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Performance Evaluation of Stochastic Forward and Reverse Supply Networks

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Abstract

The variability of the arrival and service processes has a strong impact on the performance of supply chain networks (SCNs), especially when the reverse flow to the manufacturer is considered. This paper proposes to use approximate analytical models to quickly evaluate the performance of SCN configurations during the design phase of the forward and reverse supply chains. The models are applied to the case of scrap-based steel production in which the role of the reverse flow is higher compared to the other reverse supply chains since a higher proportion of the raw material is provided by the reverse flow. As the solution methodology, an approach based on the queueing network model has been developed to represent general distributions of the stochastic parameters (i.e. arrival and processing rates). The accuracy of the proposed analytical models is assessed by comparing the results of numerical experiments against discrete-event simulations.

Keywords: forward and reverse supply chain; performance measurement; queueing networks; general distribution

1. Introduction

The study of supply chain network (SCN) configurations in the forward and reverse supply chain plays a vital role especially for the industries in which the proportion of the return rate is higher. Steel production is among these industries since it is almost 100% recyclable. This importance in the reverse supply chain is more evident in scrap-based steel production [1]. Secondary steel production will more than double by 2050 and may surpass primary production between 2050 and 2060 [2]. The recycling of scrap plays an essential role in the conservation of energy because the remelting of scrap requires much less energy than the production of iron or steel products from iron ore [3]. The US Geological Survey reports that "The US domestic steel industry recycles millions of metric tons per year of steel cans, automobiles, appliances, construction materials, and other steel products. The primary source of obsolete steel is the automobile" [4]. Steel is the most versatile industrial material, with many types in different quality classes [1].

The scrap which is used for steel production can be divided into three main categories: process (prompt, pre-consumed) scrap, obsolete (capital, post-consumed) scrap, and home (plant) scrap. Due to technology improvements, the amount of home scrap is being reduced and currently, compared to the previous two types, the proportion of this scrap type is negligible [5].

The study of forward and reverse supply chains has generated interest from approximately 1995 [6]. One of the reasons for this increasing focus is that a well-estimated return rate improves the financial health of the company [7]. Future research trends will pay more attention to this subject due to the advantages for the environment. Also, it is a step forward towards a more independent economy while managing a highly cooperated network among actors will be a challenge [8]. The combination of a forward and reverse supply chain, compared to a forward supply chain, is prone to greater uncertainty since

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the forward flow is internally controlled by the manufacturer, while the reverse flow depends on external factors characterized by greater volatility [9]. Another reason for this increasing focus is the addition of more tiers (e.g. collection and preparation centers) in the reverse flow, while in forward flow the company normally deals with fewer tiers (from the producer to the market) [10]. The uncertainty in reverse supply chain is classified into three factors: the quantity of elements (i.e. post-consumed products, scraps) in the network, the quality of returned products, and the timing of the return flow that is especially important for perishable goods [11]–[13]. Furthermore, there are other variations caused by the endogenous and exogenous factors. The endogenous factors are related to the possibility of not having a structured dataset or even not having data for some parameters. The exogenous factors are related to the uncertainties in the future estimations. Consequently, to calculate these performance measures, a method which embeds all the sources of stochasticity and gives accurate results in a timely manner is desirable.

To design the network for analyzing the feasibility of autonomous collection and preparation centers for the producer, it is necessary to optimize their location or flows based on the uncertainties in the inventory level (for inventory design) and production rates (for the design of production capacity). Another application of this uncertainty analysis is to estimate the long-term availabilities of scrap to analyze the feasibility of the expansion of production activities. The aim of this work is to propose an analytical model for the medium/long-term forecast of the production utilization rate and the average inventory level applied to a supply chain network of the steel sector. Furthermore, the proposed solution approach calculates the average waiting time for the steel scrap at the warehouse and the average production time. The calculations are based on an application case of an Italian scrap-based steel producer described in Section 2. Section 3 gives a brief literature overview on the forward and reverse network characteristics and stochastic analysis in these networks. The analytical formulas which are applicable in this context are explained in Section 4. Section 5 shows how the proposed analytical method can be applied to the case study, while testing its accuracy in different scenarios. Finally, Section 6 draws the conclusions and identifies future developments.

