Product acquisition management in a high-end server remanufacturing environment

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Abstract: Product acquisition management (PrAM) processes are considered powerful value-added product recovery activities in closed-loop supply chain (CLSC) business models. Aside from their potential manufacturing cost savings, these recovery activities are environmentally friendly and energy conservative, and the activities must abide by government regulations. Although remanufacturing of returned products is less costly than manufacturing, the variability and uncertainties in returned products' cost, quality, quantity, and timing of return remain vital issues for returned products' inventory disposition and order fulfilment. This study discusses the characteristics of PrAM processes and proposes a decision support system framework for inventory disposition and customer order fulfilment in a high-end server hybrid business model. The proposed framework incorporates clustering algorithm, multi-criteria decision-making technique, and heuristic algorithms by meeting customer requirements and budget constraints. Experimental results ensure comprehensive, efficient, and timely decision support of the proposed framework by evaluating its performance and feasibility using real-world data.

Keywords: closed-loop supply chain; CLSC; product acquisition management; PrAM; inventory disposition; customer order fulfilment; high-end server manufacturing.

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1 Introduction

The primary goal of any economic system is to meet customers' demand by delivering goods and services and increasing the standard of living. In mixed market economic conditions, the goals of the economic system must obey government regulations. Therefore, to meet customer satisfaction and government regulations, manufacturing systems have evolved over time by adopting various production theories, tools, and techniques. Inventions in metallurgy, mining, chemicals, energy, and transportation are all contributing to the advancement of manufacturing systems. Finally, the incorporation of supply chain (SC) network, more specifically, closed-loop supply chain (CLSC) network, as a consequence of the continuous growth of manufacturing not only increases customer satisfaction but also increases profits and market shares of businesses. The product acquisition management (PrAM) plays a key role in CLSC as it involves the value-added product recovery activities. PrAM focuses on the acquisition of used and discarded products, components, and materials that fall under the responsibility of companies that engage in remanufacturing. According to Guide and Jayaraman (2000), PrAM should ensure accurate forecasts of volumes of cores available by specific planning period. Moreover, PrAM can balance the acquisition of cores with final customer demands and ensures that the firm avoids disposing costly cores, or lost revenues due to unfulfilled customer orders.

The activities of PrAM include acquisition of used products, grading them into several groups for value recovery, and disposing of them for product recovery operations (PRO). PRO aims to extend the life cycle of used products by retaining their residual values. An industry can receive different types of used products through its entire life cycle. Based on the type of return objects (items or services) and return recovery options, basic return recovery networks can be classified into:

1 directly reusable network

2 remanufacturing network

3 repair service network

4 recycling network (Lu and Bostel, 2007).

There exist significant uncertainties in the timing, quality, quantity, cost of collection, and value recovered from returns (Aras et al., 2004; Sabharwal and Garg, 2013; Souza and Ketzenberg, 2002). Thus, the PrAM serves as the foundation for the development of any CLSC-based industrial systems.

The main motivations for PrAM activities are to deal with the threats caused by environmental degradation, waste management issues, and the scarcity of resources. Thus, remanufacturing could be more economical than manufacturing. Remanufacturing is environmentally friendly and abides by government regulations (Laan and Teunter, 2006; Sabharwal and Garg, 2013). Remanufacturing is advantageous from the perspectives of labour, capital, product quality, and production lead-time which has positive impacts on production cost, energy and raw material savings, balancing production lines, exploring new market markets, and developing a green, socially concerned image (Souza and Ketzenberg, 2002; Lu and Bostel, 2007; Bulmus et al., 2014; Shaharudin et al., 2015). According to a study conducted in the USA in 2003, the size of the remanufacturing sector was built on \$53 billion dollars, with 70,000 firms and 480,000 employees (Hauser and Lund, 2003). These numbers have been increasing rapidly over the years. The estimated average profit margin was more than 20%, and throughout the world, the investments on remanufacturing sectors exceeded \$100 billion (Nasr et al., 1998). It was reported that with only 20% of its effort, remanufacturing could lower the production cost of manufacturing new items up to 40%–60% (Mitra, 2007). The price of remanufactured products is generally 30%–40% of an equivalent new product (Mukherjee and Mondal, 2009). During the period 2008–2009, Fuji Xerox Australia saved \$6 million by remanufacturing more than 230,000 equipment parts rather than using new parts (Van, 2009). The governments of many countries encourage the remanufacturing process by providing tax credit benefits. Remanufacturing processes consume 15% less energy, and dismantling parts typically costs 80% less than creating new parts (Fleischmann et al., 2003). As a result, the production of remanufactured products in the USA increased from \$37.3 billion in 2009 to \$43 billion in 2011 (Treat, 2012). Thus, PrAM processes lower production and inventory costs, increased revenues and customer service levels, and improved profitability. The motivations of this research can be summarised as follows:

- Government regulations for environmental protection to minimise waste disposal and ensure environmental sustainability (Mukherjee and Mondal, 2009; Golinska and Kuebler, 2014).
- Lower product recovery costs due to the reuse of components and the increase in profits by selling the components in secondary markets (Fleischmann et al., 2003; Laan and Teunter, 2006; Sabharwal and Garg, 2013).
- Green, socially-concerned image offers competitive advantage in the marketing platform (Parlikad and McFarlane, 2007; Bulmus et al., 2014).

During the earlier ages of CLSC, technical and operational issues were the key concern. The technical and operational level bottlenecks remain a major concern while establishing a potential CLSC. Even though the remanufacturing process is technically feasible, the PrAM processes should be economically attractive and sustainable. In this perspective, research focus should be paid to the availability of right quantity of used products at the right time (time of return and quantity uncertainty), and in a reusable condition (quality uncertainty) to enable a cost-effective and sustainable PrAM process. However, the characteristics of the PrAM processes can vary significantly due to product characteristics, market condition, and government regulations. The variations of a product's PrAM processes can be attributed to its SC business model, types of product returned, and the production environment.

In this paper, we study the characteristics of PrAM process and identify important life cycle usage (LCU) factors. The main objective is to develop a decision support system (DSS) for inventory disposition of returned products and customer order fulfilment. The proposed DSS helps to manage uncontrolled accumulation of cores (value recoverable returned products) level inventory.

The rest of this paper is organised as follows: Section 2 details the relevant background and identifies the unique features of this research. Section 3 discusses the proposed DSS framework that incorporates LCU factors to support returned products' inventory disposition and order fulfilment decisions. Section 4 discusses the experimental results. Finally, conclusions and future directions of this research are addressed in Section 5.

2 Related literature

Many aspects of research and practice can be found in the literature on CLSC, including

1 collection of used products through the return logistics (RL) operations

2 sorting, testing, and disposition of different items, such as recycled materials, spare parts, remanufactured products, disposal materials, or as-is products

3 delivery of remanufactured items to distributors and end customers.

