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A system dynamics model for dynamic capacity planning of remanufacturing in closed-loop supply chains

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Abstract

Product recovery operations in reverse supply chains face continually and rapidly changing product demand characterized by an ever increasing number of product offerings with reduced lifecycles due to both technological advancements and environmental concerns. Capacity planning is a strategic issue of increased complexity importance for the profitability of reverse supply chains due to their highly variable return flows. In this work we tackle the development of efficient capacity planning policies for remanufacturing facilities in reverse supply chains, taking into account not only economic but also environmental issues, such as the take-back obligation imposed by legislation and the "green image" effect on customer demand. The behavior of the generic system under study is analyzed through a simulation model based on the principles of the system dynamics methodology. The simulation model provides an experimental tool, which can be used to evaluate alternative long-term capacity planning policies ("what-if" analysis) using total supply chain profit as measure of policy effectiveness. Validation and numerical experimentation further illustrate the applicability of the developed methodology, while providing additional intuitively sound insights.
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Keywords: Reverse supply chains; Remanufacturing; Capacity planning; System dynamics

1. Introduction

Reverse supply chain management has been an area of increasing attention during the last decade in real-world and in academia as its economic impact has been increasingly important and as legislation has been becoming stricter [1]. Reverse channel strategy and operations face the already challenging problem

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of adapting their capacity in an effort to increase supply chain profit related to recovery activities, while dealing within the confines of continuously evolving legislation. Capacity management is, thus, becoming even more complex and critical for reverse chains. It is very interesting that despite these trends almost no long-term strategic management problems in reverse logistics have been studied in the literature thus far [2].

This research is motivated by the need for the development of methodological tools that would assist the decision-making process on capacity planning of recovery activities for remanufacturing reverse chains. A capacity strategy must take into account a variety of factors including among others the predicted patterns of demand, costs of constructing and operating new facilities, new technologies and competitors' strategies [3]. Capacity planning is an extremely complex issue, since each time a company considers expanding productive capacity, it must consider a myriad of possibilities. Even after the decision to expand capacity is given, it remains to resolve key issues such as when, where and how much and all these under the two main competing objectives in capacity planning which are (i) maximization of market share and (ii) maximization of capacity utilization.

The objective of this work is to study the long-term behavior of reverse supply chains with remanufacturing and to further propose efficient remanufacturing and collection capacity expansion policies, while incorporating specific external factors that influence, directly or indirectly, profits, costs and flows. Such factors include among others, environmental consciousness, obligations and penalties imposed by legislation. The proposed policies lead to decisions that confirm the feasibility of capacity expansion and answer questions about when and how much. The optimization criterion employed is the net present value of total supply chain profit over the strategic planning horizon.

The primary modeling and analysis tool used in this research is system dynamics (SD) methodology. Forrester [4] introduced SD in the early 60's as a modeling and simulation methodology for long-term decision-making in dynamic industrial management problems. Since then, SD has been applied to various business policy and strategy problems [5–7]. There are already few publications using SD in supply chain modeling, but most of them refer to forward logistics. Forrester [4] includes a model of supply chain as one of his early examples of the SD methodology. Towill [8] uses SD in supply chain redesign to provide added insights into SD behavior and particularly into its underlying casual relationships. The outputs of the proposed model are industrial dynamics models of supply chains. Minegishi and Thiel [9] use SD to improve the understanding of the complex logistic behavior of an integrated food industry. They present a generic model and then provide practical simulation results applied to the field of poultry production and processing. Sanghwa and Maday [10] investigate effective information control of a production-distribution system by automatic feedback control techniques. Sterman [7] presents two case studies where SD is used to model reverse logistics problems. In the first one, Zamudio-Ramirez [11] analyzes part recovery and material recycling in the US auto industry to provide insights about the future of enhanced auto recycling. In the second one, Taylor [12] concentrates on the market mechanisms of paper recycling, which usually lead to instability and inefficiency in flows, prices, etc. Georgiadis and Vlachos [13] use SD methodology to estimate stocks and flows in a reverse supply chain, while providing specific paradigms with a fixed remanufacturing capacity change per year.

In the current paper we examine capacity planning policies for a single product forward and reverse supply chain with transient flows due to market, technological and regulatory parameters. Although such an analysis may differ from one product to another, we keep the proposed model as generic as possible to facilitate its implementation on a wide spectrum of real-world cases. The next section defines the problem under study. The necessary elements for the developed SD methodology including model variables, the

causal loop (influence) diagram, and the detailed mathematical formulation are presented in Section 3. The validation of the model employing indirect structure tests is presented in Section 4. Extended numerical investigation is presented in Section 5. Finally, we wrap-up with summary and conclusions in Section 6.

2. Problem definition

A key parameter for a forward supply chain is the number of echelons from the vendor of raw materials to the end user. Reverse supply chains are more complicated since return flows may include products, sub-assemblies and/or materials and may enter the forward supply chain in several return points. Fleischmann et al. [14] provide an interesting presentation of all operations and potential flows in a closed-loop supply chain, which combines forward and reverse supply chains. Specifically, they address, among others, the collection, inspection/separation, reprocessing (direct reuse, recycling, repair, remanufacturing), disposal and re-distribution of used products as the main operations of a reverse channel.

In this research we focus on a single product closed-loop supply chain which includes the following distinct operations: supply, production, distribution, use, collection (and inspection), remanufacturing and disposal. Fig. 1 presents the system under study. The forward supply chain includes two echelons (producer and distributor). In the reverse channel, we assume that the only reuse activity is remanufacturing. Remanufacturing brings the product back into an "as good as new" condition by carrying out the necessary disassembly, overhaul and replacement operations [14]. Specifically, the finished products are first transferred to the distributor and then sold to satisfy demand. The product sales at the end of their life-cycle turn into used products, which are either uncontrollably disposed or collected for reuse. The collected products after inspection are either rejected and controllably disposed or accepted and transferred for remanufacturing. The loop "closes" with the remanufacturing operation in two ways. First, through the flow of "as good as new" products to the serviceable inventory (SI in Fig. 1) and second through the impact on sales via the "green image". Raw materials input, total demand and legislation acts (take-back obligation) shape the external environment of the system.

A major assumption of our analysis is the demand for remanufacturing has a relatively low coefficient of variation. There are several supply chains of products such as printer toners, single use cameras, cell phones, etc., where this assumption is valid under certain conditions as explained below.

Guide and Van Wassenhove [15] provide the characteristics of closed-loop supply chains. The returns of refillable containers (e.g. printer cartridges in Xerox and single-use cameras in Kodak) are characterized
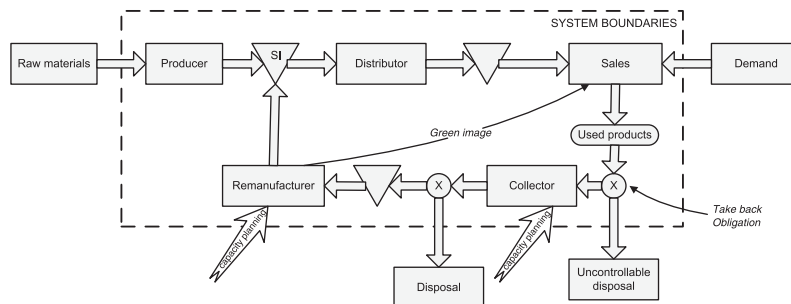

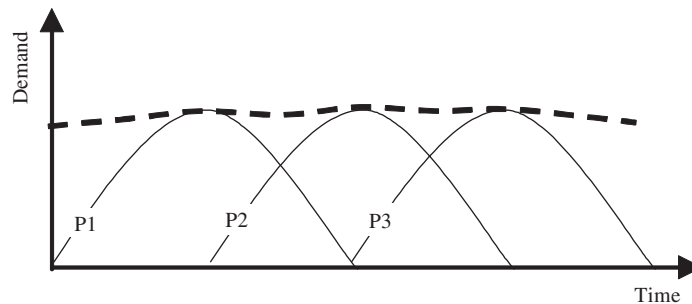Fig. 1. Closed-loop supply chain under study.

Fig. 2. Demand distribution over time (P_i is the demand of type i of cell phones belonging to the same generation).

by high volume and low variance (while total aggregate demand exhibits even a smaller coefficient of variation than that of the individual SKU due to the well-known risk pooling effect [16]). For such products with long life cycles, capacity planning occurs for the entire life-time of the product and thus, the assumption of low coefficient of variation is generally valid.

Consumer electronics on the other side are characterized by high variability of their returns [15]. Products, such as refurbished cell-phones sold to a "B" market, have shorter life cycles and capacity planning occurs for a family of product types that belong to the same generation (e.g. 2G, 2.5G cell-phones). For each type of phones we generally observe demand peaking over the maturity stage of the life time of the item and then phasing out. As incrementally improved phones of the same generation penetrate the market gradually, similar translated demand curves appear as exhibited conceptually in Fig. 2. Consequently, total aggregate demand during the entire lifetime of the generation exhibits a relatively low coefficient of variation (dashed line in Fig. 2).

Remanufacturing and collection capacities are the focal topic of the paper and we examine efficient ways to dynamically determine their levels. This determination is quite simple in a steady-state situation, but in a rapidly changing environment, as in the case under study, it is important to examine a dynamic remanufacturing and collection capacity planning policy. To develop a decision-making system for capacity planning, a firm needs to carefully balance the tradeoff between market share maximization and maximization of capacity utilization. This is done by either *leading capacity strategies*, where excess capacity is used so that the firm can absorb sudden demand surges, or *trailing capacity strategies*, where capacity lags the demand and therefore capacity is fully utilized [17]. A third form of capacity planning is the *matching capacity strategy*, which attempts to match demand capacity and demand closely over time. The three strategies are depicted in Fig. 3. In all three cases the firm is making decisions to acquire new capacity or not, at equally spaced time intervals (with length equal to review period).