2. Problem statement

The producer (P), produces different types of steel by using steel scrap as the raw material coming from different sources with different quality classes. The quality of each input scrap is checked by sampling from the trucks on their arrival at the plant. The quality control is a costly and time-consuming activity, and therefore, it is limited to a few samplings; as a consequence, the specified quality classes are prone to errors. Arriving scrap is kept in the warehouse from where it is transferred to the production line which uses the electric arc furnace (EAF). The work in process (WIP) after the quality check is then transferred to the ladle furnace (LF). The output is then checked at the second quality control. Therefore, the production rate is volatile and may be different from what is planned.

The produced steel is then transported to the manufacturers of consumer products (M). The high-quality steel produced by the producer is used mostly in the automotive sector. Therefore, the vast majority of these nodes are automotive manufacturers (around 80%).

The suppliers (S) are other steel producers that are directly sending their scraps to the steel producer (P). The collection and preparation centers (L) deal with the treatment of pre- and post-consumed scraps that are transferred to the steel producer. A large amount of post-consumed scrap is from used cars deriving from junkyards. About half of the flow to the producer is from suppliers while the other half is from the collection and preparation centers.

The reference network considered in this study is shown in Fig. 1. The external flows are the possible flows from/to the nodes not located in the reference network to/from the nodes in the reference network and are from the nodes S, M, and C. These flows are the remaining proportion of the scrap which is transferred to the other destinations for treatment and recycling. The external flows to the network are to nodes S, M, and C where the raw material from the mines, the steel from the other producers, and other steel-made products are considered respectively.

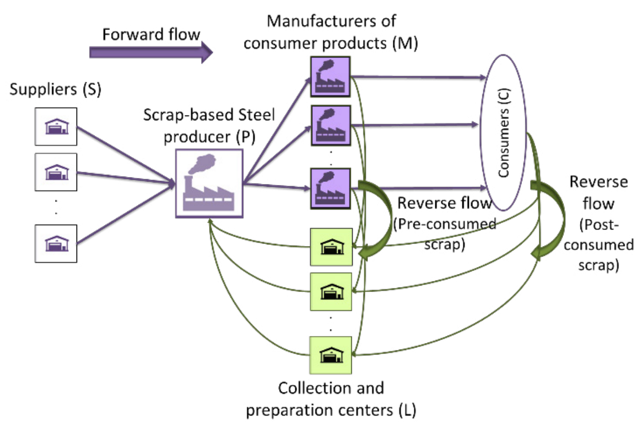

Fig. 1. Forward and reverse flow of the scrap-based steel production.

To design the network for analyzing the feasibility of autonomous collection and preparation centers for the producer and consider the uncertainties in the inventory and production rate of these nodes, the flows between the supply chain tiers and the production rates of each tier are stochastic parameters. The flows to the producer are based on the demand and can have two types of uncertainties. The first type is when there is a specific delivery time for components, but due to reasons such as disruption events caused by transportation modes or supplier delivery problems, the delivery time is not respected. The second type is when the plant defines a time slot and the delivery in any time in this slot is not important, the flows are stochastic during this time slot. Regarding the production rate, the unexpected quality problems prevent the producer from following its daily/weekly production plan and causes uncertainties in the production time.

3. State-of-the-art

The reverse flow could be in different layers of the supply chain network. Generally, these layers can be collection, rework, and disposal centers [10].

Many papers have identified randomly distributed variables for different parameters of the network. The most important random parameters are as follows:

- Production rate of the producer [14], [15]
- Demand for returned products or produced products [14]–[21]
- Disposal rate [14]
- Return flow [15], [16], [18]–[20], [22]
- Service rate in collection centers [23]

Discrete-event simulation (DES) can be used to evaluate the performance of systems like a forward and reverse supply chain. DES models are highly flexible and capable of considering different sources of uncertainty and different statistical distributions. However, the adoption of a DES-based approach can be highly time consuming both for the generation of the DES model and the execution of the simulation runs that are needed for obtaining accurate results within an acceptable confidence interval.