Research was conducted to review the analytical models proposed on these operational areas. For example, Wu (2015) discussed the strategic and operational decisions in remanufacturing environments considering sales and collection competitions. The author formulated a CLSC model to study the effect of equilibrium prices and incentives. Another study by Sabbaghi et al. (2016) investigated some equilibrium solutions for product return in the presence of heterogeneous and homogeneous consumers. The study also provided managerial insights on the factors that affect acquisition product return decisions. A theoretical model for examining the intention and perception of consumers' for retuning the used products was discussed in Jena and Sarmah (2015). Results from the study showed that the return intention is negatively influenced by the perceived risk and is positively influenced by perceived benefit and social awareness. In Zhang and Zhang (2017), the impact of strategic customer behaviour on the economic and environmental values was investigated. The interaction between trade-in remanufacturing and strategic customer behaviour needs to be considered in the strategic decision for product acquisition.

The conducted research on CLSC can be broadly divided into three categories, namely PrAM, production planning and inventory management (PPIM) and reverse distribution planning (RDP). Research contributions on PrAM are divided into two categories: market-driven and waste-driven, based on the returned product acquisition process. The market-driven PrAM is based on financial incentives to motivate end-users to return their products to a firm specialising in the reuse of those products. The waste-driven PrAM is based on diverting discarded products from landfills by making producers responsible for the collection and reuse of their products (Guide and van Wassenhove, 2001). Most research on market-driven PrAM proposed pricing policies as returned products are collected through financial incentives. Researchers took initiatives to minimise quality and quantity uncertainties, streamline value recovery processes, and resolve technical and operational levels issues. Table 1 summarises the research contributions on pricing policies of market driven PrAM.

Most researchers considered a limited number of factors as decision parameters in a make-to-stock (MTS) production system by setting cost savings or profit maximisation as the prime goal. However, the research on PrAM process for assemble-to-order (ATO) production system in CLSC business model has not been given sufficient attention. In addition, multiple decision support factors, such as quality-time sensitivity, LCU, and durability of returned products, can increase the usage of returned products for value recovery processes. The production system performs both ATO and re-ATO processes. According to Oh and Behdad (2017), the number of studies addressing the reassembly planning in remanufacturing systems is very limited.

Product acquisition in computer and electronics manufacturing has only been studied by a limited number of researchers. For example, Alcantara-Concepcion et al. (2016) investigated the environmental impacts of computers at the end of their life cycle and discussed some management alternatives. White et al. (2003) also discussed management challenges and environmental impacts of remanufacturing in computer industry. However, these studies did not consider production and inventory management and cost reduction. Thus, this study proposes a multi-attribute DSS framework for PrAM processes of an ATO-type production system in a waste-driven CLSC business model to manage uncontrolled accumulation of cores level inventory. The proposed framework is implemented in a high-end server manufacturing industry. The proposed framework can effectively reduce the uncontrolled accumulation of the returned products, carrying costs, build cycle time, and assembly cost. All these advantages can be helpful in offering competitive selling price of remanufactured products to the customers. Furthermore, waste-driven PrAM avoid shortages and enable competitive advantage by accepting all returns to have higher disposition options. Table 2 summarises the research contributions on waste-driven PrAM into four key areas.

Table 1 Research contributions on pricing policies of market-driven PrAM

Authors	*Quality class*	*Research areas*	*Time period*	*Price deciding factors*	*Contributions*
Klausner and Hendricson (2000), Vlachos and Dekker (2003), Karakayali et al. (2007), Guide et al. (2003), Ray et al. (2005), Liang et al. (2009) and Yang et al. (2016)	Single or multiple	Static acquisition and/or selling price	Single	Considered either one or two factors: • Product demand • Quality • Market condition • Future sales price	Profit maximisation/ cost savings
Xiong and Li (2013), Sun et al. (2013) and Keyvanshokooh et al. (2013)	Single or multiple	Dynamic selling price	Single or multiple	Considered either one or two factors: • Acquisition cost • Product demand • Inventory level • Customer location	Profit maximisation/ cost savings

Table 2 Research contributions on waste-driven PrAM

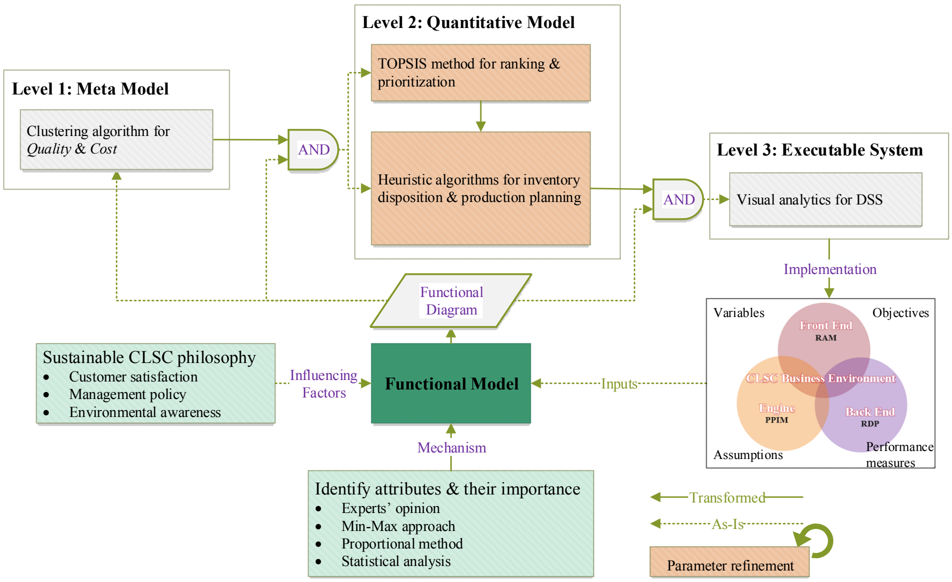
Authors	*Areas*	*Approaches*	*Contributions*
Klausner and Hendrickson (2000), Guide et al. (2003), Ray et al. (2005), Karakayali et al. (2007), Liang et al. (2009), Zhou and Yu (2011) Keyvanshokooh et al. (2013), Sun et al. (2013) and Xiong and Li (2013)	Pricing policy	Analytical formulation, econometric modelling, mathematical modelling, geometric Brownian motion, Markov decision process, mixed integer linear programming	• Buy-back price • Unit cost of RL • Price deciding factors: quality, customer location • Acquisition price and policy • Logistic network designs • Inventory decisions • Remanufactured quantity
Guide and van Wassenhove (2001), Ferguson and Tokay (2006) and Karakayali et al. (2007)	Recovery strategy	Economic value analysis, entry-deterrent strategies, heuristics algorithm	• Profitability assessment • Remanufacturing decision • Quality dependent disposition
Aras et al. (2004), Robotis et al. (2005), Galbreth and Blackburn (2006) and Zikopoulos and Tagaras (2007)	Acquisition and sorting policy	Markov decision process, mathematical modelling, analytical formulation	• Quality dependent disposition • Procurement and remanufacturing quantity • Optimal acquisition and sorting policy
Vlachos and Dekker (2003), Savaskan and van Wassenhove (2006) and Zikopoulos and Tagaras (2007)	Reverse logistics	Classical newsboy modelling, simple approximation method, mathematical modelling, analytical formulation	• Return handling options • Yield correlation with quality • Economic viability of collection channels