It appears that a decision-maker could determine capacities for all these operations once in the beginning of the planning horizon, and that this could be done using a standard management technique that incorporates steady-state conditions. However, this is not the case in the environment under study since forward and backward product flows can change dramatically for several reasons; for example environmental legislation can impose a take-back obligation for a specific percentage of sales (e.g. in some countries of Western Europe there is an obligation to the manufacturers for 100% collection of "white" goods), or the expected demand may increase or decrease progressively because environmentally conscious customers decide to patronize or not a specific provider because of the provider's "green image" (this is well documented in [18]). Although, such demand shifts take time to materialize, they
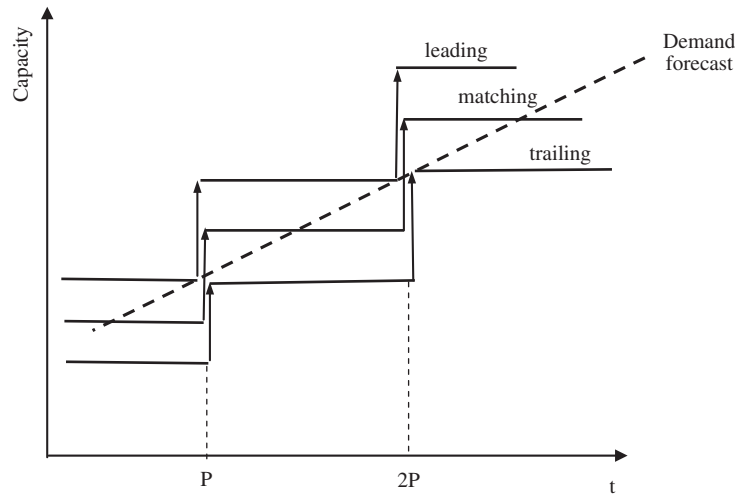
Fig. 3. Alternative capacity expansion strategies.

have to be considered for the development of efficient capacity planning policies. Thus, it is evident that the modeling methodology that will be employed needs to be able to capture the transient effects of flows in a supply chain. SD has this capacity and moreover, it easily describes the diffusion effects related to legal regulations or the firm's "green image" among customers.

3. Methodological approach

The SD methodology, which is adopted in this research, is a modeling and simulation technique specifically designed for long-term, chronic, dynamic management problems [5]. It focuses on understanding how the physical processes, information flows and managerial policies interact so as to create the dynamics of the variables of interest. The totality of the relationships between these components defines the "structure" of the system. Hence, it is said that the "structure" of the system, operating over time, generates its "dynamic behavior patterns". It is most crucial in SD that the model structure provides a valid description of the real processes. The typical purpose of a SD study is to understand how and why the dynamics of concern are generated and then search for policies to further improve the system performance. Policies refer to the long-term, macro-level decision rules used by upper management.

SD differs significantly from a traditional simulation method, such as discrete-event simulation where the most important modeling issue is a point-by-point match between the model behavior and the real behavior, i.e. an accurate forecast. Rather, for an SD model it is important to produce the major "dynamic patterns" of concern (such as exponential growth, collapse, asymptotic growth, S-shaped growth, damping or expanding oscillations, etc). Therefore, the purpose of our model would not be to predict what the total supply chain profit level would be each week for the years to come, but to reveal under what conditions and capacity planning policies the total profit would be higher, if and when it would be negative, if and how it can be controlled [7].

3.1. Model variables

The structure of a SD model contains stock (state) and flow (rate) variables. Stock variables are the accumulations (i.e. inventories) within the system. Another typical form of SD stock variables is smoothed stock variables. These stock variables are the expected values of specific variables obtained by exponential smoothing techniques (e.g. expected demand is the demand forecast using exponential smoothing with a specific smoothing factor). The flow variables represent the flows in the system (i.e. remanufacturing rate), which result from the decision-making process. Below, we define the model variables (stock, smoothed stock and flow) converters and constants and cost parameters, their explanation, where necessary, and their units. We chose to keep a nomenclature consistent with the commercial software package that we employed (discussed in Subsection 3.3); thus for the variable names we use terms with underscore since this is the requirement of the software package (it does not accept spaces). The stock variables in order that they appear in the forward and reverse chain are the following:

Raw_Materials: inventory of raw materials [items].

Serviceable_Inventory: on-hand inventory of new and remanufactured products [items].

Orders_Backlog: unsatisfied distributor's orders which will be served in a forthcoming period when serviceable inventory would be available [items].

Distributors_Inventory: on-hand inventory of the distributor [items].

Demand_Backlog: unsatisfied demand which will be served in a forthcoming period when distributor's inventory would be available [items].

Uncontrollably_Disposed_Products: a variable that accumulates the uncontrollably disposed products [items].

Collected_Products: the inventory of collected reused products [items].

Collection_Capacity: the maximum volume of products handled by the collection and inspection facilities per week [items/week].

Reusable_Products: the inventory of used products that passed inspection and are ready to be remanufactured [items].

Disposed_Products: a variable that accumulates the controllably disposed products [items].

Remanufacturing_Capacity: the maximum volume of reused products that can be remanufactured per week [items/week].

The smoothed stock variables are:

Expected_Distributors_Orders: forecast of distributor's orders using exponential smoothing with smoothing factor *a_DI* [items/week].

Expected_Demand: demand forecast using exponential smoothing with smoothing factor *a_D* [items/week].

Expected_Remanufacturing_Rate: forecast of remanufacturer rate using exponential smoothing with smoothing factor *a_RR* [items/week].

Expected_Used_Products: forecast of used products obtained using exponential smoothing with smoothing factor *a_UP* [items/week].

Desired_CC: estimation of collection capacity obtained by exponential smoothing of *Used_Products* with smoothing factor *a_CC* [items/week].

Desired_RC: estimation of remanufacturing capacity obtained by exponential smoothing of *products Accepted_for_Reuse* with smoothing factor *a_RC* [items/week].

Notice that all smoothing factors *a_xx* that are used in our model are defined as the inverse of the well-known exponential smoothing factors $\hat{a}$ where $0 < \hat{a} < 1$ and thus $a\_xx > 1$. The flow variables following accordingly the order of their associated stock variables are:

Production_Rate: [items/week].
Shipments_to_Distributor: [items/week].
Demand_Backlog_Reduction_Rate: an auxiliary variable equal to *Sales* used only for the stock-flow diagram [items/week].
Distributors_Orders: the orders placed from the distributor to the producer [items/week].
Sales: the products sold to the end users [items/week].
Demand: of end users for products of the specific firm [items/week].
Orders_Backlog_Reduction_Rate: an auxiliary variable equal to *Shipments_to_Distributor* used only for the stock-flow diagram [items/week].
Uncontrollable_Disposal: the flow of used products to disposal due to the limited collection capacity [items/week].
Collection_Rate: the flow of used products to the collection and inspection facilities [items/week].
Products_Accepted_for_Reuse: the flow of used products that have passed inspection and are appropriate to be remanufactured [items/week].
Products_Rejected_for_Reuse: the flow of used products that have not passed inspection and should be disposed [items/week].
Controllable_Disposal: the flow of surplus stock of reusable products to prevent the costly accumulation if there is not enough remanufacturing capacity to handle them [items/week].
CC_Adding_Rate: collection capacity adding rate [items/week/week].
Remanufacturing_Rate: the flow of remanufactured products through the remanufacturing facilities [items/week].
RC_Adding_Rate: remanufacturing capacity adding rate [items/week/week].

Finally, converters and constants form the fine structure of a flow variable [7]; they are presented in Appendix A in alphabetical order. Appendix A also contains the cost parameters of the model.

3.2. Causal loop diagram

The structure of a system in SD methodology is captured by causal loop diagrams. A causal loop diagram represents the major feedback mechanisms. These mechanisms are either negative feedback (balancing) or positive feedback (reinforcing) loops. A negative feedback loop exhibits goal-seeking behavior: after a disturbance, the system seeks to return to an equilibrium situation. In a positive feedback loop an initial disturbance leads to further change, suggesting the presence of an unstable equilibrium. Causal loop diagrams play two important roles in SD methodologies. First, during model development, they serve as preliminary sketches of causal hypotheses and secondly, they can simplify the representation of a model.

The first step of our analysis is to capture the relationships among the system operations in a SD manner and to construct the appropriate causal loop diagram. Fig. 4 depicts the causal loop diagram of the system

Fig. 4. Causal loop diagram of the forward-reverse supply chain with remanufacturing.

under study which includes both the forward and the reverse supply chain. To improve appearance and distinction among the variables, we removed underscores from the variable names and changed the letter style according to the variable type. Specifically, stock variables are written in capital letters, the smoothed stock variables are written in small italics and the flow variables are written in small plain letters. These variables may be quantitative, such as levels of inventories and capacities, or qualitative, such as failure mechanisms. The arrows represent the relations among variables. The direction of the influence lines displays the direction of the effect. The sign "+" or "−" at the upper end of the influence lines exhibits the sign of the effect. A "+" sign dictates that the variables change in the same direction; a "−" sign dictates the opposite.

Below we discuss in more details the causal loop diagram. For this we opted to employ the standard SD jargon that differs from the classical operations research jargon. For example, the term "expected value" in SD is used in the same sense as in the economic literature. Hence, in our model "expected values" are computed by exponential smoothing; these values would instead be referred to as "forecasted values" in the operations research literature.

The forward supply chain begins from the upper left corner of Fig. 4. *Raw_Materials* (external variable) are furnished by external suppliers. *Production_Rate*, which depletes *raw materials*, is the sum of two terms. The first is a forecasted value given by the difference of the *Expected_Distributors_Orders* minus the *Expected_Remanufacturing_Rate* (since the remanufacturing process supplements the production process). The second term is a periodical adjustment, which is proportional to the difference (*SI_Discrepancy*) between *Desired_Serviceable_Inventory* and actual *Serviceable_Inventory*, and it also depends on *SI_Adj_Time* that represents how quickly the firm tries to correct this discrepancy. Such an anchor and adjustment policy is standard in modeling specifically inventory systems in the SD literature [7]. Naturally, the *Production_Rate* is limited by *Production_Capacity*, which is assumed to be an external variable.