Also, analytical methods, and in particular, queueing networks, can be employed in place of DES to model forward and reverse supply chains and evaluate their performance. Analytical methods are typically faster than DES, but they are based on limiting modelling assumptions that may jeopardize their accuracy.

Analytical methods can be classified into two groups according to how they deal with stochastic parameters. The first group assumes a specific type of distribution for the flows and production rates. This asks to make strong and non-realistic assumptions, but the advantage is that exact formulas can be exploited to estimate the performance of the network. The second group takes a broader and more realistic approach to model the network by enabling to consider more than one distribution or even generic distributions. However, in this case there are no exact formulas, therefore approximate formulas must be adopted based on the characteristics of the network. Table 1 reports some of the papers belonging to the second group and considering general distribution for the stochastic parameters.

Table 1. The studies in which some parameters are used for the performance measurement as general distribution of forward and reverse supply chain (SC).

Reference	Forward SC	Reverse SC	Parameters
[24]	✓		Expected waiting time for the manufacturer, expected number of orders
[25]–[27]	✓	✓	Expected cycle time, expected lead time
[28]		✓	Average availability at the recovery facilities

4. The proposed model

Herein, an analytical model based on open queueing networks is proposed to represent the internal and external flows in a forward and reverse supply chain. Even if less accurate than a DES model, this approach was chosen because it is faster and better suited to support the network design since several network configurations must be assessed. Since we deal with a network design as a medium/long-term decision, the mentioned uncertainties are stable during the time and therefore, the model could be built in a steady-state situation. Another view of the network of Fig. 1 is shown in Fig. 2 where, for each tier, it is assumed that there is only one node. This figure represents external flows, the proportion of flows between the nodes, and the production rates of the nodes S, P, M, and L, as well as the consumption rate of the market (C) as reported in Table 2.

Table 2. Nomenclature.

ρ or ρ_i	Utilization factor of each node
μ or μ_i	Production/consumption rate of each node
C_a^2 or $C_a^2(i)$	Squared coefficient of variation (SCV) of the arrival to each node
C_{pr}^2 or $C_{pr}^2(i)$	SCV of production for each node
C_{pr}	Coefficient of variation (CV) of production for each node
C_d^2 or $C_d^2(i)$	SCV of departures from each node
$C_{a-ext}^2(i)$	SCV of the external arrival to each node
$C_{a-ext}(i)$	CV of the external arrival to each node
m	Number of servers at each node
λ or λ_i	Arrival rate to each node
$\mu_{ext}(i)$	Arrival rate of the external flow to each node
q_{ij}	Proportion of the flows from node i to node j
CI	Confidence interval

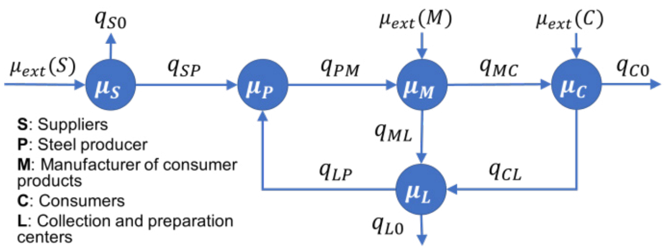

Fig. 2. Internal and external flows between the tiers of the supply chain and the production rates of each tier.

The internal flows between the nodes could be calculated according to traffic equations. A typical assumption for calculating the average amount of scrap is to consider the arrival rates ($\mu_{ext}(S)$, $\mu_{ext}(M)$, $\mu_{ext}(P)$) and production rates (μ_i) as exponential distribution [14], [15]. However, based on the characteristics of the problem, assuming that all the parameters in the industry are exponentially distributed is a strict assumption [29]. According to Section 2, the two types of uncertainties in the flows and the quality problems for the production rate can follow three statistical distributions: exponential, normal, and uniform. Besides, if there is a historical data set, but it is not possible to define a specific distribution, we can consider a general distribution with a specific mean and variance to have a more realistic result [25]. Therefore, independent external arrivals with general distribution (GI), production rates with general distribution (G) and m production/consumption centers are the characteristics of this queueing network (GI/G/m). Furthermore, since the key feature of GI/G/m queueing network is infinite inventory capacity, it is aligned with the characteristics of the network design. Therefore, the inventory capacity could be calculated according to the average inventory level obtained from the queueing network models. In the models of these queueing network types, there are not exact analytical formulas, and so, we use estimations to calculate the expected waiting time (EW) for a tier in the supply chain. This could be calculated by two of the widely-used estimations proposed in the literature for each node of the network. The first one is derived from the heavy traffic approximations with the addition of a correction factor (i.e. $\Phi(\rho, C_a^2, C_{pr}^2, m)$ [30]:

$$EW(GI/G/m) = \Phi(\rho, C_a^2, C_{pr}^2, m)\left(\frac{C_a^2 + C_{pr}^2}{2}\right)EW(M/M/m) \qquad (1)$$

The calculations for the coefficient $\Phi(\rho, C_a^2, C_{pr}^2, m)$ are shown in the appendix A.

And the second one is calculated as follows [31]:

$$EW(GI/G/m) = \frac{C_a^2(1-(1-\rho)C_a^2)/\rho + C_{pr}^2}{2} EW(M/M/m) \qquad (2)$$

Where $EW(M/M/m)$, the expected waiting time for the exponential arrival and production rates, is calculated as follows:

$$EW(M/M/m) = \frac{m^{m-1}\rho^m}{m!\mu(1-\rho)^2} \cdot \frac{1}{\sum_{k=0}^{m-1}\frac{(m\rho)^k}{k!} \cdot \frac{m^m\rho^m}{m!(1-\rho)}} \qquad (3)$$

The calculation of the squared coefficient of variation (SCV) of the arrival to each node (i) depends on the SCV of the departure from the other nodes (j) and external flows. The estimation equations are as follows [31]:

$$C_a^2(i) = \sum_j \frac{\lambda_j q_{ji}}{\lambda_i}.(q_{ji}C_d^2(j) + (1-q_{ji})) + \frac{\gamma_i \mu_{ext}(i)}{\lambda_i}.[\gamma_i C_{a-ext}^2(i) + (1-\gamma_i)] \qquad (4)$$

$$C_d^2(j) = (1-\rho_j^2).C_a^2(j) + \rho_j^2 C_{pr}^2(j) \qquad (5)$$

Where γ_i is the fraction of the external flow to node i ($\gamma_i = \frac{\mu_{ext}(i)}{\lambda_i}$).

5. Model application and results

The analytical formulas in the previous section are applied to the forward and reverse network of Fig. 2 for the scrap-based steel production. The focus of the calculations in this study is on the average availability at node *L*. Other performance measures (i.e., average inventory level and the average availability of scrap in the production phase) could be obtained from Little's theorem. Therefore, the goal of this section is to solve the problem stated in Section 2 for designing the forward and reverse supply chains. The average inventory level is useful to assign the inventory capacity for the nodes *P* or *L*. The average availability of scrap in the production phase is useful to assign the production capacity. The input parameters are the mean and standard deviations of the external arrivals (to nodes *S*, *M*, *C*), mean and standard deviation of the production rates of each node, and the proportion of the flows in the network. To initialize the calculations, the arrival rate at each node is calculated according to the traffic equations. The main input data taken from the producer are the mean and standard deviations of the production rate, considering the variations of the quality of input scrap, the input flows from the suppliers and collection and preparation centers as well as the output flow to the manufacturers of consumer products. In addition, the data for the collection and preparation centers are based on the data from a company which is the main supplier (in node *L*) for the producer. The remaining data for the other nodes is based on the estimation from the statistical data.