3 Research methodology

The proposed research methodology for inventory disposition and management, production planning, and customer order management in CLSC business environment is shown in Figure 1. The proposed methodology consists of four models, namely functional model, level 1: Meta model, level 2: quantitative model, and level 3: executable system. The framework takes inputs (e.g., variables, objectives, assumption, performance measures, etc.) from the CLSC business environment through the functional model. The outputs of the functional diagram are directly fed into level 1. For levels 2 and 3, the outputs of the functional diagram are combined with the lower level outputs with the help of an AND gate to feed the respective level. The models in levels 1 and 2 create new attributes, based on the activity diagram and attributes provided by the functional diagram. The new attributes are combined with the existing attributes of the functional diagram to feed the models of the next level. The fault tree analysis approach is applied to combine series of lower level events using Boolean logic to feed upper levels (Tyagi et al., 2010). The attributes obtained from the Meta models in level 1 are connected with an OR gate. The OR gate is activated when any of the level 1 models creates new attributes. The AND gate incorporates the new attributes obtained from the Meta models with the functional diagram. The outputs of the AND gates are the activity diagram and the attributes that feed the models in level 2. Similarly, new attributes created by level 2 are also incorporated with the functional diagram using the AND gate. Level 3 (executable system) takes the activity diagram attributes as inputs and provides DSS outputs that can be implemented in the business environment. The following discussion illustrates the methodology and provides justification for each step of the four models that forms the proposed framework.

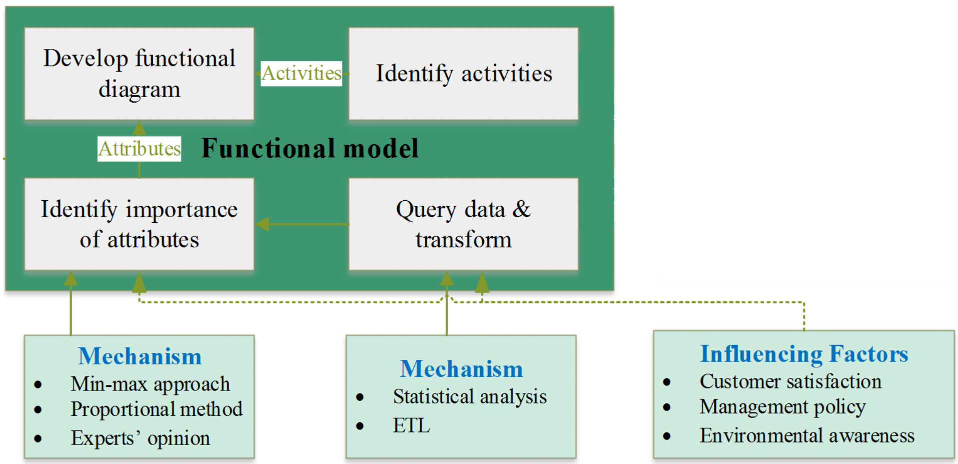
The functional model, in Figure 2, is a structured representation of processes to logically model the behaviour of a real-world scenario for achieving objectives/goals. Thus, it relates to the modelling of objects or relations that have an objective/goal (Gadomski, 2006). The functional model describes logical flow of activities, how objects and attributes move, performs transformation of inputs to develop the functional diagram. However, it does not prescribe how functional diagram can be implemented. Meta and quantitative models of the framework take functional diagram as input, apply model steps to create new attributes for the activities of the functional diagram, and finally, feed them into the executable system to develop the DSS that can be implemented in the CLSC business environment.

Figure 1 Research framework (see online version for colours)



Understanding of the problem is very crucial to identify the activities and influencing factors for the functional diagram. To identify the attributes and activities for the functional diagram, the data requirements for the inputs is first determined. In general, the data sources can be classified into internal (e.g., product design, reliability, disposition, production, location, life cycle, logistics, sales, procurement, inventory, and supply) and external (e.g., marketing, consumers, government legislation, corporate and environmental policies, advanced process, and similar businesses). Data can be collected using various data collection techniques, such as interviews, registration, questionnaires and surveys, direct and indirect observations, scientific research, data logging, documents and records, and focus groups. The collected data are stored in structured and unstructured data format. No source of data can be more meaningful than the value of perfect data. Thus, finding out the data sources, deciding on the collection techniques, collecting appropriate data in the right format are some of the key challenges mechanisms, e.g., statistical analysis and extract, transform, load (ETL) help to extract data from different (homogeneous and heterogeneous) sources, transform data into proper format for query and analysis, and load them into the functional model. They also clean the input data in order to improve their quality. Some of the common causes of data quality issues include misspellings, missing information, duplicate entries, contradictory values, structural conflicts, inconsistent data or other invalid data during the data entry processes. The need of data cleansing is increasing important with the increased use of data for solving problems.

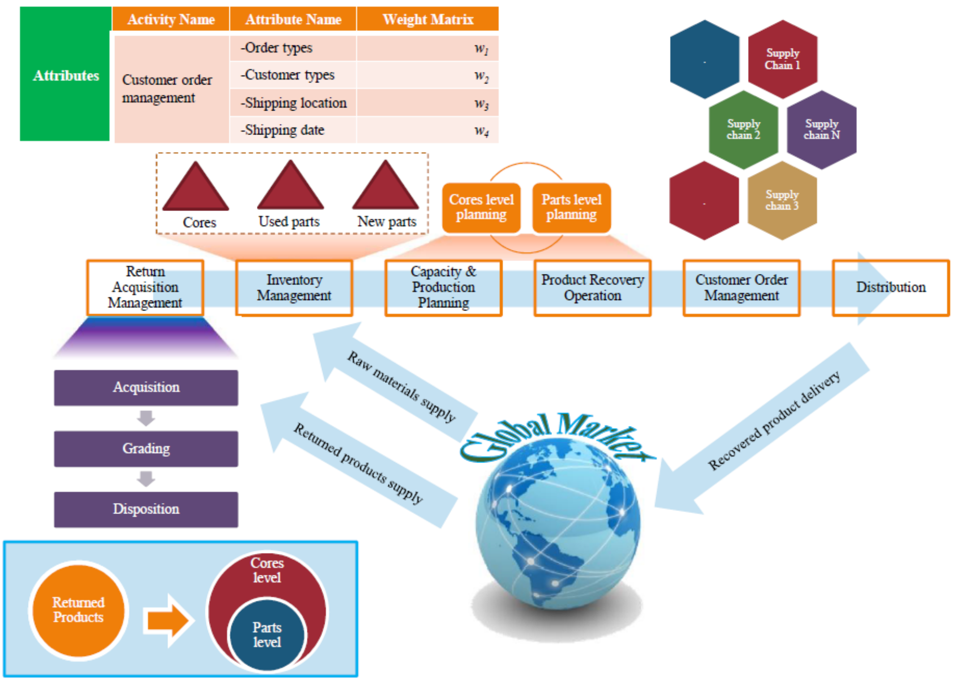
Figure 2 Hierarchical functional model (see online version for colours)



Competitive advantage of a company relies on the extent of stakeholders' influence in value-creating decisions. Stakeholders are accountable for environmental, economical, and social aspects of a company's decisions (Parmigiani et al., 2011). Thus, stakeholders' interests are important factors to consider when selecting and determining the attributes' weights and importance. For the proposed framework, customer satisfaction, managerial policy, and environmental awareness are considered as the influencing factors. These factors can influence the mechanism element so that the DSS can enable economic and environmental sustainability by generating revenue, meeting government regulations, and satisfying both customers and employees.