The *Desired_Serviceable_Inventory* depends on the *Expected_Distributors_Orders* and the required *SI_Cover_Time* (equivalent to the safety stock in operations research jargon). *Serviceable_Inventory*, consisting of new (*Production_Rate*) and remanufactured products (*Remanufacturing_Rate*), is depleted to satisfy as many as possible of the *Distributors_Orders* through *Shipments_to_Distributor*, which take *Shipment_Time*. The *Distributors_Orders* depend on *Expected_Demand*, the discrepancy (*DI_Discrepancy*) of *Desired_Distributors_Inventory* and actual *Distributors_Inventory* and the *DI_Adj_Time* (also an anchor and adjustment policy). The *Desired_Distributors_Inventory* depends on the *Expected_Demand* and *DI_Cover_Time*, which determines the safety stock of the distributor's inventory. All unsatisfied distributor's orders are backlogged (*Orders_Backlog*) and may be satisfied in a forthcoming time period.

The *Distributors_Inventory* is depleted to satisfy *Demand* through *Sales*. This process requires *Delivery_Time*. All unsatisfied demand is backlogged (*Demand_Backlog*) and may be satisfied in a forthcoming time period. Product demand (*Demand*) is defined by the firm's *Market_Share* and the *Total_demand* (external variable) that captures total product demand among all competitors.

Sales after their current *Usage_Duration* turn into *Used_Products*. The distribution of this time depends on the specific product characteristics and it is easy to estimate by statistical analysis (external variable). Then, *Used_Products* are either disposed (*Uncontrollable_Disposal*) or collected for reuse (*Collected_Products*). The reverse channel starts with the collection and inspection procedures.

Collected_Products are increased by *Collection_Rate* which depends on *Collection_Capacity* and are decreased by the number of products either accepted after inspection (*Products_Accepted_for_Reuse*)

or rejected (*Products_Rejected_for_Reuse*). The determination of collection capacity is a focal point of the paper and it is discussed in the following subsection. The outcome of inspection, which takes *Inspection_Time*, depends on the specific product characteristics (number of reuses, strength and quality) and the *Failure_Percentage* can easily be estimated by statistical analysis (external variable).

The stock of *Reusable_Products* may be used for remanufacturing if the *Remanufacturing_Capacity* which confines the *Remanufacturing_Rate* is adequate. The determination of remanufacturing capacity is also discussed in the following subsection. To prevent an endless accumulation of reusable products a controllable disposal mechanism has been developed that drains them (*Controllable_Disposal*) if they remain unused for some time (*Reusable_Stock_Keeping_Time*).

Before discussing reverse channel capacity determination, there are two more points covered by the model of Fig. 4. The first is the impact of reuse in demand and the second is the take-back obligations imposed by environmental legislation.

Demand depends on the market and the product characteristics, promotion and competition. We assume that there is elasticity in the generally stationary demand, due to the "green image" of the firm. This "green image" effect on product demand depends on the market's awareness that the specific producer supports and promotes product collection recovery and reuse. A quantitative measure for the "green image" effect that we consider is the *Reuse_Ratio*, defined as the ratio of the *Expected_Remanufactured_Rate* to the number of *Expected_Used_Products* which captures the remanufacturing/reuse activities. Handfield et al. [18] in their Delphi group study that includes supply chain managers from several Fortune 500 companies, identify the remanufacturing/reuse activity as one of the top 10 most important and easily assessed criteria for environmental strategy in supply chain management. This ratio further affects directly demand, as explained in Subsection 3.3.

The take-back obligation is enforced by regulatory legislation using a penalty charged per item when the collection level is lower than a predetermined penalty level (usually defined as a percentage of used products). Therefore, the take-back obligation affects the cost structure of the model and it is fully accommodated in our model and its associated commercial software code (see also Subsection 3.3). However, this impact does not appear in Fig. 4, since we chose not to display the entire cost structure (where the take-back penalty cost should appear) so that the Fig. 4 remains readable.

3.2.1. Modeling of capacity planning decision-making

The description of the proposed policy for collection and remanufacturing capacity is further illustrated in the causal loop diagram in Fig. 4 (the bottom left and right-hand side clusters of variables). Then, we explain the policy for collection capacity; the policy is the same for remanufacturing capacity. *Collection_Capacity* is reviewed periodically every P_c time units and then a decision is made whether or not to invest on capacity and to what extent. The length of the review period generally depends on the product life cycle (*Usage_Duration*) and the construction cost of collection facilities, but it is a decision variable in our model. The collection capacity expansion level (*CC_Expansion_Rate*) depends on the discrepancy (*CC_discrepancy*) of desired collection capacity (*Desired_CC*) and the actual level of *Collection_Capacity*. *CC_Expansion_Rate* determines the rate of change of capacity towards the desired value and it is positive for the time epochs (integer multiples of P_c) that a decision of increasing capacity is made. This is modeled by pulse functions (standard tool in SD). The magnitude of each pulse is proportional to the *CC_Discrepancy* at the specific time epoch, multiplied by a parameter K_c; this parameter represents alternative remanufacturing capacity expansion strategies. Values of $K_c > 1$ represent a leading capacity expansion strategy, values of $K_c < 1$ represent a trailing strategy, and values of

K_c close to 1 represent a matching strategy. Naturally, a serious lead time elapses between a capacity increase decision and the construction and operation of the corresponding facility. The capacity adding rate (*CC_Adding _Rate*) captures this construction time and is determined by delaying the values of the *CC_Expansion_Rate*.

Therefore, the decision parameters of the proposed policies are K_c and P_c for collection and K_r and P_r for remanufacturing capacity. Their optimal values, which maximize *Total_Supply_Chain_Profit* throughout a long time horizon, can be found via simulation. A decision-maker and/or regulator can employ the developed model to capture the impact of various policies using various levels of the above parameters, in other words the model can be used for the conduct of various "what-if" analyses.

The above presented capacity planning modeling may be used both for capacity expansion and for capacity contraction since the discrepancy between actual and desired value may be either positive or negative. However, since in this work we consider the maturity phase of the product life cycle, we address only capacity expansion in reverse channel operations since product demand and therefore potential returns are relatively constant.

3.2.2. Cost structure

The main criterion that is employed to evaluate the performance of the entire supply chain is *Total_Supply_Chain_Profit* for the planning horizon. For strategic planning horizons of a few years a net present value approach is an appropriate criterion.

Most of the cost parameters presented in Section 3.1 are more or less typical in supply chain management (holding, transportation, and manufacturing costs). In our model, we assume that the forward supply chain operates for a time period, long enough to consider that all associated cost parameters are constant and the related costs depend only on the product flows. The cost modeling in a reverse supply chain is more complicated and especially in the determination of capacity construction costs which generally depends on the capacity expansion size due to economies of scale. Nahmias [3] presents an empirical method to represent the economies of scale in a variety of industries, according to which the cost $f(y)$ of capacity expansion of size y is given by

$$f(y) = ky^a,$$ (1)

where k is a constant of proportionality. The exponent a, measures the ratio of the incremental to the average costs of a unit of plant capacity. A value of a, that is typically employed is 0.6. As long as $a < 1$ there are economies of scale in capacity construction since doubling the capacity extension level will result in less than doubling of the investment costs. As noted at the end of Section 3.2 we opted not to present the cost structure in Fig. 4 only to maintain the figure easy to read.

3.3. Mathematical formulation

The next step of SD methodology includes the development of the mathematical model, usually presented as a stock-flow diagram that captures the model structure and the interrelationships among the variables. The stock-flow diagram is easily translated to a system of differential equations, which is then solved via simulation. Nowadays, high-level graphical simulation programs (such as *i-think*®, *Powersim*®, *Vensim*®, and *Stella*®) support such an analysis.

The stock-flow diagram of our model, which has been developed using the *Powersim*® 2.5*c* software, is exhibited in Fig. 5. The diagram is constructed using building blocks (variables) categorized as stocks,
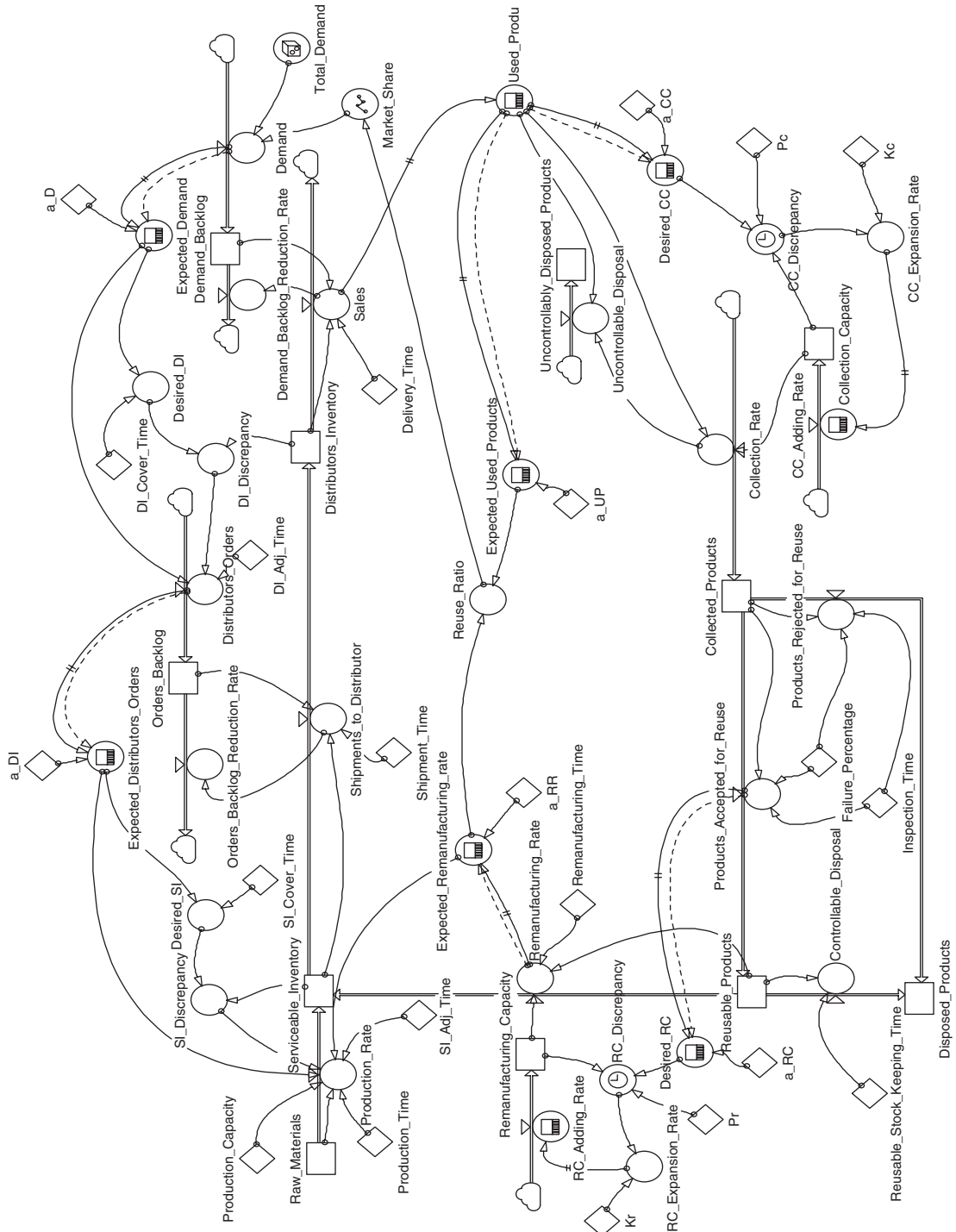
Fig. 5. Stock-flow diagram.