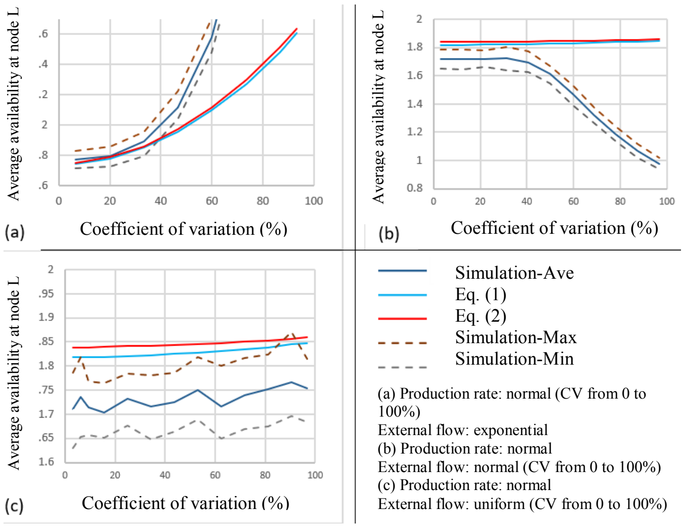

Fig. 3. Analysis of the accuracy of the models against the changes of CV.

To check the accuracy of the equations, a set of experiments have been implemented in which, by increasing the standard deviation of the external flows and the production rates for a specific mean (i.e. coefficient of variation), the changes of the average availability amount of scrap is analyzed. To make the coefficient of variation (CV) changes for both the production rate and external flows comparable, CV is shown as a percentage on the graphs. The accuracy of the results obtained by the analytical formulas is assessed by making a comparison with a discrete-event simulation implemented in Java Modelling Tools (JMT) [32]. In the simulation, exponential, uniform, and normal distributions are used for the external flows and production rates. Each simulation run is replicated five times since more replications do not further improve the accuracy of the results. Fig. 3 shows an example of three graphs for these calculations. In Fig. 3 (a), the increase in the CV of the production rate as a normal distribution causes an increasing and nonlinear trend of the average availability of scrap. The same interpretation is valid for the increase in the CV of external flow with the normal distribution in Fig. 3 (b). Fig. 3 (c) shows the changes in the uniform distribution of the external flow, which is almost linear and stable around a fixed amount of average availability (1.7). The confidence interval for the simulation results is 95% except for some cases in which the CV is around one. In the latter case, the confidence interval reduces to around 85% due to the higher variations. As a general observation, by increasing the coefficient of variation of both external flows and production rate until around 40%, Eq. (1) gives better results compared to Eq. (2) except in cases where the distribution of the external flow is exponential. In the latter case, Eq. (2) gives accurate results until 40% of the CV. For more than 40% of the coefficient of variation, the results are not reliable.

Although the results of Eq. (2) are closer to the simulation results for most of the cases, they show overestimations in some cases. To study the effect of different factors on these overestimations, a set of experiments have been designed. For each experiment, three factors are considered with two different levels for each one. The factors are the utilization factor, the squared coefficient of variation (SCV) of the arrival, and the SCV of the production rate of the nodes (Table 3). The range of the changes for each factor is based on the result of the previous set of experiments. Therefore, the SCV of arrival changes between 0.01 and 0.03 to be aligned within the 40% of the CV. The difference between the Eq. (1) and the maximum amount obtained by the simulation ('max' column) is calculated to show the distance in which the result is acceptable. The results of the experiments show that for low values of the utilization factor (0.2), the approximation is very accurate, or with negligible overestimations (less than 0.05), while it is overestimated for high utilization factors (0.8). However, more experiments show that sometimes, for high utilization factors, the results are exact. To check the accuracy more in detail, Table 4 shows the trend of the accuracy of the formula against the changes of utilization factor. The other two factors in the previous experiment (SCV of external arrival and production) are kept fixed for these sets of experiments. The trend shows that, until around the utilization factor of 0.5, the model gives exact results while from 0.5 onwards, it results in overestimations.

Table 3. Experiments on the accuracy of the models on the application case ((1): Eq. (1), Diff.: Difference between the Eq. and simulation in case of overestimation, Ave: Average, Acc.: Accuracy, Over: Overestimation).