In Figure 3, the activities and attributes of the CLSC business model functional diagram are presented. The PrAM operation includes the acquisition, grading, and disposition activities on return products. The returned products, also called cores, are used either 'as-is' or are torn down into part level. Inventory is managed into cores, used, and new parts levels. Planning for capacity, production as well as PRO management should be made for both core and part levels. Customer order management stage handles customer orders of various SCs. Distribution stage delivers the recovered products to the global market. Along with the activities, Figure 3 also shows the weight matrix (W_l) for the customer order management attributes.

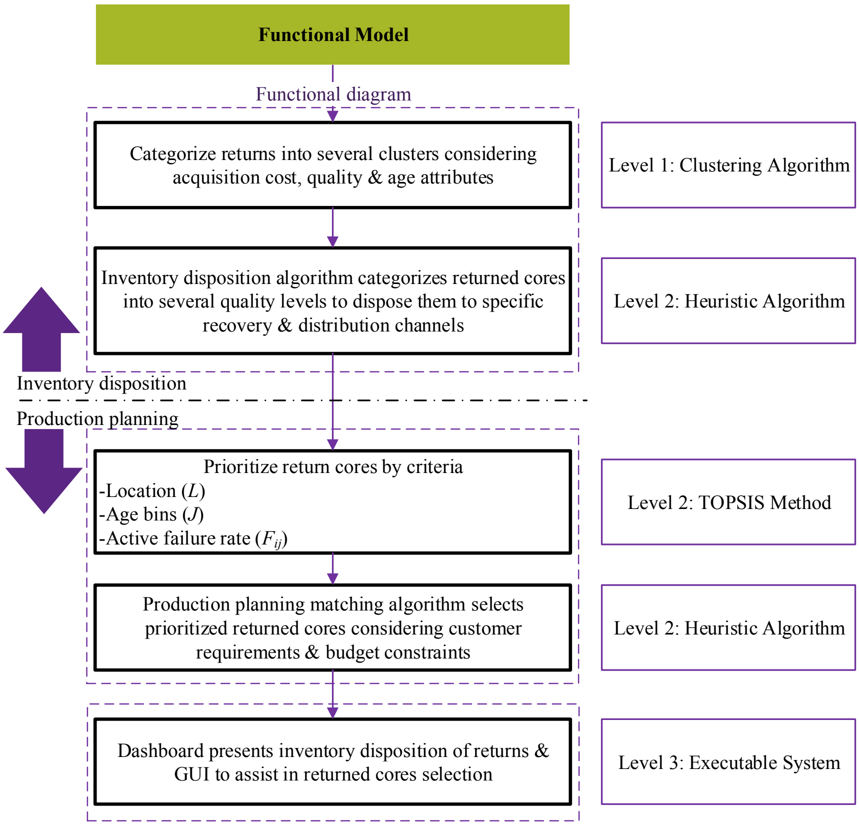
Figure 3 Illustration of attributes and activities in functional diagram (see online version for colours)



3.1 Decision support system

Figure 4 illustrates the methodology of the proposed DSS that assists value recovery disposition decision and selection of returned cores for order fulfilment. The functional model provides a functional diagram that contains the activity and attributes for the succeeding models. In level 1, clustering algorithm categorises the returned cores into several clusters using quality, cost, and some other attributes. The algorithm creates an attribute for each returned product to describe its condition. The inventory disposition heuristic algorithm in level 2 categorises returned cores into several quality levels to dispose them to specific recovery and distribution channels. In level 2, the technique for order of preference by similarity to ideal solution (TOPSIS) method provides a prioritised list of returned cores based on condition, age bins, and active failure rate criteria. The matching algorithm in production planning heuristic algorithm selects a returned core from the prioritised returned cores list for order fulfilment. Finally, in level 3, the executable system develops a dashboard that presents the output of the inventory disposition algorithm and incorporates a graphical user interface (GUI) to assist the user in the returned cores selection process.

Figure 4 Proposed DSS for inventory disposition and production planning (see online version for colours)



3.1.1 Cost calculation

The cost metrics play a crucial role in deciding the inventory disposition, order fulfilment, and selling price of returned cores. Therefore, at the time of core acquisition, returned cores' fair market value (FMV) (F_i), age, and total acquisition of cost of all on-hand cores are taken as inputs for calculating the adjusted fair market (F_i') value (F_i' is a dynamic attribute as it considers the current date during its value calculation) for the returned cores and competitive selling price (S_i) for the recovered products. The cost attributes are calculated using the following equations (Kalfayan and Patterson, 2008):

$$FR_i = \frac{F_i}{\sum_{i=1}^{S} F_i} \tag{1}$$

$$A_i = T - B_i \tag{2}$$

$$AC_i = FR_i \times TC \tag{3}$$

$$DR_i = \frac{\sum_{i=1}^{S} AC_i - \sum_{i=1}^{S} RV_i}{A_i} \tag{4}$$

$$F_i^c = \max\left(0, F_i - \left(A_i \times DR_i\right)\right) \tag{5}$$

$$F_i^{'} = F_i^C + \sum_{j=1}^{R_i} RC_{ij} \tag{6}$$

$$S_i = F_i^{'} + \sum_{j=1}^{N_i} NC_{ij} + \left(F_i^{'} \times \alpha\right) \tag{7}$$

Notations

S	available returned products
R_i	number of parts replaced at customer sites for i^{th} product $\forall i = 1 \dots S$
N_i	number of new parts added for order fulfilment for i^{th} product $\forall i = 1 \dots S$
F_i	FMV of i^{th} product $\forall i = 1 \dots S$
TC	total acquisition cost
$F_i^{'}$	adjusted FMV of i^{th} product $\forall i = 1 \dots S$
F_i^C	FMV of i^{th} product on current date $\forall i = 1 \dots S$
FR_i	FMV rate of i^{th} product $\forall i = 1 \dots S$
AC_i	acquisition cost of i^{th} product $\forall i = 1 \dots S$
RV_i	residual value of i^{th} product $\forall i = 1 \dots S$
DR_i	depreciation rate of i^{th} product $\forall i = 1 \dots S$
RC_{ij}	replaced parts' cost of i^{th} product for j^{th} part $\forall i = 1 \dots S, j = 1 \dots N_i$
NC_{ij}	new parts' cost of i^{th} product for j^{th} part $\forall i = 1 \dots S, j = 1 \dots N_i$
A_i	age of i^{th} machine in days $\forall i = 1 \dots S$
B_i	build date of i^{th} product $\forall i = 1 \dots S$
T	current date in $YYYY - MM - DD$ format
S_i	selling price of i^{th} product $\forall i = 1 \dots S$
α	profit margin.