flows, delays, converters and constants. Stock variables (symbolized by rectangles) are the state variables, flow variables (symbolized by valves) are the rates of change in stock variables and they represent those activities, which fill in or drain the stock variables. Delays introduce time delay in material or information channels. In a material channel the output of a delay is a flow variable. In our model there exist three material delays: *Used_Products* as a delay of *Sales*, *CC_Adding_Rate* as a delay of *CC_Expansion_Rate*, and *RC_Adding_Rate* as a delay of *RC_Expansion_Rate*. In an information channel the output of the delay is a stock variable. Such stock variables with information delay are the smoothed stock variables discussed in Subsection 3.1. In *PowerSim*® 2.5*c* both the output of an information delay and a material delay are represented by the same symbol (a rectangular within a circle). Although delays exist in all product flows, only the significant ones (compared with the simulation time step) are included in the model [4]. Converters (represented by circles) are intermediate variables used for auxiliary calculations. Constants (represented by rhombuses) are the model parameters. Finally, the connectors, represented by simple arrows, are the information links representing the cause and effects within the model structure, while the double line arrows represent product flows. Double lines across the arrows indicate a delayed information or material flow.

The stock-flow diagram is a graphical representation of the mathematical model. The embedded mathematical equations are divided into two main categories: the stock equations, defining the accumulations within the system through the time integrals of the net flow rates, and the rate equations, defining the flows among the stocks as functions of time. In the remaining of this section, we present selected formulations related to important model assumptions. All model equations with their initial values for stock variables are given in Appendix B.

The equations related to collection capacity planning policy are the following:

$Desired\_CC(t) = DELAYINF(Used\_Products, \ a\_CC, \ 1, \ Used\_Products))$,
$Collection\_Capacity(0) = 0$,
$Collection\_Capacity(t + \mathrm{d}t) = Collection\_Capacity(t) + \mathrm{d}t \ * \ CC\_Adding\_Rate$,
$CC\_Adding\_Rate = DELAYMTR(CC\_Expansion\_Rate, \ 24, \ 3, \ 0)$,
$CC\_Discrepancy = PULSE(Desired\_CC - Collection\_Capacity, \ 50, Pc)$,
$CC\_Expansion\_Rate = max(Kc \ * \ CC\_Discrepancy, 0)$,

Desired_CC is a first order exponential smoothing of *Used_Products* with smoothing coefficient *a_CC*. Its initial value is the initial value of *Used_Products. Collection_Capacity* begins at zero and changes following *CC_Adding_Rate*, which is a delayed capacity expansion decision (*CC_Expansion_Rate*) with an average delay time of 24 time units, an order of delay equal to 3 and initial value equal to zero at $t = 0$. *CC_Expansion_Rate* is proportional to the *CC_Discrepancy* between the desired and actual collection capacity, multiplied by K_c. The pulse function determines when the first decision is made (50 time units) and the review period P_c. Similar equations dictate the remanufacturing capacity planning policy.

As mentioned in Subsection 3.2, we employ the reuse ratio as the main driver of the market share which determines product demand. The dependency between reuse ratio and demand is depicted in Fig. 6. The S-shape curve represents the small change of the customer preferences when reuse is either poor or extensive. S-shape growth is typical in SD modeling [7]. Alternative forms of this dependency have been further studied by Georgiadis and Vlachos [13]. Below we provide the cost and profit related formulations.
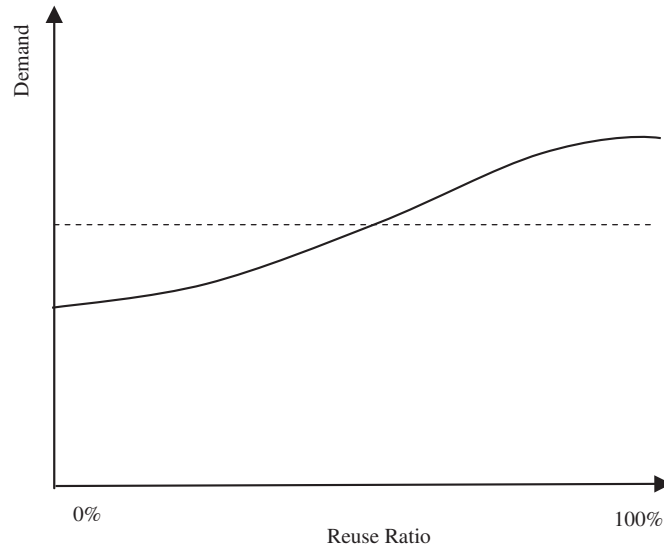
Fig. 6. Effect of *Reuse_Ratio* on Demand Level ("green image" effect).

The total profit per period is given from:

$$Total\_Profit\_per\_Period = Total\_Revenue\_per\_Period - Total\_Cost\_per\_Period,$$

where

$$Total\_Cost\_per\_Period = Investment\_Cost + Operational\_Cost + Penalty\_Cost,$$
$$Total\_Revenue\_per\_Period = Sales * Price,$$

$$Investment\_Cost = (CC\_Expansion\_rate)^{0.6} * Col\_Cap\_Construction\_Cost$$
$$+ (RC\_Expansion\_rate)^{0.6} * Rem\_Cap\_Construction\_Cost,$$

$$Operational\_Cost = Collection\_Rate * Collection\_Cost$$
$$+ Remanufacturing\_Rate * Remanufacturing\_Cost$$
$$+ Production\_Rate * Production\_Cost$$
$$+ Reusable\_Products * Holding\_Cost$$
$$+ Sales * DI\_Transportation\_Cost$$
$$+ Distributors\_Inventory * DI\_Holding\_Cost$$
$$+ Shipments\_to\_Distributor * SI\_Transportation\_Cost$$
$$+ Serviceable\_Inventory * SI\_Holding\_Cost,$$

$$Penalty\_Cost = max(Penalty\_Limit - Collection\_Rate, 0) * Unit\_Penalty\_Cost.$$

The *Penalty_Limit* is the minimum acceptable collection level, usually defined in legislation as a percentage of used products:

$$Penalty\_limit = Used\_products \ * \ Percentage.$$

Finally, the total supply chain profit, which is the objective function we use to evaluate the effectiveness of a policy, is the net present value of total profit per period:

$$Total\_Supply\_Chain\_Profit = NPV(Total\_Profit\_per\_Period, \ Discount\_Factor).$$

4. Model validation

The main criterion for SD models validation is *structure* validity, which is the validity of the set of relations used in the model, as compared with the real processes. The validity of the *behavior* is also important, but less than in forecasting models since first, behavior validity is meaningful only after the structure validity is established and secondly, a point-by-point match between the model behavior and the real behavior is neither possible nor as important as it is in classical forecasting modeling [19,20].

For detection of structural flaws in system dynamics models, certain procedures and tests are used. These structure validity tests are grouped as "direct structure tests" and "indirect structure tests". Direct structure tests involve comparative evaluation of each model equation against its counterpart in the real system (or in the relevant literature). Direct structure testing is important, yet it evolves a very qualitative, subjective process that needs comparing the forms of equations against "real relationships". It is therefore, very hard to communicate to others in a quantitative and structured way [19]. Indirect structure testing on the other hand, is a more quantitative and structured method of testing the validity of the model structure. The two most significant and practical indirect structure tests are extreme-condition and behavior sensitivity tests. Extreme-condition tests involve assigning extreme values to selected model parameters and comparing the model generated behavior to the "anticipated" behavior of the real system under the same extreme condition. The test exploits the fact that we, human beings, are weak in anticipating the dynamics of a complex dynamic system in arbitrary operating conditions, but are much better in anticipating the behavior of the system in extreme conditions. If the model has any hidden structural flaws or inconsistencies, they would be revealed by such tests [19]. Behavior sensitivity test consists of determining those parameters to which the model is highly sensitive and asking if these sensitivities would make sense in the real system. If we discover certain parameters to which the model behavior is surprisingly sensitive, it may indicate a flaw in the model equations. Alternatively, all model equations may be valid, in which case this may lead to the discovery of an unknown, non-intuitive property of the system under study.