ρ	C_{pr}^2	C_{a-ext}^2	Simulation			(1)	Acc.	Diff.	CI
			Ave	Min	Max				
0.8	0.09	0.09	1.41	1.35	1.47	1.63	Over.	0.17	95%
0.2	0.09	0.09	0.21	0.20	0.22	0.21	Exact		
0.2	0.09	0.01	0.21	0.20	0.22	0.21	Exact		
0.8	0.01	0.09	1.28	1.24	1.32	1.51	Over.	0.19	
0.8	0.09	0.01	1.31	1.24	1.39	1.59	Over.	0.2	
0.2	0.01	0.09	0.21	0.20	0.21	0.21	Exact		
0.2	0.01	0.01	0.21	0.20	0.22	0.21	Exact		
0.8	0.01	0.01	1.23	1.17	1.28	1.47	Over.	0.18	

Table 4. The accuracy of the analytical model against the changes of the utilization factor.

ρ	C_{pr}^2	C_{a-ext}^2	Simulation			(1)	Acc.	Diff.	CI
			Ave	Min	Max				
0.1	0.09	0.09	0.1	0.1	0.11	0.1	Exact		95%
0.5			0.59	0.57	0.6	0.6	Exact		
0.8			1.4	1.34	1.47	1.63	Over.	0.16	
0.9			2.49	2.39	2.61	3	Over.	0.39	

All in all, Fig. 4 represents the general solution approach and conditions to use each of the analytical models. The first point is to check the standard deviation and its proportion to the mean for the production rate of the node and the external flows to the network (i.e., the coefficient of variation). The assumption of this study is to have a range of CV between zero and one. If the standard deviation of the external flow is almost equal to the mean (CV=1), Eq. (2) is the appropriate one to use. Otherwise, if the utilization factor of the node is up to 0.5, Eq. (1) gives the exact results (or if there is an overestimation, it is negligible). For the higher utilization factors, Eq. (1) could be applied with some overestimations. The calculation time for the analytical models in MATLAB is less than one second. Regarding the discrete-event simulation, the running time in JMT depends on the values of the standard deviation and the utilization factor and is between around 10 and 30 seconds for five replications, calculating the average, minimum, and maximum values for each replication. Therefore, the analytical models are both more efficient and stable in the calculation time.

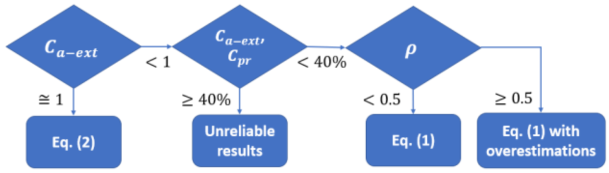

Fig. 4. Solution approach.

6. Conclusion

This paper proposes a solution approach to estimate the performance measures in the design phase of forward and reverse supply chains of scrap-based steel production. The real distribution of the inbound flows and production rates of the nodes are unknown. To validate the models, we design and run a set of experiments where the variables have exponential, normal, or uniform distributions. In this way, the solution approach identifies how to use the models in different configurations. It is verified that the analytical models are much quicker compared to the discrete-event simulation. Moreover, the experiments show that for the calculations of the performance measures of a specific node, the variability of the production rate of the other nodes does not affect the solution.

The results of the analyses help the decision-makers for designing the forward and reverse supply network to have a reliable estimation of the inventory and production capacity for both the producer and collection and preparation centers.

In cases where the analysis of all the tiers in the network is not desired, the models could be applied to a part of the network. In this case, the internal flows that are not considered in the new configuration are counted as the external flows. In addition, the proposed solution approach could be applied for the workstations and buffers in the production lines with a similar configuration of this study.

Further studies could be focused on the reduction of the overestimations of the results of the analytical formulas compared to the simulation, the analysis of the effect of the quality variations of the scrap on the stochasticity of the production rate, and the possible correlations between the flows and production rates.