Equation (1) calculates the FMV rate (FR) for the product as a function of FMVs (F) for the cores. Equation (2) calculates the age of the product (in days). Equation (3) calculates the acquisition cost of the product. Equation (4) calculates the depreciation rate. The current FMV and the adjusted FMV of the product are represented by equations (5) and (6), respectively. Equation (7) calculates the final selling price for the product. The cost metrics of the on-hand returned cores are taken into consideration when the succeeding steps of the proposed model are developed.

3.1.2 Rule-based clustering algorithm

The rule-based clustering algorithms classify the returned products into three different clusters to guide them into the inventory locations (L): intermediate consumption (IC), short-term consumption (STC) and long-term consumption (LTC). The algorithm uses the attributes: age, expected conversation cost, waiting time, features count, FMV, replaced parts quantity of the returned cores, and visual and quality inspections test results. The returned cores are tracked by their serial identification numbers. While developing clusters, it is also important to take the business (strategic) goal into consideration. To form a cluster, higher values of some attributes and lower values of some other attributes may be preferred. Thus, two sets of cluster algorithms are proposed. In one set (cluster algorithm 1), those attributes of returned cores where higher values are preferred are considered, and in another set (cluster algorithm 2), those attributes of returned cores where lower values are preferred are considered. Finally, a rule-based classification rule combines the outputs of two sets of cluster algorithms along with the 'visual and quality inspections' attribute and proposes the inventory disposition decision. The steps of the algorithm are summarised as follows:

Step 1 Develop clusters of returned products based on their attributes to categorise them into three clusters

- Cluster algorithm 1 considers waiting time, features count, FMV, and replaced parts quantity to create three clusters.
- Cluster algorithm 2 considers age and expected conversion cost to create three clusters.

Step 2 Apply rule-based classification algorithm to combine the outputs of the two sets of cluster algorithms along with the 'visual and quality inspections' attribute and guide them into the inventory locations.

The average silhouette index (SI_i) is a method of interpretation and validation of the data clusters. SI_i can be applied for evaluation of clustering validity, as well as to decide how sound the number of selected clusters by Kaufman and Rousseeuw (1990). SI_i can be defined as:

$$SI_i = \frac{a_i - b_i}{\max\{a_i, b_i\}} \tag{8}$$

where a_i is average dissimilarity of i^{th} object to all other objects in the same cluster, and b_i is the minimum of average dissimilarity of i^{th} object to all objects in another cluster (in the closest cluster). It follows the formula $-1 \le SI_i \le 1$ and if SI_i value is close to 1, it means that the sample is 'well-clustered' and assigned to an appropriate cluster. Therefore, average SI_i is considered as the performance measure for the data clusters. The following rule guides the returned products into the inventory locations.

- IC: Low quality, low recovery cost, high waiting time, and high FMV of returned machines.
- STC: High quality, high recovery cost, low waiting time, and low FMV of returned machines.
- LTC: Rest of the returned products.

3.1.3 Failure rate analysis

While using returned cores for customer order fulfilment, knowledge regarding their durability is crucial. Durability of each machine type is calculated using the LCU attributes, namely product build date, repair occurrence, repair date, total number of products of that machine type and it is named as average active-failure rate (F_{ij}). Usually, failure-rate of a product is calculated by dividing the total number of repairs by the total number of active products. Whereas, F_{ij} takes into account the active time of each product while calculating failure rate. This active time helps in quantifying the durability of a product in the long run. The age of a product is calculated dynamically by subtracting a product's build date from the current date. As shown in Figure 5, for each machine type, considering the age (in years) of products the data are split into age bins. For each age bin and machine type, F_{ij} is calculated using the following equations:

$$N = \sum_{i=1}^{I} \sum_{j=1}^{J} M_{ij} \tag{9}$$

$$R = \sum_{i=1}^{I} \sum_{j=1}^{J} P_{ij} \tag{10}$$

$$A_{kij} = T - B_{kij} \text{ for } k = 1 \ldots M_{ij}, i = 1 \ldots I, j = 1 \ldots J \tag{11}$$

$$Y_{kij} = \frac{A_{kij}}{365} \text{ for } k = 1 \ldots M_{ij}, i = 1 \ldots I, j = 1 \ldots J \tag{12}$$

$$MY_{ij} = \frac{\sum_{k=1}^{M_{ij}} Y_{kij}}{M_{ij}} \text{ for } i = 1 \ldots I, j = 1 \ldots J \tag{13}$$

$$F_{ij} = \frac{P_{ij}}{M_{ij} \times MY_{ij}} \times 100 \text{ for } i = 1 \ldots I, j = 1 \ldots J \tag{14}$$

$$F_j = \frac{\sum_{i=1}^{I} F_{ij}}{I} \text{ for } j = 1 \ldots J \tag{15}$$

Notations

N total number of active products

R total number of repairs

I total number of machine types (types of products) (1 bin = 365 days)

J number of age bins (1 bin = 365 days)

T current date in $YYYY - MM - DD$ format

M_{ij} number of active products in j^{th} bin for i^{th} machine type $\forall i = 1\ldots\text{I}, j = 1\ldots J$

P_{ij} number of repairs of j^{th} bin for i^{th} machine type $\forall i = 1\ldots\text{I}, j = 1\ldots J$

F_{ij} average active-failure rate of j^{th} bin for i^{th} machine type $\forall i = 1\ldots\text{I}, j = 1\ldots J$

F_j average active-failure rate of j^{th} bin for all machine types $j = 1\ldots J$

Y_{kij} machine-year (age of a product in years) of k^{th} product in j^{th} bin for i^{th} machine type $\forall k = 1\ldots M_{ij}, i = 1\ldots I, j = 1\ldots J$

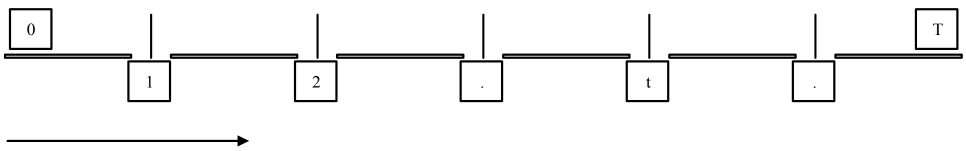
MY_{ij} average machine-year of j^{th} bin for i^{th} machine type $\forall i = 1\ldots\text{I}, j = 1\ldots J$

A_{kij} age in days of k^{th} product in j^{th} bin for i^{th} machine type $\forall k = 1\ldots M_{ij}, i = 1\ldots I, j = 1\ldots J$

B_{kij} build date of k^{th} product in j^{th} bin for i^{th} machine type $\forall k = 1\ldots M_{ij}, i = 1\ldots S, j = 1\ldots J$.

Equation (9) calculates the total number of active products. Equation (10) calculates the total number of repairs. Equation (11) calculates the age of the product. Equation (12) calculates the number of years for the product in the bin, and provides the age of the machine in years. Equation (13) calculates the average machine-year of the bin. Equation (14) calculates the average active failure rate of the bin for the machine. The higher the value of F_{ij}, the lower the durability or longevity of the j^{th} age bin for the i^{th} machine type and vice versa. The F_{ij} attribute is considered in the order prioritisation tool to prioritise the returned cores. Equation (15) calculates the average active failure rate of the bin for all machines.

