SC} = u_A(t)/(u_A(t) + u_{Ar}(t))$
    $P_{AC} = u_{Ar}(t)/(u_A(t) + u_{Ar}(t))$
    For ($i = 1$ to $u_A(t)$)
        For ($j = 1$ to $u_{Ar}(t)$)
            If ($i \cdot q_{pm} + j \cdot q_{pr} < = q_L$)
                $P_{m2co} = i/(i + j)$
                $P_{R2CO} = j/(i + j)$
                $h[k] = P_{m2co}$
                $B[k] = P_{R2CO}$
                $v[k] = i$
                $c[k] = j$
                k++
            End if
        End for
    End for
    lignenear = **Near** (h, P_{SC},B, P_{AC})
    $i = v[lignenear]$, $j = c[lignenear]$
End if
$u_A(t) = i$
$u_{Ar}(t) = j$

Appendix C

Algorithm 3: Pseudo-code of couple of coordinates, iterative neighborhood.

```
Iterative_Neighborhood (Vres; Delta)
Do
  Vtest = Vres
  C_Min_Temp = Cost_Function (Vtest)
  For (i = 1 to nb_var-1)
    For (j = i + 1; j < nb_var; j++)
      Switch (l = 0; l < 4; l++)
        l = 0:
          Positive_Variation (Vtest [i])
          Positive_Variation (Vtest [j])
        l = 1:
          Positive_Variation (Vtest [i])
          Negative_Variation (Vtest [j])
        l = 2:
          Negative_Variation (Vtest [i])
          Positive_Variation (Vtest [j])
        l = 3:
          Negative_Variation (Vtest [i])
          Negative_Variation (Vtest [j])
      End Switch//on l
      If (Constraints_Respected (V))
        C_Temp = Cost_Function (V)
        If (C_Temp < C_Min_Temp)
          Vres = V
        End if
      End if
    End for//j
  End for//i
While (Vres! = Vtest)
```

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