Appendix A. The correction factor for Eq. (1)

The calculations for the correction factor $\Phi(\rho, C_a^2, C_{pr}^2, m)$ in Eq. (1) are as follows:

$$\Phi(\rho, C_a^2, C_{pr}^2, m) = \begin{cases} \left(\frac{4(C_a^2 - C_{pr}^2)}{4C_a^2 - 3C_{pr}^2}\right)\Phi_1(m,\rho) + \left(\frac{C_{pr}^2}{4C_a^2 - 3C_{pr}^2}\right)\Psi(c^2, m, \rho), & C_a^2 \geq C_{pr}^2 \\ \left(\frac{C_{pr}^2 - C_a^2}{2(C_a^2 + C_{pr}^2)}\right)\Phi_3(m,\rho) + \left(\frac{C_{pr}^2 - 3C_a^2}{2(C_a^2 + C_{pr}^2)}\right)\Psi(c^2, m, \rho), & C_a^2 \leq C_{pr}^2 \end{cases}$$

$$\Phi_1(m,\rho) = 1 + \gamma(m,\rho) \quad ; \quad \Phi_3(m,\rho) = (1 - 4\gamma(m,\rho))\, e^{-\frac{2(1-\rho)}{3\rho}}$$

$$\Psi(c^2, m, \rho) = \{ \begin{matrix} 1, & c^2 \geq 1 \\ \Phi_4(m,\rho)^{2(1-c^2)}, & 0 \leq c^2 \leq 1 \end{matrix}$$

$$\gamma(m,\rho) = \min\{ 0.24 , \frac{(1-\rho)(m-1)[(4+5m)^{0.5} - 2]}{16m\rho} \}$$

$$c^2 = \frac{C_a^2 + C_{pr}^2}{2} \quad ; \quad \Phi_4(m,\rho) = \min\{1, \frac{\Phi_1(m,\rho) + \Phi_3(m,\rho)}{2}\}$$

References

[1] EUROFER, "Steel and the Circular Economy," 2015. [Online]. Available: http://www.eurofer.org/News&Events/PublicationsLinksList/20151016_CircularEconomyA4.pdf.

[2] S. Pauliuk, R. L. Milford, D. B. Muller, and J. M. Allwood, "The Steel Scrap Age," *Environ. Sci. Technol.*, vol. 47, no. 7, p. pp.3448-3454, 2013.

[3] M. D. Fenton, "Iron and steel scrap," in *Minerals yearbook*, vol. 1, 2010, p. 38.1.

[4] U.S. Geological Survey, "Iron and steel scrap," 2017.

[5] D. Janke, L. Savov, H.-J. Weddige, and E. Schulz, "Scrap-Based Steel Production and Recycling of Steel," *Mater. Tehnol.*, vol. 34, no. 6, pp. 387–399, 2000.

[6] S. Rubio, A. Chamorro, and F. J. Miranda, "Characteristics of the research on reverse logistics (1995-2005)," *Int. J. Prod. Res.*, vol. 46, no. 4, pp. 1099–1120, 2008.

[7] S. Bhattacharjee and J. Cruz, "Economic sustainability of closed loop supply chains: A holistic model for decision and policy analysis," *Decis. Support Syst.*, vol. 77, pp. 67–86, 2015.

[8] T. Tolio, G. Copani, and W. Terkaj, "Key Research Priorities for Factories of the Future—Part I: Missions," in *Factories of the Future*, Cham: Springer International Publishing, 2019, pp. 433–474.

[9] M. Fleischmann, H. R. Krikke, R. Dekker, and S. D. P. Flapper, "A characterisation of logistics networks for product recovery," *Omega*, vol. 28, no. 6, pp. 653–666, 2000.

[10] M. T. Melo, S. Nickel, and F. Saldanha-da-Gama, "Facility location and supply chain management - A review," *Eur. J. Oper. Res.*, vol. 196, no. 2, pp. 401–412, 2009.

[11] A. Atasu, V. D. R. Guide, and L. N. Van Wassenhove, "Product Reuse Economics in Closed-Loop Supply Chain Research," *Prod. Oper. Manag.*, vol. 17, no. 5, pp. 483–496, Sep. 2008.

[12] M. de Keizer, R. Akkerman, M. Grunow, J. M. Bloemhof, R. Haijema, and J. G. A. J. van der Vorst, "Logistics network design for perishable products with heterogeneous quality decay," *Eur. J. Oper. Res.*, vol. 262, no. 2, pp. 535–549, 2017.

[13] P. Chanintrakul, "Reverse logistics network design : a state-of-the-art literature review Adrian E . Coronado Mondragon , Chandra Lalwani and Chee Yew Wong *," vol. 1, no. 1, 2009.