Figure 5 Age bins for failure rate analysis



3.1.4 Order prioritisation tool

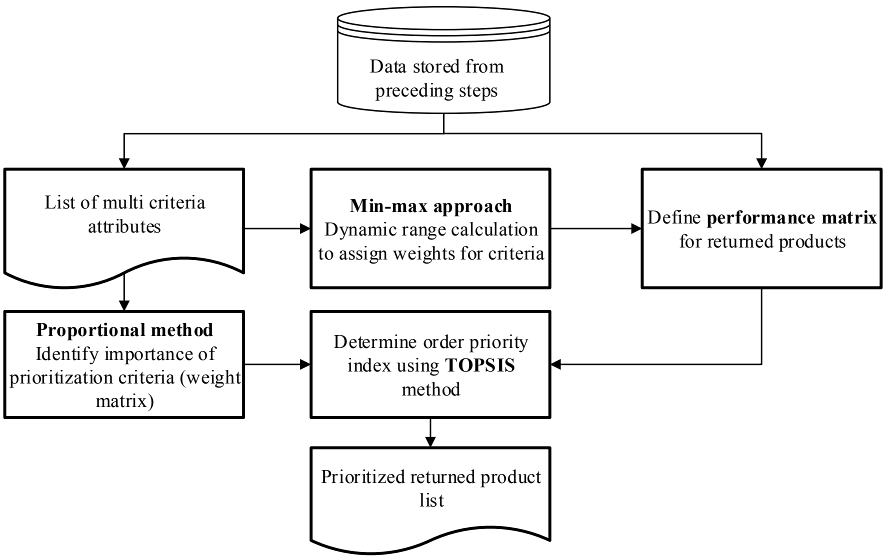
The order prioritisation tool prioritises the returned cores based on the inventory location (L) (output of the rule-based clustering model), active failure rate (F_{ij}) and age bin (J) attributes. Based on the number of available returned cores, a min-max approach is applied to calculate the dynamic weights for each criterion. For quantitative types of data, minimum and maximum values are identified for a particular criterion for all the available returned cores during that time. Then, the dynamic range between the maximum and minimum values is divided into nine categories and each category receives a weight between 1 and 9, where 9 is the highest and 1 is the lowest weight. For qualitative types of data, weights are assigned based on experts' opinions between 1 and 9, where 9 is the highest weight and 1 is the lowest weight. The performance matrix assigns weights for all the criteria of all the available returned cores using the dynamic weight category calculated by min-max approach. It is noted that every criterion does not have equal importance to prioritise a returned core. Thus, the importance of the prioritisation criteria is identified using a proportional method, a pairwise comparison approach between two criteria. In this method, the proportions of all pairs are included in a matrix, which is named as proportional matrix where $a_{lm} + a_{ml} = 1$ and $0 \leq a_{lm}, a_{ml} \leq 1$, and the diagonal elements are zero (Aldian and Taylor, 2005). The proportional matrix and relative weights for the weight matrix are determined using the following two steps:

1 $$\begin{bmatrix} 0 & a_{12} & \cdots & a_{1n} \\ 1-a_{12} & 0 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1-a_{1n} & 1-a_{2n} & \cdots & 0 \end{bmatrix} = \begin{bmatrix} 0 & b_{12} & \cdots & b_{1n} \\ b_{12} & 0 & \cdots & b_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ b_{n1} & b_{n2} & \cdots & 0 \end{bmatrix}$$

2 $$w_l = \frac{\sum_{m=1}^{n} b_{lm}}{\left(n \times \left(\frac{n-1}{2}\right)\right)}$$

Many approaches, such as analytic hierarchy process (AHP), analytic network process (ANP), and TOPSIS have been applied to assist the decision-making process that involves multiple criteria in various domains. AHP is a top-down approach that does the pair-wise comparison criteria and sub-criteria for organising and analysing complex decisions. However, it cannot handle large data sets. ANP is a more general approach, based on the description of the problem by means of a network instead of a hierarchy as in AHP. ANP is a complex decision-making tool with feedback loop to treat criteria and sub-criteria equally. However, often times, it is too complex to explain its concept and process.

Figure 6 Returned products order prioritisation process



On the other hand, TOPSIS is a well-known multi-criteria decision making (MCDM) technique because it has a simple yet comprehensive computation procedure (Mahdavi et al., 2008; Eraslan and Tandel, 2011). TOPSIS was first proposed by Hwang and Yoon (1981). This method is applicable for qualitative, quantitative, and cost criteria data types (Wijk et al., 2006). TOPSIS method normalises the weight factors to scale values and provides information about the solution robustness. However, it assumes that the criteria are independent of each other (Wang and Wang, 2014). In this study, the multi-attributes are independent in nature. Therefore, TOPSIS method is applied as a MCDM technique to obtain the prioritised indexes for return cores. Figure 6 illustrates the returned products order prioritisation process.

The returned cores' priority indexes are determined using the TOPSIS method that provides positive and negative ideal solutions using geometric distance for multi-criteria decision-making models (Tong et al., 2005; Wijk et al., 2006). The final scores range between 0 (negative ideal solution) and 1 (positive ideal solution). The order priority indexes are obtained using the following TOPSIS steps:

1 Establish the performance matrix

$$\mathbf{D} = \begin{array}{c} \\ A_1 \\ A_2 \\ . \\ A_m \end{array} \begin{array}{c} \begin{array}{ccccc} X_1 & X_2 & . & . & X_n \end{array} \\ \begin{bmatrix} x_{11} & x_{12} & . & . & x_{1n} \\ x_{12} & x_{22} & . & . & x_{2n} \\ . & . & . & . & . \\ x_{m1} & x_{m2} & . & . & x_{mn} \end{bmatrix} \end{array} \tag{16}$$

2 Normalise performance matrix

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{17}$$

3 Multiply performance matrix with its associated weights from weight matrix

$$\mathbf{V} = \begin{bmatrix} w_1 r_{11} & w_2 r_{12} & . & . & w_n r_{1n} \\ w_1 r_{21} & w_2 r_{22} & . & . & w_n r_{2n} \\ . & . & . & . & . \\ w_1 r_{m1} & w_2 r_{m1} & . & . & w_n r_{mn} \end{bmatrix} = \begin{bmatrix} v_{11} & v_{12} & . & . & v_{1n} \\ v_{21} & v_{22} & . & . & v_{2n} \\ . & . & . & . & . \\ v_{m1} & v_{m1} & . & . & vr_{mn} \end{bmatrix} \tag{18}$$

4 Determine ideal and negative ideal solutions

$$V^+ = \left\{ \left(\max v_{ij} \middle| j \in J \right) or \left(\min v_{ij} \middle| j \in J' \right), i = 1, 2, \cdots, m \right\} = \left\{ v_1^+, v_2^+, \cdots, v_n^+ \right\} \tag{19}$$

$$V^- = \left\{ \left(\min v_{ij} \middle| j \in J \right) or \left(\max v_{ij} \middle| j \in J' \right), i = 1, 2, \cdots, m \right\} = \left\{ v_1^-, v_2^-, \cdots, v_n^- \right\} \tag{20}$$

where

$$\mathbf{J} = \left\{ j = 1, 2, \cdots, n \middle| v_{ij}, \textit{a large response is desired} \right\}$$

$$\mathbf{J}' = \left\{ j = 1, 2, \cdots, n \middle| v_{ij}, \textit{a small response is desired} \right\}$$