In this section, we illustrate the application of some indirect structure tests to the developed model. The *behavior validation* of the model with respect to real data is also important and desirable; however, no long-term data compatible with the time horizon of the model were available. Nor is it possible to collect such long term field data within the scope of this research. Therefore, we conducted *structural validation* tests, which confirmed that the model structure yields meaningful behavior under extreme parameter values. More specifically, the model behavior exhibits meaningful sensitivity to parameters *Raw_Materials*, *Production_Capacity*, *Remanufacturing_Capacity*, *Collection_Capacity*, "green image" effect, and *Sales*. This behavior is consistent with the empirical and theoretical evidence. Finally,
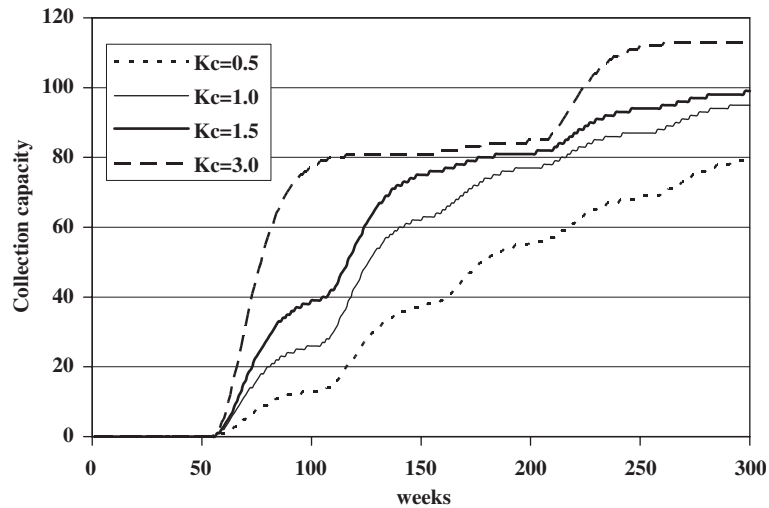
Fig. 7. Impact of K_c on *Collection_Capacity* (basic scenario).

reasonable variations (up to 10%) of these parameters yielded the same qualitative behavior. Figs. 7, 8 and 10 of the next section further validate the model's behavior.

5. Numerical investigation

In this section we demonstrate the application of the developed methodology using a number of numerical examples and discuss few interesting insights that are obtained. The model presented in the previous section includes several types of parameters:

- Physical parameters, which depend on product and operation characteristics. Such parameters are processing times and costs, usage duration, and capacity construction times.
- Operational parameters, i.e. the parameters that describe inventory control policies or capacity planning policies.
- Dynamic parameters, which are the necessary parameters to develop an SD model. Such parameters are adjustment times and smoothing coefficients.

The decision variables, that fully determine the capacity planning policies studied in this work, are: K_c, K_r, P_c, and P_r. A complete numerical investigation would include the study of the impact of all possible combinations of various levels of system parameters on these decision variables. The conduct of such an exhaustive design of experiments is not possible in our case since the number of model parameters is large (about 30). For this reason, we decided to consider a number of parameters (physical and dynamic parameters and the inventory control policies parameters) as constants and to investigate the system's sensitivity on various levels of input parameters. The optimal values of decision variables for the various sets of parameters obtained using grid search and simulation. Since the available software does not support grid search, appropriate programs were created using *Excel*® macros that "call" *Powersim*®. Finally, the *Powersim*® execution results are transferred back to *Excel*®.
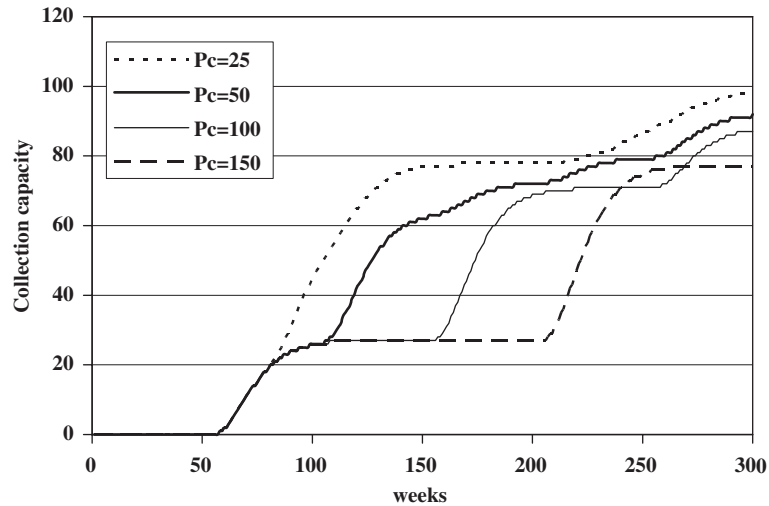
Fig. 8. Impact of P_c on *Collection_Capacity* (basic scenario).

The basic scenario's parameters are the following: all stocks in the beginning of the planning horizon are equal to zero. *Total_Demand* is assumed to follow a normal pattern with mean equal to 1000 items per week and a coefficient of variation equal to 0.1. The *Market_Share* if there is no "green image" effect is set to 10%. The marginal "green image" effect on market share is $\pm 3\%$; this implies that a firm the products of which are fully remanufactured may increase its market share up to 13%; else the market share of a firm with poor remanufacturing operation may decrease down to 7%. We assume that the *Production_Capacity* exceeds all potential demand. Such an assumption is valid if we consider that the need for production capacity decreases with the development of the reverse channel. Moreover, the initial conditions for collection and remanufacturing capacities are set to zero. The length of the time horizon is 300 weeks. The *Failure_Percentage* is assumed equal to 20%. The cost parameters for the basic scenario are the following: *Production_Cost* is the reference cost and it is set equal to 100€. All holding and transportation costs are set to 0.4€ per item per week and 1€ per item respectively. The other costs are: *Collection_Cost* $= 10$€/item, *Remanufacturing_Cost* $= 50$€/item, *Col_Cap_Construction_Cost* $= 1000$€ per item increase in collection capacity, *Rem_Cap_Construction_Cost* $= 5000$€ per item increase in remanufacturing capacity, *Unit_Penalty_Cost* $= 0$€. The sale price is 120€/item. The *Discount_Factor* is set to 0.1% per week. The values of remaining variables such as operation lead times, smoothing coefficients, etc. for the basic scenario are presented in Appendix C.

The first results we present refer to the basic scenario. Figs. 7 and 8 illustrate the effect of various levels of the K_c and P_c, respectively on collection capacity, while keeping the other parameter constant. Similar graphs are obtained for remanufacturing capacity. Starting from week 50 where the first capacity expansion decision arises, the capacity increases faster for higher K_c (Fig. 7) and for P_c (Fig. 8). Such a predictable result further verifies the model structure.

Fig. 9 presents the evolution of *Total_Supply_Chain_Profit* during the planning horizon. For the specific example (basic scenario) *Total_Supply_Chain_Profit* increases with time with small regressions due to periodically charged capacity construction costs.
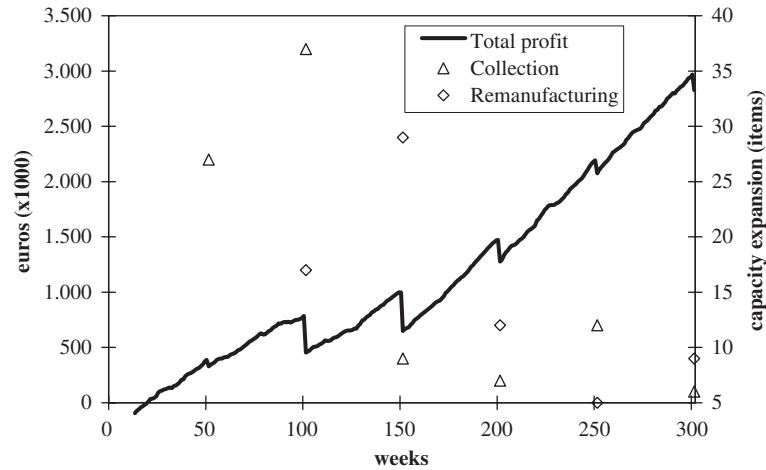
Fig. 9. Impact of capacity expansions on *Total_Supply_Chain_Profit* (basic scenario).
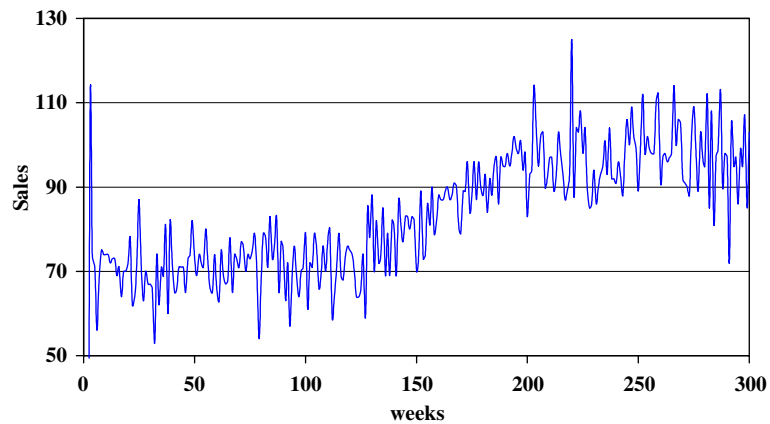

Fig. 10. Sales (basic scenario).

The temporal behavior of *Sales* evolution with time is displayed in Fig. 10. As time goes by the firm increases reverse channel capacity, which affects positively its "green image". Therefore, there is a sales shift to a higher level; that is a reasonable behavior further verifying the validity of the developed model.