[14] A. Korugan, S. Ata, and M. Fadiloglu, "The Impact of Orbit Dependent Return Rate on the Control Policies of a Hybrid Production System," in *SMMSO 2017*, 2017, pp. 201–208.

[15] H. Zerhouni, J. P. Gayon, and Y. Frein, "Influence of dependency between demands and returns in a reverse logistics system," *Int. J. Prod. Econ.*, vol. 143, no. 1, pp. 62–71, 2013.

[16] M. Fleischmann, R. Kuik, and R. Dekker, "Controlling inventories with stochastic item returns: A basic model," *Eur. J. Oper. Res.*, vol. 138, no. 1, pp. 63–75, 2002.

[17] X.-M. Yuan and K. L. Cheung, "Modeling returns of merchandise in an inventory system," *OR Spektrum*, vol. 20, no. 3, pp. 147–154, 1998.

[18] G. P. Kiesmüller and E. A. Van der Laan, "An inventory model with dependent product demands and returns," *Int. J. Prod. Econ.*, vol. 72, no. 1, pp. 73–87, 2001.

[19] M. Ferguson, V. D. Guide, E. Koca, and G. C. Van Souza, "The value of quality grading in remanufacturing," *Prod. Oper. Manag.*, vol. 18, no. 3, pp. 300–314, 2009.

[20] E. van der Laan, M. Salomon, R. Dekker, and L. Van Wassenhove, "Inventory Control in Hybrid Systems with Remanufacturing," *Manage. Sci.*, vol. 45, no. 5, pp. 733–747, 1999.

[21] L. B. Toktay, L. M. Wein, and S. A. Zenios, "Inventory Management of Remanufacturable Products," *Manage. Sci.*, vol. 46, no. 11, pp. 1412–1426, 2000.

[22] M. P. de Brito and R. Dekker, "Modelling product returns in inventory control - Exploring the validity of general assumptions," *Int. J. Prod. Econ.*, vol. 81, no. 82, pp. 225–241, 2003.

[23] B. Vahdani, R. Tavakkoli-Moghaddam, M. Modarres, and A. Baboli, "Reliable design of a forward/reverse logistics network under uncertainty: A robust-M/M/c queuing model," *Transp. Res. Part E Logist. Transp. Rev.*, vol. 48, no. 6, pp. 1152–1168, 2012.

[24] S. Srivathsan and M. Kamath, "An analytical performance modeling approach for supply chain networks," *IEEE Trans. Autom. Sci. Eng.*, vol. 9, no. 2, pp. 265–275, 2012.

[25] K. Lieckens and N. Vandaele, "Reverse logistics network design with stochastic lead times," *Comput. Oper. Res.*, vol. 34, no. 2, pp. 395–416, 2007.

[26] K. Lieckens and N. Vandaele, "Multi-level reverse logistics network design under uncertainty," *Int. J. Prod. Res.*, vol. 50, no. 1, pp. 23–40, 2012.

[27] K. T. Lieckens, P. J. Colen, and M. R. Lambrecht, "Optimization of a stochastic remanufacturing network with an exchange option," *Decis. Support Syst.*, vol. 54, no. 4, pp. 1548–1557, 2013.

[28] D. Si-Bo and H. Wei-lai, "Reverse Logistics Optimization Based on GI/G/m," in *InService Systems and Service Management*, 2007.

[29] W. . Hopp and M. L. Spearman, *Factory physics*, Waveland P. 2011.

[30] W. Whitt, "Approximations for the GI/G/m queue," *Prod. Oper. Manag.*, vol. 2, no. 2, pp. 114–161, 1993.

[31] J. Buzacott and J. Shanthikumar, *Stochastic models of manufacturing systems*. Englewood Cliffs, NJ: Prentice Hall, 1993.

[32] M. Bertoli, P. Milano, M. Hall, and G. Serazzi, "JMT - Performance Engineering Tools for System Modeling," *ACM SIGMETRICS Perform. Eval. Rev.*, vol. 36, no. 4, pp. 10–15, 2009.