5 Calculate separation measures

$$S_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^+\right)^2} \quad (21)$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)^2} \quad (22)$$

6 Calculate relative closeness to ideal solution and rank returned cores arranging them according to the descending order of the relative closeness values

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-} \quad (23)$$

Notations

n total number of criteria

a_{lm} importance of l^{th} criterion compared with m^{th} criterion $\forall m = 1 \ldots n$, $l = 1 \ldots n$

b_{lm} proportional weight of l^{th} criterion compared with m^{th} criterion $\forall m = 1 \ldots n$, $l = 1 \ldots n$

w_l weights of l^{th} criterion ($l = 1 \ \forall \ J$, $l = 2 \ \forall \ F_{ij}$, $l = 3 \ \forall \ L$)

u_{lp} dynamic weight l^{th} criterion p^{th} sub-criterion ($l = 1 \ \forall \ J$, $l = 2 \ \forall \ F_{ij}$, $l = 3 \ \forall \ L$, $p = 1 \ldots 9$)

A available returned cores

X criteria relating to returned cores

x_{ij} value of j^{th} criterion for i^{th} returned cores $\forall i = 1 \ldots A$, $j = 1 \ldots X$

r_{ij} normalised performance of i^{th} returned cores with respect to j^{th} criterion $\forall i = 1 \ldots A$, $j = 1 \ldots X$

w_j weight of j^{th} criteria obtained from weight matrix (w_l) $\forall j = l = 1 \ldots X$

v_{ij} weight normalised performance of returned cores with respect to criterion j $\forall i = 1 \ldots A$, $j = 1 \ldots X$

V, V^+, V^- performance matrix, ideal, and negative ideal value sets, respectively

S_i^+, S_i^- separation measures from ideal and negative ideal solutions, respectively $\forall i = 1 \ldots A$

C_i relative closeness ($0 \leq C_i \leq 1$) $\forall i = 1 \ldots A$.

The returned cores are ranked by arranging them according to the descending order of the C_i values obtained from TOPSIS method. The closer C_i moves towards 1, the higher its priority of i^{th} returned cores among the available returned cores (A). Then, the prioritised list of returned cores is used in the matching algorithm for customer order fulfilment. The matching algorithm finds the closely matched returned cores to fulfil customer orders. Considering the user requirements, i.e., machine type, product specifications and budget constraints (*budget* ± x%), the matching algorithm proposes y number of closely matched returned cores from the inventory locations in an order proposed by the prioritisation tool.

4 Experimental results

The proposed DSS framework is implemented in a CLSC business environment of a high-end server manufacturing industry that maintains ATO production philosophy. The industry produces low volume, high value and long life-cycle type mainframe computers (Aqlan et al., 2016). The LCU data management system keeps track of all the sold products and gather information on products' usage and health. The industry follows the waste-driven used products collection process. According to Guide and van Wassenhove (2001), in the waste-driven system firms passively accept all product returns from the waste stream. Moreover, the result of the product returns mandates and policies is a large uncontrolled volume of used products flowing back to the original equipment manufacturers. This is case for the industry under study.

To evaluate the proposed methodology, 54 on-hand returned cores are taken into consideration. The F_i, R_{vi}, and AC_i of the returned cores attributes are used to calculate the $F_i^{'}$ and S_i of i^{th} returned cores. Both K-means and two-step methods are applied to develop the two sets of clustering algorithms. However, average S_i (0.8) of the K-means method out-performs average S_i (0.7) of the two-step method. Thus, the K-means method is taken into consideration for clustering model development. The K-means method proposes two sets of cluster algorithms using the attributes of the 54 on-hand returned cores. Each clustering algorithm splits the 54 returned cores into three clusters. Then, the rule-based classification algorithm guides the returned cores into three inventory locations. Table 3 provides a snapshot of the disposition of on-hand inventories into three inventory locations.

Table 3 Returned products' disposition to inventory locations (L)

Classification	*Product count*
L_{IC}	22
L_{STC}	18
L_{LTC}	14

About 350,000 data records are analysed to calculate the average active-failure rate F_{ij} of all the machine types. Table 4 presents the average active-failure rate of various machines in different age bins. For example, i = 11,241, F_{i5} = 88.19 is calculated for 5th age bin using the number of repairs count P_{i5} = 832, the number of active products M_{i5} = 210, and average machine-year MY_{i5} = 943.42. Higher value of F_{ij} indicates lower durability or longevity of j^{th} age bin for the i^{th} machine type and vice versa. For missing value of F_{ij} at j^{th} age bin for i^{th} machine type, average F_j value of j^{th} age bin is considered while prioritising the returned cores using the order prioritisation tool.

Table 4 F_{ij} of various machines in different age bins (J)

J	F_j	F_{ij}														
		11,111	*11,122*	*33,988*	*11,144*	*11,155*	*77,022*	*11,177*	*11,188*	*52,411*	*11,200*	*91,177*	*11,222*	*11,233*	*11,244*	*94,066*	*11,266*
1	50.83	16.09	2.60	10.71	448.99	271.71	13.10	6.02	22.33	765.73	15.63	182.59	0.00	224.00	0.00	18,976.13	0.00
2	28.38	14.39	2.94	16.49	377.31	1,685.51	25.59	11.48	18.49	1,713.91	31.38	87.74	0.00	0.00	541.74	5,135.19	222.11
3	39.37	12.06	0.70	42.56	18.85	496.60	45.16	26.76	25.39	0.00	0.00	115.76	0.00	0.00	60.77	2,393.32	0.00
4	38.01	15.98	0.90	51.79	27.59	153.76	38.35	0.00	23.56	0.00	0.00	85.37	0.00	0.00	132.78	1,005.08	0.00
5	36.47	16.31	0.60	62.08	25.94	29.23	47.55	0.00	30.16	25.70	0.00	80.01	156.90	0.00	88.19	1,115.92	0.00
6	32.00	17.48	0.67	66.41	32.56	26.40	0.00	0.00	31.55	34.50	0.00	66.81	170.53	11.71	169.82	39.63	225.41
7	31.50	19.21	0.95	57.05	27.94	30.89	0.00	0.00	0.00	40.29	0.00	57.43	165.62	17.55	38.76	41.12	205.51
8	37.65	24.63	1.20	31.46	28.39	44.06	0.00	0.00	0.00	0.00	0.00	77.25	191.19	0.00	201.95	40.76	0.00
9	64.26	362.43	1.17	44.29	32.87	61.88	0.00	0.00	0.00	0.00	0.00	80.95	138.47	0.00	129.54	139.80	11.93
10	52.78	0.00	0.75	32.41	45.21	111.11	0.00	0.00	0.00	0.00	0.00	61.59	258.80	0.00	87.88	123.80	163.27
11	68.95	0.00	1.12	45.18	48.14	85.00	0.00	0.00	0.00	0.00	0.00	62.26	392.41	0.00	214.82	130.43	0.00

The order prioritisation tool incorporates the F_{ij}, J and L attributes in the TOPSIS algorithm. The weight matrix (w_l) for F_{ij}, J and L attributes are 7, 9, and 4, respectively. Table 5 presents the dynamic weight matrix (u_{lp}) of the sub-criteria. Subject matter experts' opinions are taken into consideration while determining the w_l and u_{lp} weight matrices.