Moreover, it is interesting to study the shape of the objective function and how its value is affected by simultaneous changes of various decision variables. To this end we conducted three experiments. In the first experiment we change simultaneously K_c and K_r, in the second for P_c and P_r and in the third, K_r and P_r. Fig. 11 exhibits *Total_Supply_Chain_Profit* for various combinations of K_c and K_r. All other parameters are set at their levels of the basic scenario while P_c and P_r are set to 50 weeks. We observe that when remanufacturing capacity strategy is trailing, the effect of a leading collection capacity policy on total supply chain profit is negligible. Moreover, an interesting result is that when both capacity planning policies are leading, the isoprofit curve illustrates that they act synergistically, i.e. the total supply chain
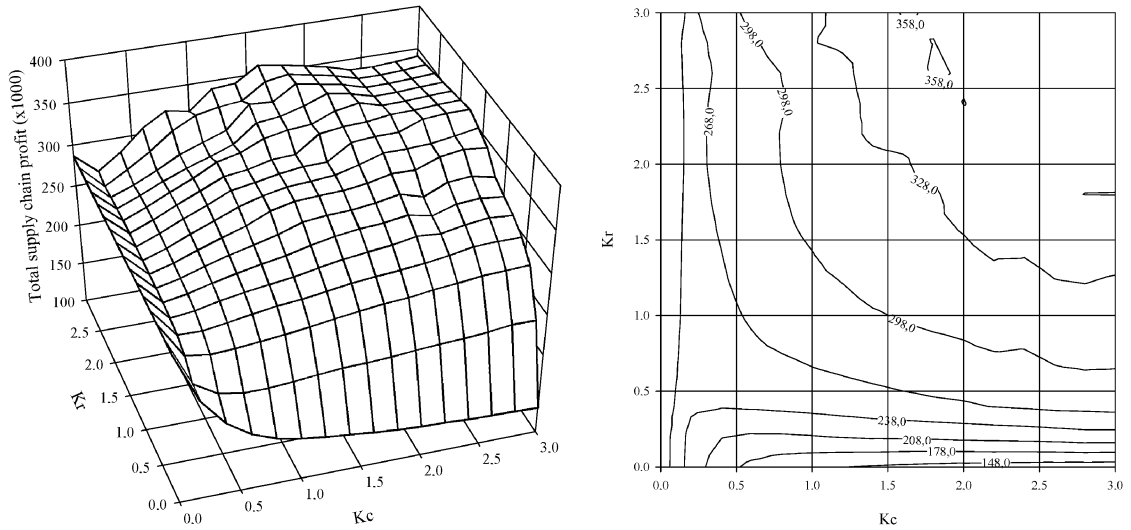
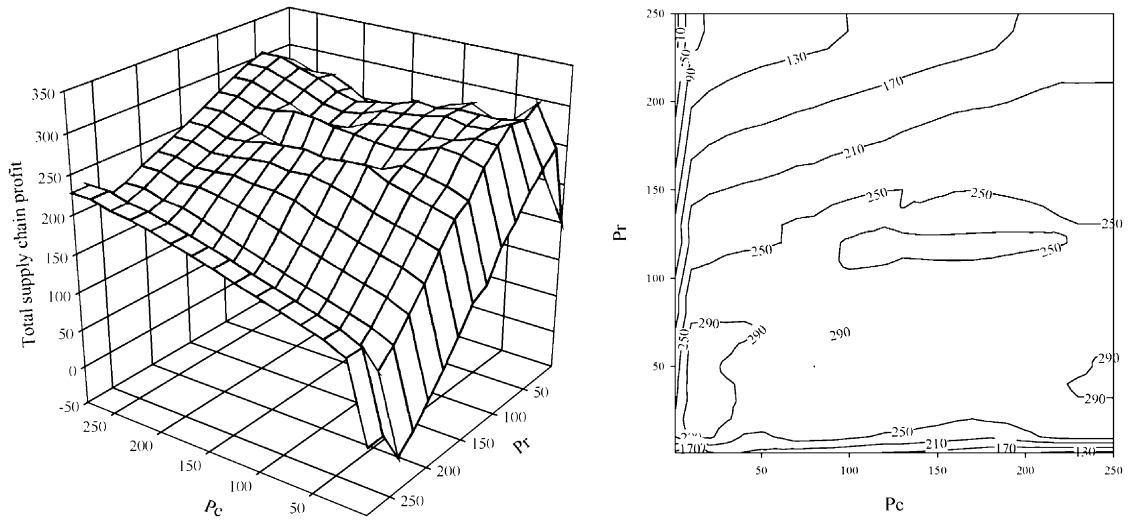Fig. 11. Impact of K_c and K_r on *Total_Supply_Chain_Profit*.

Fig. 12. Impact of P_c and P_r on *Total_Supply_Chain_Profit*.

profit increases if we increase either K_c or K_r up to the optimal combination of K_c and K_r. Such properties remain the same for different costs of the reverse channel operations (remanufacturing cost, collection cost).

A similar experimentation is presented in Fig. 12, where we focus on review periods of collection and remanufacturing capacity planning policies. We observe that the optimal combination is for short review periods. However, such a result depends on the cost of the additional capacity that needs to be acquired. Specifically, as construction cost increases, both values of the optimal pair of review periods increase.
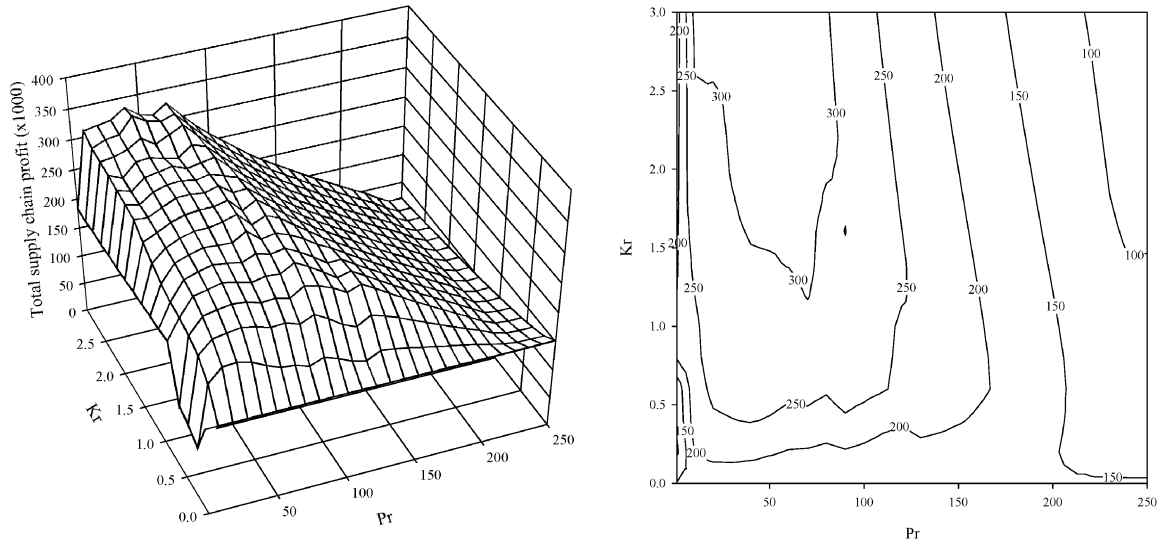
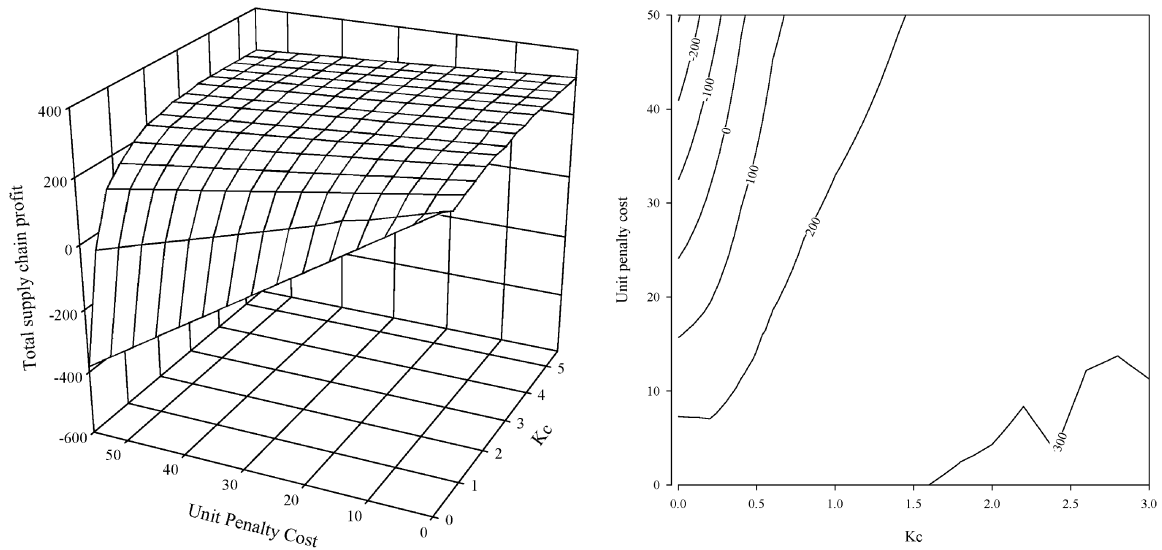Fig. 13. Impact of K_r and P_r on *Total_Supply_Chain_Profit*.

Fig. 14. Impact of penalty cost and K_c on *Total_Supply_Chain_Profit*.

Fig. 13 displays the results for simultaneous changes of K_r and P_r. We observe that the length of review period affects *Total_Supply_Chain_Profit* only for trailing strategies ($K_r > 1$). Further, the shorter the review period the less aggressive the leading strategy needs to be.

Finally, we examined the impact of the penalty level; Fig. 14 exhibits the impact of the penalty level on the optimal capacity planning policy. The results correspond to a *Percentage* value of 0.8; thus, the penalty

Table 1
Impact of *Failure_Percentage* on optimal capacity planning policies

Failure_ percentage	K_c	K_r	P_c	P_r	Total_Supply_ Chain_Profit ($\times 1000$)
0.1	3.94	1.96	> 20	40	419.2
0.2	1.98	2.49	20	40	384.3
0.3	1.96	2.50	20	40	351.2
0.4	0	0	—	—	351.2

Table 2
Impact of "green image" effect magnitude on optimal capacity planning policies

Green image effect magnitude	K_c	K_r	P_c	P_r	Total_supply_ chain_profit ($\times 1000$)
0	1.20	2.80	50	50	449.5
$\pm 1\%$	1.40	2.60	50	50	420.6
$\pm 2\%$	1.60	2.55	20	40	399.8
$\pm 3\%$	1.98	2.49	20	40	384.3

is charged if the collection rate is under 80% of the returns of used products. As expected, the diagram of Fig. 14 further illustrates that when the penalty level increases a similar performance is obtained for higher levels of K_c.