As shown in Table 6 the returned cores are ranked by arranging them according to the descending order of the C_i values obtained from TOPSIS method. The closer C_i moves towards 1, the higher its priority of i^{th} returned cores among the available returned cores (A). Then, the prioritised list of returned cores is used in the matching algorithm for customer order fulfilment. The prioritised list of returned cores is validated by the subject matter experts.

Figure 7 shows the user interface of the matching algorithm that stores the outputs in an excel file if returned cores fall within the range of user inputs.

Figure 7 User interface of the matching algorithm (see online version for colours)

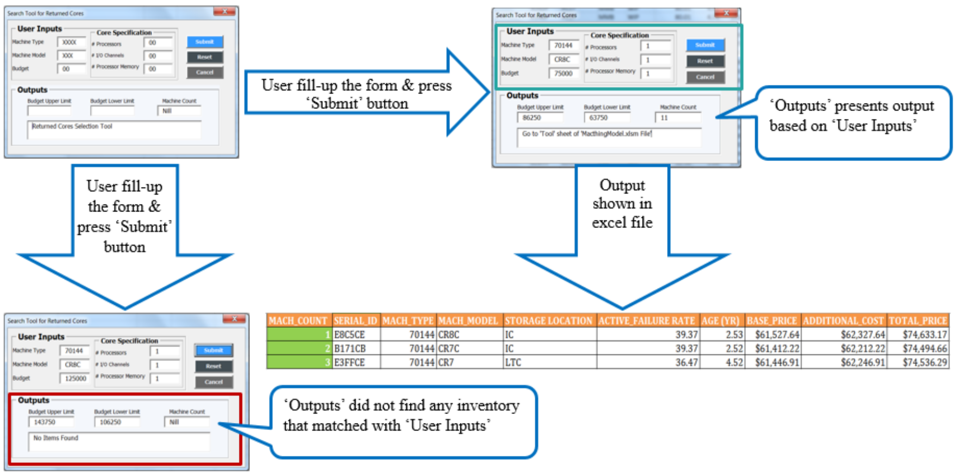


Table 5 Sub-criteria dynamic weight (u_{lp}) matrix

J	u_{1p}	F_{ij}	u_{2p}	L	u_{3p}
J >= 16	9	F_{ij} >= 200	9	L_{IC}	9
14 <= J < 16	8	180 <= F_{ij} < 200	8	L_{STC}	6
12 <= J < 14	7	150 <= F_{ij} < 180	7	L_{LTC}	3
10 <= J <12	6	120 <= F_{ij} < 150	6		
8 <= J <10	5	100 <= F_{ij} < 120	5		
6 <= J <8	4	70 <= F_{ij} < 100	4		
4 <= J <6	3	50 <= F_{ij} < 70	3		
2 <= J <4	2	30 <= F_{ij} < 50	2		
J < 2	1	F_{ij} < 30	1		

The proposed DSS framework demonstrated cost savings by reducing the assembly cycle time, production cost, and uncontrolled accumulation of cores. Table 7 shows the expected savings obtained from the implementation of the framework.

Table 6 Prioritised returned cores using order prioritisation tool

Serial ID#	*M/C type (I)*	*M/C model*	*L*	F_{ij}	*J*	C_i	*Rank*
1425190	94066	P42P	STC	1,000.081	4	0.806	1
1902794	94066	T69T	STC	5,135.192	2	0.786	2
1344931	91177	MMBM	IC	80.007	5	0.498	3
1294214	91177	MTBM	IC	80.007	5	0.498	4
1974356	91177	ILBI	IC	80.007	5	0.498	5

Table 7 Expected savings from the implementation of the DSS framework

Savings	*Scopes*	*Operations*	*Benefits*
Hard savings	Time savings	50% × each inventory manpower: 50% × \$50,000/year × 2	\$50,000/year
		40% × each production manpower: 40% × \$50,000/year × 8	\$160,000/year
Soft savings	30% reduction of the number of accumulated cores		Inventory management
	20% less teardown volume in a quarter		
	25% less usage of new parts in a quarter		Production efficiency
	Energy conservation and waste reduction		Environmental awareness
Total savings			\$210,000/year

5 Conclusions and future directions

This study discussed the characteristics of PrAM processes and proposed a DSS framework for inventory disposition and customer order fulfilment of PrAM for CLSC business model. It was identified that LCU information is helpful in quantifying uncertainties of the PRO within PrAM processes, and availability of LCU information is relatively higher in CLSC business model that has a greater amount of LCU information compared with other business models. Thus, a multi-attribute DSS model was proposed relying on the LCU information for inventory disposition and customer order fulfilment processes of PrAM in CLSC business model. The proposed inventory disposition and selection of returned cores for customer order fulfilment mechanism can minimise assembly cycle time, production cost, and uncontrolled accumulation of cores. It also increases usage of returned cores for order fulfilment, conserves energy, reduces waste, and satisfies customers by competitive selling price. The proposed framework was implemented in a high-end server manufacturing industry that maintains ATO production philosophy and waste-driven PrAM processes. Results from the case study shows that a total cost savings of \$210 K/year can result from implementing the frameworks in server re-manufacturing SCs.

The proposed framework can also be implemented in industries that produce high value and longer life-cycle type products, such as automobiles, transportation vehicles, capital machinery, electrical and electronics equipment. Although CLSC has enormous opportunities from economic, ecologic, and sustainability perspectives, there are certain issues that prevent the industries to operate PRO in an efficient way. Being a relatively new sector, the PrAM processes are still unorganised and evolving compared to the traditional manufacturing operations. Some of the reasons could be inherent uncertainties in quality, quantity, cost, and timing metrics of returned products. In addition, volatility and high risks associated with the product demands in the secondary markets are causing challenges in this potential sector. Finally, CLSC research should consider resource conservation, environment protection, and social development-related attributes to enable environmental sustainability.

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Abbreviations

AHP	Analytic hierarchy process
ANP	Analytic network process
ATO	Assemble-to-order
CLSC	Closed-loop supply chain
DSS	Decision support system
FMV	Fair market value
GUI	Graphical user interface
IC	Intermediate consumption
LCU	Life cycle usage
LTC	Long-term consumption
MCDM	Multi-criteria decision making
MTS	Make-to-order
MTS	Make-to-stock
PPIM	Production planning and inventory management
PRO	Product recovery operations
PrAM	Product acquisition management
RDP	Reverse distribution planning
RL	Reverse logistics
SC	Supply chain
SI	Silhouette index
STC	Short-term consumption
TOPSIS	Technique for order of preference by similarity to ideal solution