Another set of investigations aim to provide useful insights on system reaction to input parameters variation. We first study the parameter *Failure_Percentage*. The value of this parameter is related to the average number of reuse cycles of a product. For example, the value 0.2 of the basic scenario implies that a product will be remanufactured 5 times on average before its disposal. Therefore, reasonable values for this parameter are between 0.1 and 0.3. Table 1 exhibits the optimal capacity planning policy parameters for *Failure_Percentage* values of 0.1, 0.2 and 0.3, respectively. However, for *Failure_Percentage* = 0.4, which implies that a product will be remanufactured no more than once, the optimal policy is not to invest on reuse activities ($K_c = K_r = 0$). Generally, we observe that an increase in failure percentage decreases *Total_Supply_Chain_Profit*. The optimal values of K_c decrease while the corresponding values of K_r increase. The optimal review periods are not affected.

Another investigation refers to the impact of the "green image" on optimal capacity planning policies. Table 2 presents the results for various levels of this impact on market share. We observe that higher levels of impact lead to capacity planning policies with higher K_c and at the same time to shorter review periods. Although this result is intuitively sound, we also observe that the "green image" has a negative effect on *Total_Supply_Chain_Profit*. This can be explained by the fact that the poor initial reuse ratio (due to the assumption of zero initial capacities) takes too much time to correct; thus having a negative impact on sales. However, if the initial capacities are positive, the initial reuse ratio will increase leading to "green image" enhancement. Therefore, both sales and profits will be improved considerably.

Table 3
Impact of *a_CC* and *a_RC* on optimal capacity planning policies

a_CC	*a_RC*	K_c	K_r	P_c	P_r	*Total_supply_ chain_profit* (×1000)
12	12	1.98	2.49	20	40	384.3
24	12	2.30	2.80	10	30	369.9
50	12	3.80	3.00	10	30	371.0
12	24	3.80	2.20	> 30	40	365.6
12	50	3.70	3.20	> 30	50	367.0
24	24	2.20	3.80	10	40	373.0

Finally, Table 3 displays the dependency of optimal policies on input parameters such as the smoothing factors. We observe that higher values of *a_CC* and *a_RC* tend to push for more aggressive strategies in optimality (with higher levels of *K*). However, the selection of their values is important since it affects *Total_Supply_Chain_Profit*.

Finally, concluding our numerical experimentation it is clear that if we decide to develop reverse channel operations, this must be done using leading capacity expansion strategies. This is intuitively sound given the volatile nature of the corresponding working environment that forces a firm to adopt aggressive "preemptive" planning policies.

6. Summary and conclusions

We presented the development of a dynamic SD-based model for strategic remanufacturing and collection capacity planning of a single product reverse supply chain for product recovery. For reverse chains ever increasing environmental concerns impose constant pressure on regulators for stricter policies and/or legislation. The developed model allows the comprehensive description and analysis of the system operations (product flows and stocks) taking into account capacity considerations, alternative environmental protection policies involving a take-back obligation and a "green image" effect on product demand. We first validated the SD simulator employing indirect structural tests and then proceeded with numerical investigation. The latter provides us with insights that can be employed in developing efficient capacity planning policies in a dynamic manner.

The model can be used to analyze various scenarios (i.e. to conduct various "what-if" analyses) thus identifying efficient policies and further to answer questions about the long-term operation of reverse supply chains using total supply chain profit as the measure of performance. The model could further be adopted and used not only for product recovery, but also for material recycling systems. Thus, it may prove useful to policy-makers/regulators and decision-makers dealing with long-term strategic reverse supply chain management issues along with researchers in environmental management.

Appendix A.

A.1. Constants, converters

CC_Discrepancy: Discrepancy between desired and actual collection capacity [items/week].

CC_Expansion_Rate: Collection capacity expansion rate [items/week/week].

Delivery_Time: Order lead time for the end user, i.e. time that is needed to transfer products from distributor to end users [weeks].

Desired_DI: Desired Distribution inventory [items].

Desired_SI: Desired Serviceable inventory [items].

DI_Discrepancy: Discrepancy between desired and actual distributor's inventory [items].

DI_Adj_Time: Distributor's inventory adjustment time [weeks].

DI_Cover_Time: Distributor's inventory cover time [weeks].

Discount Factor: [dimensionless].

Failure_Percentage: percentage of collected products that are rejected during inspection process [dimensionless].

Inspection_Time: time needed for the inspection process [weeks].

K_c: control variable for collection capacity [1/week].

K_r: control variable for remanufacturing capacity [1/week].

Market_Share: the percentage of the firm's demand over total demand among competitors [dimensionless].

P_c: collection capacity review period [weeks].

Penalty_Limit: the minimum acceptable limit for collected products imposed by legislation [items/week].

Percentage: the minimum acceptable limit for collected to used products imposed by legislation [dimensionless].

P_r: remanufacturing capacity review period [weeks].

Production_Capacity: [items/week].

Production_Time: [weeks].

RC_Discrepancy: discrepancy between desired and actual remanufacturing capacity [items/week].

RC_Expansion_Rate: remanufacturing capacity expansion rate [items/week/week].

Remanufacturing_Time: [weeks].

Reusable_Stock_Keeping_Time: [weeks].

Reuse_Ratio: the ratio of *Expected_Remanufacturing_Capacity* to *Expected_Used_Products* [dimensionless].

Shipment_Time: time that is needed to transfer products from producer to distributor [weeks].

SI_Adj_Time: serviceable inventory adjustment time [weeks].

SI_Cover_Time: serviceable inventory cover time [weeks].

SI_Discrepancy: discrepancy between desired and actual serviceable inventory [items].

Total_Demand: total market demand among all competitors [items/week].

Usage_Duration: the duration of one cycle of product usage [weeks].

Used_Products: [items/week].

A.2. Cost parameters

Production_Cost: [€/item].
SI_Holding_Cost: holding cost of serviceable inventory [€/week/item].
SI_Transportation_Cost: transportation cost from producer to distributor [€/item].
DI_Holding_Cost: holding cost of distributor's inventory [€/week/item].
DI_Transportation_Cost: transportation cost from distributor to end user [€/item].
Collection_Cost: it includes collection, inspection and transportation cost from the end user to the collector [€/item].
Holding_Cost: holding cost for reusable products [€/week/item].
Remanufacturing_Cost: actual cost of remanufacturing process plus the transportation cost from the collector to the remanufacturer [€/item].
Col_Cap_Construction_Cost: the average cost of construction of one unit of collection capacity; it depends on the size of capacity adding decision [€/item].
Rem_Cap_Construction_Cost: the average cost of construction of one unit of capacity; it depends on the size of capacity adding decision [€/item].
Unit_Penalty_Cost: the take-back obligation cost, i.e. the penalty charged per item of a collection shortfall compared to the legislation limits [€/item].
Price: product selling price [€/item].

Appendix B.

B.1. Model equations

Collected_Products$(0) = 0$
Collected_Products $(t + dt) =$ *Collected_Products*(t)
$+ dt * $ *Collection_Rate*
$- dt * $ *Products_Rejected_for_Reuse*
$- dt * $ *Products_accepted_for_reuse*
Collection_Capacity $(0) = 0$
Collection_Capacity $(t + dt) =$ *Collection_Capacity*(t)
$+ dt * $ *CC_Adding_Rate*
Demand_Backlog $(0) = 0$
Demand_Backlog $(t + dt) =$ *Demand_Backlog*(t)
$- dt * $ *Demand_Backlog_Reduction_Rate*
$+ dt * $ *Demand*
Disposed_Products $(0) = 0$
Disposed_Products $(t + dt) =$ *Disposed_Products*(t)
$+ dt * $ *Products_Rejected_for_Reuse*
$+ dt * $ *Controllable_Disposal*
Distributors_Inventory $(0) = 0$

$Distributors\_Inventory\ (t + \mathrm{d}t) =$ $Distributors\_Inventory(t)$
$-\mathrm{d}t\ *\ Sales$
$+\mathrm{d}t\ *\ Shipments\_to\_Distributor$

$Orders\_Backlog\ (0) = 0$
$Orders\_Backlog\ (t + \mathrm{d}t) =$ $Orders\_Backlog(t)$
$+\mathrm{d}t\ *\ Distributors\_Orders$
$-\mathrm{d}t\ *\ Orders\_Backlog\_Reduction\_Rate$

$Raw\_Materials\ (0) = INFINITY$
$Raw\_Materials(t + \mathrm{d}t) =$ $Raw\_Materials(t)$
$-\mathrm{d}t\ *\ Production\_Rate$

$Remanufacturing\_Capacity\ (0) = 0$
$Remanufacturing\_Capacity(t + \mathrm{d}t) =$ $Remanufacturing\_Capacity(t)$
$+\mathrm{d}t\ *\ RC\_Adding\_Rate$

$Reusable\_Products(0) = 0$
$Reusable\_Products\ (t + \mathrm{d}t) =$ $Reusable\_Products\ (t)$
$+\mathrm{d}t\ *\ Products\_Accepted\_for\_Reuse$
$-\mathrm{d}t\ *\ Controllable\_Disposal$
$-\mathrm{d}t\ *\ Remanufacturing\_Rate$

$Serviceable\_Inventory\ (0) = 0$
$Serviceable\_Inventory\ (t + \mathrm{d}t) =$ $Serviceable\_Inventory\ (t)$
$+\mathrm{d}t\ *\ Production\_Rate$
$-\mathrm{d}t\ *\ Shipments\_to\_Distributor$
$+\mathrm{d}t\ *\ Remanufacturing\_rate$

$Uncontrollably\_Disposed\_Products\ (0) = 0$
$Uncontrollably\_Disposed\_Products(t + \mathrm{d}t) =$ $Uncontrollably\_Disposed\_Products(t)$
$+\mathrm{d}t\ *\ Uncontrollable\_Disposal$

$CC\_Adding\_Rate = DELAYMTR(CC\_Expansion\_Rate, 24, 3, 0)$
$Collection\_Rate = min(Collection\_Capacity, Used\_Products)$
$Controllable\_Disposal = (Reusable\_Products)/Reusable\_Stock\_Keeping\_Time$
$Demand = Total\_Demand * Market\_Share$
$Demand\_Backlog\_Reduction\_Rate = Sales$
$Distributors\_Orders = Expected\_Demand + DI\_Discrepancy/DI\_Adj\_Time$
$Orders\_Backlog\_Reduction\_Rate = Shipments\_to\_Distributor$
$Production\_Rate = MAX(MIN(Raw\_Materials/Production\_Time, Production\_Capacity,$
     $Expected\_Distributors\_Orders - Expected\_Remanufacturing\_rate +$
     $SI\_Discrepancy/SI\_Adj\_Time), 0)$
$Products\_Accepted\_for\_Reuse = Collected\_products * (1 - Failure\_Percentage)/\ Inspection\_Time$
$Products\_Rejected\_for\_Reuse = Collected\_Products * Failure\_Percentage/Inspection\_Time$
$RC\_Adding\_Rate = DELAYMTR(RC\_Expansion\_Rate, 24, 3, 0)$
$Remanufacturing\_Rate = min(Reusable\_Products/Remanufacturing\_Time,$
     $Remanufacturing\_Capacity)$
$Sales = MIN(Demand\_Backlog, Distributors\_Inventory)/Delivery\_Time$
$Shipments\_to\_Distributor = (min(Serviceable\_Inventory, Orders\_Backlog)/Shipment\_Time)$

$Uncontrollable\_Disposal = Used\_Products - Collection\_Rate$

$CC\_Discrepancy = PULSE(Desired\_CC - Collection\_Capacity, 50, Pc)$

$CC\_Expansion\_Rate = max(Kc * CC\_Discrepancy, 0)$

$Desired\_CC = DELAYINF(Used\_Products, a\_CC, 1, Used\_Products)$

$Desired\_DI = Expected\_Demand * DI\_Cover\_Time$

$Desired\_RC = DELAYINF(Products\_Accepted\_for\_Reuse, a\_RC, 1, Products\_Accepted\_for\_Reuse)$

$Desired\_SI = Expected\_Distributors\_Orders * SI\_Cover\_Time$

$DI\_discrepancy = max(Desired\_DI - Distributors\_Inventory, 0)$

$Expected\_Demand = DELAYINF(Demand, a\_D, 1, Demand)$

$Expected\_Distributors\_Orders = DELAYINF(Distributors\_Orders, a\_DI, 1, Distributors\_Orders)$

$Expected\_Production\_Rate = Expected\_Distributors\_Orders - Expected\_Remanufacturing\_Rate$

$Expected\_Remanufacturing\_Rate =$
  $DELAYINF(Remanufacturing\_Rate, a\_RR, 1, Remanufacturing\_Rate)$

$Expected\_Used\_Products = DELAYINF(Used\_Products, a\_UP, 1, Used\_Products)$

$Investment\_Cost = (CC\_Expansion\_Rate)\hat{}0.6$
  $*Col\_Cap\_Construction\_Cost + (RC\_Expansion\_Rate)\hat{}0.6 * Rem\_Cap\_Construction\_Cost$

$Market\_Share = 0.1 + 0.03 * GRAPH(Reuse\_Ratio, 0, 0.1, [-1.0, -0.615, -0.335, -0.165, -0.05,$
  $0, 0.05, 0.165, 0.335, 0.615, 1.0``\ Min: -1.0; Max: 1.0; Zoom"])$

$Operational\_cost =$
  $Collection\_Cost * Collection\_Rate + Remanufacturing\_Rate * Remanufacturing\_Cost + Productio$
  $n\_Cost * Production\_Rate + Reusable\_Products * Holding\_Cost + Sales * DI\_Transportation\_Cost$
  $+DI\_Holding\_Cost * Distributors\_Inventory + Shipments\_to\_Distributor * SI\_Transportation\_C$
  $ost + Serviceable\_Inventory * SI\_Holding\_Cost$

$Penalty\_Cost = max(Penalty\_Limit - Collection\_Rate, 0) * Unit\_Penalty\_Cost$

$Penalty\_Limit = Used\_Products * Percentage$

$RC\_Discrepancy = PULSE(Desired\_RC - Remanufacturing\_Capacity, 50, Pr)$

$RC\_Expansion\_Rate = max(Kr * RC\_Discrepancy, 0)$

$Reuse\_Ratio = Expected\_Remanufacturing\_Rate\ DIVZ0\ Expected\_Used\_Products$

$SI\_Discrepancy = Desired\_SI - Serviceable\_Inventory$

$Total\_Cost\_per\_Period = Investment\_Cost + Operational\_Cost + Penalty\_Cost$

$Total\_Demand = NORMAL(1000, 100, 2)$

$Total\_Income\_per\_Period = Sales * Price$

$Total\_Profit\_per\_Period = Total\_Income\_per\_Period - Total\_Cost\_per\_Period$

$Total\_Supply\_Chain\_Profit = NPV(Total\_Profit\_per\_Period,\ Discount\_Factor)$

$Used\_Products = DELAYMTR(Sales, 50, 3, 0)$

Appendix C.

C.1. Model constants

$a\_CC = 12$
$a\_D = 12$
$a\_DI = 12$
$a\_RC = 12$

a_RR = 48
a_UP = 48
CC_Review_Period = 50
Col_Cap_Construction_Cost = 1000
Collection_Cost = 10
Delivery_Time = 1
DI_Adj_Time = 2
DI_Cover_Time = 1.2
DI_Holding_Cost = 0.4
DI_Transportation_Cost = 1
Discount_Factor = 0.001
Failure_Percentage = 0.2
Holding_Cost = 0.4
Inspection_Time = 1
Kc = 1
Kr = 1
Percentage = 0
Pc = 50
Pr = 50
Price = 120
Production_Capacity = 1000
Production_Cost = 100
Production_Time = 2
Rem_Cap_Construction_Cost = 5000
Remanufacturing_Cost = 50
Remanufacturing_Time = 2
Reusable_Stock_Keeping_Time = 2
Shipment_Time = 1
SI_Adj_Time = 2
SI_Cover_Time = 1.2
SI_Holding_Cost = 0.4
SI_Transportation_Cost = 1
Unit_Penalty_Cost = 30

References

[1] De Brito M, Dekker R. A framework for reverse logistics. In: Dekker R, Fleischmann M, Interfurth K, Van Wassenhove L, editors. Reverse logistics-quantitative models for closed-loop supply chains. Berlin: Springer; 2004. p. 3–27.

[2] Fleischmann M. Quantitative models for reverse logistics. PhD thesis, Erasmus University, Rotterdam, The Netherlands, 2000.

[3] Nahmias S. Production and operation analysis. 5th ed., New York: McGraw-Hill; 2004.

[4] Forrester JW. Industrial dynamics. Cambridge, MA: MIT Press; 1961.

[5] Barlas Y. System dynamics: systemic feedback modeling for policy analysis in knowledge for sustainable development—an insight into the encyclopedia of life support systems. Paris, France, Oxford, UK: UNESCO Publishing—Eolss Publishers; 2002.

[6] Coyle RG. System dynamics modelling: a practical approach. London: Chapman & Hall; 1996.

[7] Sterman JD. Business dynamics: systems thinking and modeling for a complex world. New York: McGraw-Hill; 2000.

[8] Towill D. Industrial dynamics modeling of supply chains. International Journal of Physical Distribution & Logistics Management 1995;26(2):23–42.

[9] Minegishi S, Thiel D. System dynamics modeling and simulation of a particular food supply chain. Simulation—Practice and Theory 2000;8:321–39.

[10] Sanghwa J, Maday CJ. Dynamic information control for multi-echelon production-distribution systems with constrained production capacity. System Dynamics Review 1996;12(4):331–43.

[11] Zamudio-Ramirez P. The economics of automobile recycling. MS thesis, MIT, Cambridge, MA 02142, 1996 (unpublished).

[12] Taylor H. Modeling paper material flows and recycling in the US Macroeconomy. PhD thesis, Department of Civil Engineering MIT, Cambridge, MA 02139, 1999 (unpublished).

[13] Georgiadis P, Vlachos D. The effect of environmental awareness on product recovery networks design. European Journal of Operational Research 2004;157:449–64.

[14] Fleischmann M, Dekker R, Van der Laan E, Van Numen J, Van Wassenhove L, Ruwaard J. Quantitative models for reverse logistics: a review. European Journal of Operational Research 1997;103:1–17.

[15] Guide Jr VDR, Van Wassenhove L. Closed-loop supply chains. In: Klose A, Speranza MG, van Wassenhove L, editors. Quantitative approaches to distribution logistics and supply chain management. Berlin: Springer; 2002. p. 47–60.

[16] Simchi-Levi D, Kaminsky P, Simchi-Levi E. Designing and managing the supply chain. 2nd ed., New York: McGraw-Hill, Irwin; 2003.

[17] Martinich JS. Production and operations management. New York: Wiley; 1997.

[18] Handfield R, Walton S, Sroufe R, Melnyk A. Applying environmental criteria to supplier assessment: a study in the application of the analytical hierarchy process. European Journal of Operational Research 2002;141(1):70–87.

[19] Barlas Y. Formal aspects of model validity and validation in system dynamics. System Dynamics Review 2000;12(3): 183–210.

[20] Forrester JW, Senge PM. Tests for building confidence in system dynamics models. TIMS Studies in the Management Sciences 1980;14:209–28.